

How Does Bank Behaviour Affect Systemic Risk?

An Adaptive Contagion Mapping Methodology (A-CoMap)

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Abstract

This paper presents an adaptive contagion mapping methodology (A-CoMap) to study the interbank network of euro area significant and less-significant institutions' large exposures within the global banking system. We draw on a unique dataset composed by granular bank and exposure level information on 2,800 consolidated banking groups worldwide. The paper documents the spread of contagion by modelling banks and market's reactions to possible distress and default events via solvency and liquidity risks within a multipolar regulatory environment. We show that banks' behavioural responses may either increase or decrease the degree of stress to some specific banks, although on average they tend to mitigate contagion spillovers in the interbank market. We use this methodology to assess the effectiveness in mitigating contagion of an increase in minimum capital requirements relative to an increase in capital buffers as well as to study the too-many-too fail problem by simulating simultaneous multiple defaults and distress events.

Keywords: Network Analysis, Systemic Risk, Contagion Mapping (CoMap), Prudential Regulation, Microstructural model.

JEL Codes: D85, G17, G33, L1.

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”Solvency and liquidity are two conditions that all private organizations must always satisfy. Failure to satisfy either condition, or even coming close to failing, lead to action by others that affect profoundly the status of the organization” (Minsky, 1982: 146)

“Since the crisis, regulation has become multi-polar. But the impact of this regime shift on analytical models and real-world behavior remains largely uncharted territory. This defines a whole new, and exciting, research frontier.” (Haldane, 2015: 397).

1. Introduction

As the global financial crisis shook the role of the interbank market as the central provider of liquidity to the banking system, the post-crisis banking regulation has tried to bring back to normal the system’s behaviours and restore confidence. That lack of confidence among banks led to such behaviours as liquidity hoarding and fire sales, stigmatizing the entire financial system to the point of reshaping the structure of the banking network: a star system with the central bank at the centre. The markets had been too deeply interconnected and opaque for ad-hoc interventions to forestall cascade effects due to contagion and successfully prevent transformation of risks from the idiosyncratic to systemic.

Hence, market confidence is an endogenous self-fulfilling process determining winners and losers in the system as an on-off trigger. Various determinants interacting with binding regulatory requirements may signal to market participants the deterioration of an agent’s solvency and liquidity positions, causing common market reactions.¹ In turn, these behaviours might intensify liquidity problems of distressed banks and also affect non-distressed banks, leading to possible financial market turmoil among the industry peers. This mechanism may spread quickly across agents, sectors and countries via bilateral linkages and the direct and indirect cross-holdings of assets. The understanding of the dynamics of contagion and the channels turning idiosyncratic risk into a systemic crisis is an essential step to set up effective prudential regulations, and thus curb risks to financial stability.

In this vein, the paper focuses on the mechanisms underpinning the collapse of the interbank market by studying the role of confidence in triggering and exacerbating liquidity crisis and

¹ The nature of the signalling may vary considerably and it can be associated with a breach of a prudential requirement, negative earning news or a reputational shock.

fire sales. We construct the actual network of euro area significant and less-significant institutions' large exposures and jointly model banks' behaviours as adaptive agents within the global banking system. Hence, we study the role of regional domestic banks in amplifying contagion and how shocks to the periphery of the network may provoke system-wide losses to the core.

In the survey of simulation methods, Upper (2011) identifies the absence of behavioural foundations as a major shortcoming in this literature. This refers to the observation that in many cases when a counterparty is in distress, counterparties can react by cutting credit lines or not rolling over debt instead of watching idly as has been assumed in many studies. The starting point of our analysis is the Contagion Mapping Model (CoMap) developed in (Covi et al., 2019). It is augmented by modelling banks' reactions to multiple distress events. Rule of thumbs and heuristics to model liquidity hoarding behaviours and fire sales mechanisms are developed upon the funding crisis framework of Kapadia et al. (2013) and the empirical evidence brought about by Acharya and Merrouche (2012). In this respect, we allow the breach of regulatory constraints on capital, liquidity and leverage requirements and capital buffers to play an active role in providing information to market participants and to trigger banks' precautionary actions. This signalling mechanism is thus pre-defined by each bank's regulatory thresholds, and it is endogenously derived since it is the result of the equilibrium behaviours of agents conditional to the initial shock (Freixas and Holthausen, 2005). Consequently, it is not only the distressed bank acting defensively, but other banks are allowed to respond to such a signal and withdraw short-term funding from the distressed entity, turning, potentially, an idiosyncratic shock into a system-wide liquidity crisis. In such a framework, a natural trade-off can be studied between improving the short-term liquidity position to the detriment of a higher likelihood of experiencing credit losses on the long-term part of the exposure lent to the distressed bank. The likelihood of one effect dominating the other depends on the additional amplification channels captured in the model. To this extent, we complement the framework by exploiting limits on the liquidity coverage ratio and leverage ratio, which, if breached, lead to liquidity hoarding and fire sales behaviours (Cont and Schaanning, 2017; Caballero and Simsek, 2013). Moreover, by accounting for interbank market contagion we assess losses due to a bank failure via counterparty credit risk (Eisenberg and Noe, 2001; Espinoza-Vega and Sole', 2010 Rogers and Veraart, 2013). Hence, the modelling of the interplay between credit, liquidity and fire-sale risks jointly with the multi-polar regulatory environment makes our A-CoMap methodology a practical risk

assessment tool providing estimates of an entity's degree of contagion and vulnerability within the euro area banking system.

In achieving this, we construct, and so, rely on the most comprehensive and granular euro area centric dataset covering large exposures among 2.800 consolidated banking groups within the global banking system. In this respect, the analysis is not limited to the interbank network of euro area significant institutions, but includes less-significant institutions to investigate implications for euro area financial stability with a complete within-country network perspective.² This allows us to capture amplification effects arising from the domestic banking system and jointly model them together with international spillovers to study the complex interactions of a domestic network within a multi-country perspective. Next, we move a step forward in terms of analysing credit and liquidity risks since we model loss given default and liquidity shortfall parameters by exploiting granular exposure-specific information on collateral pledged and maturity structure. The network infrastructure is complemented with a heterogeneous set of individual banks' characteristics retrieved and calibrated on ECB proprietary supervisory data, and ultimately parametrized as bank-specific parameters.

We find that non-linearities in contagion spillovers arise, not only from the interaction of various contagion channels as shown by Kok and Montagna (2016), but also from the completeness of the network coverage, in our case by mapping shocks reverberating among and between euro area significant institutions, less significant institutions and non-euro area banks. Next, we find that liquidity hoarding behaviours triggered by a bank's breach of regulatory requirements on average tend to mitigate contagion, although in some cases, depending on the source of the shock, it may also amplify it. Moreover, we find that increasing minimum capital requirements effectively reduce contagion, although the policy effectiveness varies depending on whether the increase is applied to minimum capital requirements or capital buffer requirements, on the size of the capital surcharge, as well as on the intrinsic characteristics of the bank. In the end, the paper show that contagion potential mimicking too-many-too-fail problem is as relevant as much as the too-big-too-fail problem.

² Other studies have exploited the interlinkages among SIs and LSIs but they missed the cross-country perspective (Purh et al. 2012; Craig and von Peter 2014; Craig et al. 2014; Veld and Van Lelyveld 2014; and Bargigli et al. 2015). In fact, they focused exclusively, due to the confidential nature and availability of the data, on the Austrian, German, Dutch and Italian interbank market, respectively.

The remainder of the paper is organized as follows. Section 2 presents the data set and illustrates the topology of the euro area interbank network of large exposures. Section 3 illustrates the Adaptive Contagion Mapping (A-CoMap) methodology, while Section 4 discusses the results and performs sensitivity analysis to the model parameters. Section 5 concludes.

2. Data

The core of our data infrastructure is the large exposures dataset and based on ECB's supervisory COREP C.27-28 templates. Precisely, this dataset tracks all euro area banks' exposures higher than 10% of an institution's eligible capital or larger than EUR 300 million, covering approximately 90% of euro area banks' exposures vis-à-vis credit institutions.³

In this exercise, in order to capture additional contagion channels, previously limited to consolidated groups of euro area significant institutions (SIs) and global banks, we extend the interbank network to including euro area less-significant institutions (LSIs). This has the major advantage in increasing the number of interlinkages and, thus the complexity and volumes of the network by a factor of 7 and 2, respectively. Moreover, by exploiting the 10th largest funding sources template, COREP C.67, we complement the large exposure network with i) euro area banks' funding sources from non-euro area banks and ii) euro area less-significant institutions' funding sources (LSIs) from euro area significant institutions (SIs), which otherwise wouldn't be possible to capture with the large exposures data set alone.⁴ Moreover, the large exposures network does not only capture debt contracts such as loans, but also derivative, equity, and off-balance sheet exposures on a direct and indirect counterparty basis.⁵ This brings a very comprehensive picture of the euro area interbank market within the global banking system.

Table 1 presents the summary statistics of the interbank network of large exposures in Q4 2017. It consists of 11.930 exposures and 2.4 Euro trillion of gross exposures, for a total of 2.830 consolidated banking groups, of which 2.604 and 226 domiciled respectively within and outside the euro area. On the one hand, 25% of the exposures are from euro area SIs,

³ For a detailed overview of the data infrastructure see Covi et al. (2019).

⁴ The reason for this is exposures from significant institutions vis-à-vis less-significant institutions are mostly below the large exposures reporting threshold.

⁵ Off-balance sheet exposures account for a small share of total exposures and since we model only on-balance sheet accountings we exclude them from this analysis.

71.5% from LSIs and 3.5% from non-euro area banks; on the other hand, the number of exposures towards the non-euro area banking sector takes a larger share close to 17.5%, compared to 56% towards SIs, and 26.5% towards LSIs. This is due to the construction of the dataset, since we exploit information from euro area reporting banks, and we lack the coverage of interlinkages among non-euro area banks. This is the reason why we define our analysis as a euro area centric perspective.

Table 1: Interbank Network of Large Exposures

Data Sample	Network	Euro Area			Extra Euro Area		
<i>Entities</i>	Total	Total	SI	LSI	Total	GSIB	REST
Consolidated Banking Groups	2830	2604	101	2503	226	23	203
Counterparties	1721	1520	94	1426	201	23	178
Reporting	2604	2553	101	2452	51	18	33
<i>Number of Exposures</i>							
From	11931	11523	2990	8533	408	250	158
To	11931	9849	6663	3186	2082	1074	1008
<i>Total Exposures Amount (Borrowed)</i>							
Gross Amount	2437	1853	1265	588	584	369	215
- Exemptions	1130	1041	732	309	89	27	62
Gross Amount minus Exemptions	1307	812	533	279	495	342	153
- Credit Risk Mitigations	438	329	159	170	109	87	22
Net Amount	869	483	374	109	386	255	131
<i>Total Exposures Amount (Lent)</i>							
Gross Amount	2437	2310	1650	660	127	94	34
- Exemptions	1130	1110	665	445	20	18	3
Gross Amount minus Exemptions	1307	1200	982	218	107	76	31
- Credit Risk Mitigations	438	401	313	88	37	23	14
Net Amount	869	799	669	130	70	53	17

Note: Amounts are expressed in billions of euros. Outstanding amounts as of Q4 2017. Gross amount minus exemptions is the reference metrics of this study. A threshold of 100.000 Euro 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.

However, in terms of Euro volumes, the picture radically changes. Euro area banks are exposed approximately by 1.85 Euro trillion in gross terms, of which 68% is vis-a-vis SIs. In this respect, 24% of credit exposures are held by non-euro banks, almost the same amount borrowed from euro area LSIs. In net amounts, that is, after deducting exemptions and credit risk mitigations⁶, non-euro area banks captured almost 44% of the counterparty credit risk, more than euro area SIs (43%) and LSIs (13%). To what may concern funding risk, funding sources from non-euro are banks represent only 5% of the total exposure amounts in gross terms, while euro area SIs and LSIs capture respectively 68% and 27% of the total.

⁶ Exemptions refer to the part of exposure exempted from large exposure calculation, while credit risk mitigations refer to the part of exposure that is secured by collateral or a guarantee.

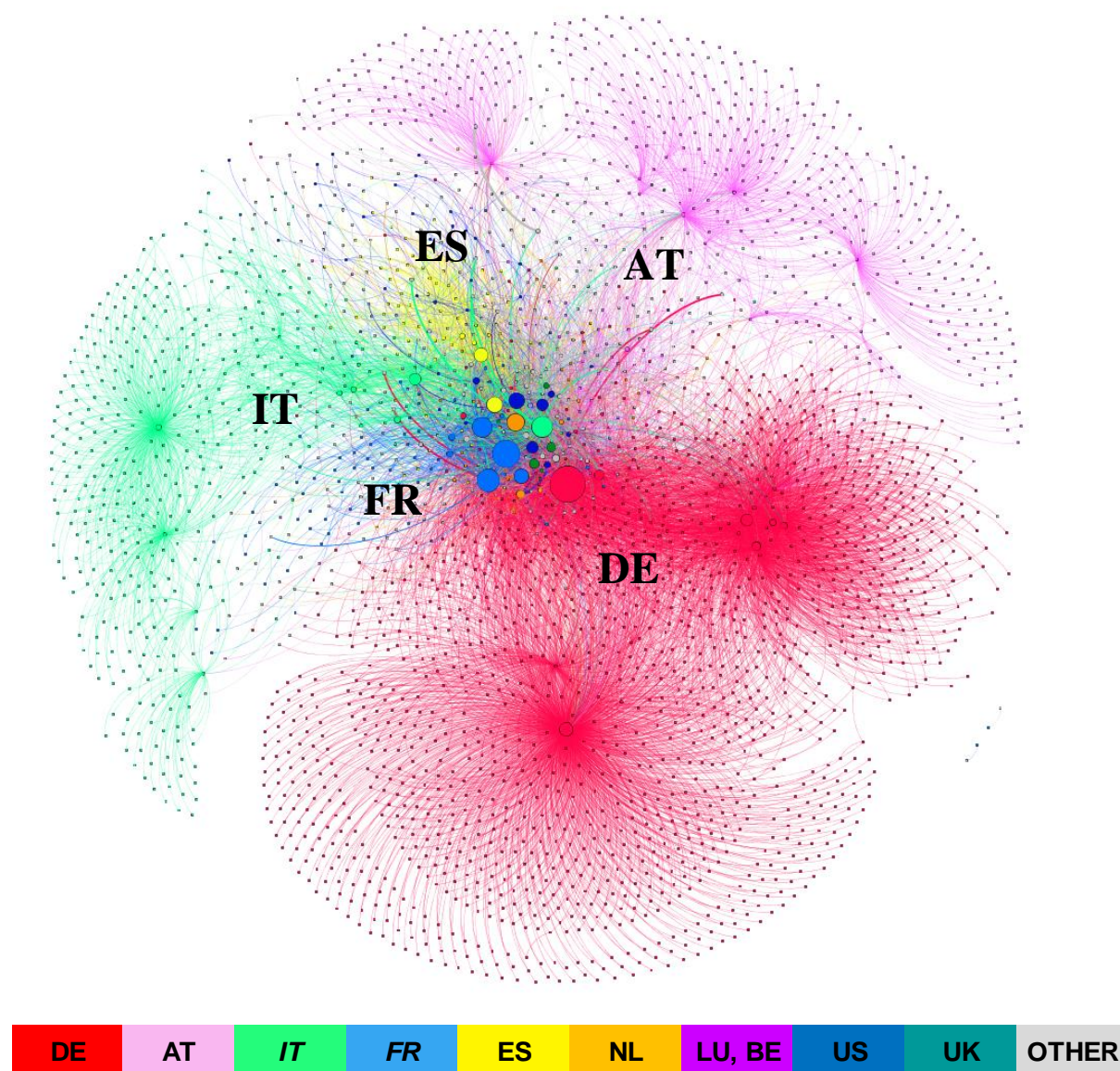
In this respect, *Figure 1* plots the euro area interbank network of large exposures in its entirety. In order to highlight the added value coming from the domestic relationships among significant institutions and less-significant institutions, we decide to assign to the edges the color of the source node, whose size is given by the sum of incoming and outgoing exposures. Therefore, the size of the node tends to over-emphasize euro area banks relative to non-euro area banks since the latter have only few outgoing exposures by construction. Nonetheless, US and UK banks appear to have sizeable shape of the nodes, and they are placed close to the nucleus of the network. This corroborates previous evidence brought in Covi et al. (2019) on the relevance of international spillovers within the euro area interbank network.

Moreover, we can notice how the introduction of LSIs into the network highlights some important patterns for Germany, Italy and Austria. In fact, LSI cooperative and savings banks tend to define the periphery of the network by clustering around one specific entity with who creates an almost standalone network. This central entity, in turn, is the exclusive channel of connection between the periphery and the nucleus of the network. This network is characterized by a low density (0.001), an average path length equal to 3.5 and a diameter of 9.⁷ Overall, we can state that the euro area interbank network of large exposures is based on a clear core-periphery structure.

In the end, the core of our data infrastructure - the network of large exposures - is framed by granular bank and exposure level information retrieved from other supervisory templates allowing us to exploit the relevance of banks' and exposures' heterogeneity in the transmission and degree of contagion. In fact, a detailed picture of banks' balance sheet allows us to more precisely determine the solvency and liquidity conditions of a bank and model its reaction vis-à-vis other banks given respectively its level of capital surplus above minimum capital requirements and its holding of HQLA and non-HQLA assets relative to credit and/or liquidity shocks. In addition, exposure level information on collateralized amounts and maturity structure contributes to clarify banks' relationship among each other given that they are the reflection of counterparty risk.

⁷ Only 0.1% of all possible links are present. Average path length and diameter refer respectively to the average graph-distance between all pairs of nodes and to how far apart are the two most distant nodes.

Figure 1: Euro Area Interbank of Large Exposures



Note: The size of the nodes captures the weighted degree of interconnectedness. The colors of nodes are clustered by country of origin, the thickness of the flows summarizes the value of the exposures in EUR billions. The color of the flows refers to the source of the node's color capturing the lender perspective.
Source: COREP C.27-C.28.

3. Adaptive Contagion Mapping Methodology

3.1 Model Set-up and Behavioral Mechanics

This section describes the augmented balance-sheet based CoMap methodology to including the heuristics and behavioral mechanics of bank and market reactions to counterparty distress and/or default events determining liquidity and credit shocks in the euro area interbank market.

Few studies have investigated the interaction between credit and liquidity risks in a system-wide context via modelling banks' and market's reactions conditional to multiple regulatory events. The key innovation in the modeling framework is thus the behavioral liquidity hoarding component modelled accordingly to a set of heuristics retrieved from empirical studies. This feature leads to a shift to a more organic system architecture that takes into account banks' ability to react to changes in their own solvency and liquidity conditions and respond pro-actively to other banks' changing conditions. Hence, modeling the ability of banks' behavioral responses results in a complex set of equations, which is stock-flow consistent across banks' balance sheets. In addition, a key ingredient and innovation is the modelling of information flows, essential feature defining the sequencing of banks' responses. In this regard, a mixture of heterogeneous and endogenous signals linked to the breach of regulatory thresholds exogenously defining solvency, liquidity and leverage distress and default events, is used to render banks' private information public, which in turn determines banks' actions⁸. Overall, we define six possible events related to the breach of regulatory binding constraints (*Table 2*).

A bank may be considered in *solvency default (i)* if the bank breaches minimum capital requirements also defined default threshold (c_i^{df}), i.e. if the difference between the capital base (c_i) and the sum of experienced losses due to credit and liquidity risks (L_i) is smaller than (c_i^{df}). Next, a bank may be considered into *liquidity default (ii)* when it is not able to fulfill its payment obligations, i.e. if the discounted pool of non-HQLA assets available for sales $(1 - \delta_i)(\theta_i)$ is smaller than the funding shock experienced (τ_i) after deducting the

⁸ In the asymmetric information literature, the signaling of counterparty credit risk or solvency probability is modelled as an exogenous component in Broecker (1990) and Flannery (1996), while as endogenous in Rochet and Tirole (1996), Freixas and Holthausen (2005), and Heider et al. (2015) among others.

amount of HQLA above the LCR requirements⁹. Hence, we assume that the bank may not decrease its pool of HQLA assets below its LCR requirement. This default assumption holds only if the run-off rate of deposits and the haircut of the assets assumed in the LCR given a 30-day distress scenario is consistent with the actual scenario¹⁰. In the sensitivity analysis, this assumption will be relaxed. In the end, a bank may be considered in *leverage default (iii)* when a bank faces a tight binding leverage ratio constraint below 1%.¹¹

These events may take place jointly and the “bank reaction” would imply a default on its bilateral exposures consisting of its counterparties facing losses equal to the unsecured amount of the exposure, thereby recovering only the collateralized part. Moreover, in case the default event takes place directly without passing by a distress situation, the bank would be able to withdraw the short-term funding amount. However no funding withdrawal from other banks is allowed. Therefore a defaulted bank is assumed to have a first-move advantage, it acts before all other banks in the network realizes the sudden event. This implies that the counterparties of the defaulted bank will write-off both the short-term and long-term unsecured part of the exposure. It follows that, \mathcal{Z} is the complete set of all banks in the network, whereas \mathcal{Y} represents the set of banks which face a solvency (i), liquidity (ii) and/or leverage (iii) default condition.

Up to now, we have assumed that banks are privately informed about their short-term solvency, liquidity, and leverage conditions, and this asymmetric information impedes counterparties of a defaulted bank to trigger a bank run before experiencing losses on both their short and long term exposures. This is the case when a large and sudden shock pushes one or more banks directly into default. However, when the size of the shock is not large enough to trigger a default, a bank may still get into temporary distress. In this case, the distressed bank has still the possibility to take recovery actions in order to reduce its distress level, and at the same time, other banks may reduce their exposures vis-à-vis the distressed

⁹ It is assumed that HQLA assets can be pledged to the central banks in exchange of liquidity. This feature captures the accommodative stance of central banks during period of distress, and allows to mimic the change in network structure towards a star-system as described in Gai et al. (2011).

¹⁰ When the run-off rate of deposits or the haircut applied in the LCR are larger than the actual, our model should over estimate contagion and amplification effects due to funding shocks, vice versa when the LCR scenario is milder than the actual, we should under estimate contagion.

¹¹ The required leverage ratio is meant to make sure that banks get into regulatory monitoring before they actually become insolvent. However, there might be a critical level of leverage ratio for which the bank is actually impaired.

bank. In this regard, we introduce three distress thresholds, respectively targeting solvency, liquidity and leverage requirements.

A bank may be considered in *solvency distress* (iv) if the difference between the capital base (c_i) and the losses incurred (L_i) is smaller than the required minimum capital and buffer requirements, also called distress threshold (c_i^{ds}). This event forces the distress bank to engage in a precautionary withdrawal of short-term funding from other banks in the network. This behavioral dynamic is consistent with Acharya and Merrouche (2012)'s empirical investigation on UK banks' hoarding behaviors during periods of financial distress such as the financial crisis. In this respect, they found that banks with higher funding and solvency risk hoarded more liquidity and they did that for precautionary reasons against potential funding risks so as to build-up a liquidity buffer. Always for precautionary reasons, banks may also hoard liquidity in anticipation of a market breakdown (Heider et al., 2015; Diamond and Rajan, 2011). Moreover, the breach of the required capital buffer imposes on the distressed bank the prohibition to pay out dividends, thus signaling to market participants the distress situation and the increased counterparty risk. Other banks are assumed to respond defensively and so to reduce their exposure vis-à-vis the distressed bank by the short-term amount.¹² This type of triggering event may be interpreted also as a reputational shock or a Stigma. For instance, when a bank is perceived riskier than others, i.e. in distress, a run on the bank may be triggered (Acharya and Merrouche, 2012; Armantier et al. 2010). The intuition behind this market reaction is that banks are forward-looking and prefer to limit the amount of losses they will face in case of a counterparty default. The combined sequence of events may improve (deteriorate) the bank's liquidity position depending on whether the bank is a short-term net liquidity provider (taker) in the network. Ultimately, \mathcal{D} represents the set of banks which meet the solvency distress condition.

In a different case, a bank may experience a liquidity shock (funding withdrawal) which forces the bank to pledge HQLA assets to the central bank to meet its liquidity needs and thus maintaining its business portfolio. If the shock is big enough to exhaust the HQLA liquidity buffer (γ_i) so that the liquidity coverage ratio becomes binding, the bank is considered to being in *liquidity distress* (v). A liquidity distressed bank is assumed to not roll-over a share

¹² Another common behaviour in the interbank market in response to a higher counterparty risk is the increase in the borrowing rate at which the distress bank refinances itself from the other banks.

of the short-term provision of interbank loans in order to replenish the HQLA buffer up to a safe zone here defined as 110% of the liquidity coverage ratio.¹³ In this situation, no market reaction is supposed to take place since the bank is neither liquidity constrained nor in solvency distress. However, in case the combined liquidity amount recovered from the HQLA buffer and the funding withdrawal is not enough to cover the funding shortfall, the bank is allowed to sell non-HQLA financial assets at a discount rate (fire sales) to fulfill the incoming liquidity needs. \mathcal{R} represents the set of banks which meet the liquidity distress condition.

Table 2: Mechanisms of Interbank Contagion

Events	Trigger	Set	Bank Reaction	Market Reaction
1 Solvency Default	$c_i - L_i < c_i^{df}$			
2 Liquidity Default	$(1 - \delta_i) \theta_i < \max\{0, (\tau_i - \gamma_i)\}$	$\mathcal{Y} \subset \mathcal{Z}$	Default on Bilateral Exposures ST Funding Withdrawal	Recovery Secured Amount
3 Leverage Default	$LR_i: \frac{c_i - L_i}{a_i} < 1\%$			
4 Solvency Distress	$c_i^{df} < c_i - L_i < c_i^{ds}$	$\mathcal{D} \subset \mathcal{Z}$	ST Funding Withdrawal	ST Funding Withdrawal
5 Liquidity Distress	$\gamma_i \leq 0$	$\mathcal{R} \subset \mathcal{Z}$	ST Funding Withdrawal	/
6 Leverage Distress	$LR_i: \frac{c_i - L_i}{a_i} < 3\%$	$\mathcal{L} \subset \mathcal{Z}$	Deleveraging Process	ST Funding Withdrawal

Note: ST funding withdrawal refers to the short-term exposure amount. HQLA buffer refers to the surplus of HQLA assets above the minimum LCR ratio. Pool of assets refers to the amount of non-HQLA financial assets available for sale.

By experiencing fire sale losses on the trading book or credit losses on bilateral exposures due to a counterparty failure, the capital base (c_i) may reduce to the point that the leverage ratio becomes binding. In such a case, the bank is considered to being in *leverage distress* (vi). A leverage distressed bank is assumed to sell HQLA assets at market price or to withdraw the short-term exposures in order to reduce its volumes of operations (deleveraging process) to the point that the leverage ratio becomes unbinding. However, this event signals to market participants and industry peers an increased counterparty risk (as previously motivated), thereby triggering a market reaction of short-term funding withdrawal. If the bank has already exhausted the HQLA liquidity buffer and is facing funding withdrawal, the

¹³ The liquidity coverage ratio becomes binding when the ratio between the HQLA buffer and net funding outflows is below 100%.

bank is likely to end-up in a deleveraging spiral of non-HQLA assets leading to a default. \mathcal{L} represents the set of banks which meet the leverage distress condition.

Overall, all distress and default events can take place simultaneously. Among distress events, market reactions in solvency and leverage distress are not additive since they suppose the very same action. This is true also for all default events. On the contrary, bank reactions as in the case of a liquidity and leverage distress or a solvency and leverage distress may be additive, while a solvency and liquidity distress is not, since the complete withdrawal of short-term funding in the former state overrules the partial withdrawn of short-term funding in the latter state.

The outcome of such individualistic behaviors among distressed and non-distressed banks aimed at improving a bank's own short-term position may lead to a bad equilibrium. In fact, a liquidity distress bank may face funding withdrawals because other banks may turn into a liquidity distress situation given the initial reaction of the distressed bank. Therefore, we are able to capture how an idiosyncratic shock may become a system-wide crisis via market reaction or because a bank reaction may trigger autonomously another distress event.

In this regard, a key feature of the modelling framework is the sequencing of banks' actions and responses conditional to the set of information available to bank prior acting. Hence, it follows the mapping of the flows of funds among banks' balance sheet according to the set of rules described in **Table 2**.

3.2 Balance Sheet Dynamics: *Credit Losses*

The initial set-up of the model is based on the CoMap methodology developed in Covi et al. (2019) starting with the following stylized balance sheet identity of *bank i*:

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

where x_{ij}^k stands for *bank i*'s claims of (instrument) type k on *bank j*, a_i stands for other assets, c_i stands for capital, b_i is 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, *bank j*'s claims on *bank i*. Moreover, \mathcal{Z} is the complete set of all banks in the network, whereas \mathcal{Y} represents the set of banks which face a solvency, liquidity or leverage default condition.

Banks that experience at least one type of failure (insolvency, illiquidity or leverage-driven), they are assumed to default on all their obligations to other banks. As a result, creditor banks incur losses on their claims to varying degrees depending on the nature and counterparty of their exposures. We capture this heterogeneity by incorporating exposure-specific loss-given-default rates¹⁴. In response to a subset ($\mathcal{Y} \subset \mathcal{Z}$) of banks 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 .

$$\sum_{j \in \mathcal{Y}} \sum_k \lambda_{ij}^k x_{ij}^k \quad \forall i \in \mathcal{Z}, \text{ where } \lambda_{ij}^k \in [0,1] \quad (2)$$

To simplify notation, we aggregate all exposures across types (k) for any given pair of counterparties while using the average loss-given-default rate weighted by the share of each exposure types between them.

$$\text{Credit Losses: } \sum_{j \in \mathcal{Y}} \lambda_{ij} x_{ij}, \quad \forall i \in \mathcal{Z}, \quad \text{where } \lambda_{ij} \in [0,1] \quad (3)$$

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

$$\sum_{j \in \mathcal{Z} \setminus \mathcal{Y}} x_{ij} + [a_i + \sum_{j \in \mathcal{Y}} (1 - \lambda_{ij}) x_{ij}] = [c_i^0 - \sum_{j \in \mathcal{Y}} \lambda_{ij} x_{ij}] + d_i + b_i + \sum_s x_{si}, \quad \forall i \in \mathcal{Z} \quad (4)$$

The recovered portion of the bank's defaulted claims is kept as highly liquid, increasing its HQLA and therefore liquidity surplus, γ_i :

$$\text{Liquidity Surplus: } \gamma_i' = \gamma_i^0 + \sum_{j \in \mathcal{Y}} (1 - \lambda_{ij}) x_{ij} \quad \forall i \in \mathcal{Z} \quad (5)$$

We also track the impact of a *bank h*'s default on its own balance sheet. The collateralized (recovered by the counterparty) portion of *bank h*'s obligations are deducted from its assets, while the uncollateralized portion (written off by the counterparty) is transferred to *bank h*'s other liabilities.

$$\sum_j x_{hj} + [a_h - \sum_s (1 - \lambda_{sh}) x_{sh}] = c_h + d_h + [b_h + \sum_s \lambda_{sh} x_{sh}] \quad \forall h \in \mathcal{Y} \quad (6)$$

Since bank h is potentially subject to other failed banks' defaulting on their obligations, incorporating Equation (4) into Equation (6) leads to:

¹⁴ For the calibration of the model parameters see *Appendix A*.

$$\begin{aligned} \sum_{j \in \mathcal{Z} \setminus \mathcal{Y}} x_{hj} + [a_h + \sum_{j \in \mathcal{Y}} (1 - \lambda_{hj}) x_{hj} - \sum_s (1 - \lambda_{sh}) x_{sh}] &= [c_h - \sum_{j \in \mathcal{Y}} \lambda_{hj} x_{hj}] + d_h + \\ [b_h + \sum_s \lambda_{sh} x_{sh}] &\quad \forall h \in \mathcal{Y} \end{aligned} \quad (7)$$

Banks that are under liquidity or leverage distress starting with the knowledge of their liquidity (η_i^0) or deleveraging (φ_i^0) needs update their information set based on changing conditions (credit default and funding withdrawals) within the same round. Therefore, their optimization decision and the ultimate impact on their balance sheets are formulated upon culmination of the default and withdrawal events.

Hence, we define two new variables these banks monitor as part of their information set. Banks under liquidity distress, $\mathcal{R} \subset \mathcal{Z}$, update their liquidity replenishment needs, η_i , as the recovered assets kept in highly liquid form reduces the amount needed to bring their HQLA to a more desirable level.

$$\text{Liquidity Needs: } \eta'_i = \eta_i^0 - \sum_{j \in \mathcal{Y}} (1 - \lambda_{ij}) x_{ij} \quad \forall i \in \mathcal{R} \quad (8)$$

As for the banks under leverage-related distress $\mathcal{L} \subset \mathcal{Z}$, there are two offsetting effects on their deleveraging needs. While the decline in the capital base due to losses associated with the credit default further deteriorates their leverage ratio, the reduction in their total assets due to writing-off of a portion of the credit exposure improves the ratio. Overall, their deleveraging needs φ_i , in terms of the amount of assets they would need to wind down can be expressed as:

$$\text{Deleveraging Needs: } \varphi'_i = \varphi_i^0 - \sum_{j \in \mathcal{Y}} \lambda_{ij} x_{ij} + 1/\hat{\mu} (\sum_{j \in \mathcal{Y}} \lambda_{ij} x_{ij}) \quad \forall i \in \mathcal{L} \quad (9)$$

Where $\hat{\mu}$ represents the leverage ratio *bank i* aims to achieve by deleveraging. For a *bank h* under leverage distress that also defaults on its credit obligations, its deleveraging needs are further reduced by the collateral that was recovered by its counterparties and hence:

$$\text{Deleveraging Needs: } \varphi'_h = \varphi_h^0 + \left(1/\hat{\mu} - 1\right) (\sum_{j \in \mathcal{Y}} \lambda_{hj} x_{hj}) - \sum_s (1 - \lambda_{sh}) x_{sh} \quad \forall h \in \mathcal{L} \cap \mathcal{Y} \quad (10)$$

3.4 Balance Sheet Dynamics: Funding Withdrawal

Banks that experience at least one type of failure (insolvency, illiquidity or leverage-driven) also withdraw all short-term funding from their counterparties. Moreover, banks that are in solvency distress (breach of capital buffer) \mathcal{D} , partake in precautionary withdrawal of short-term funding. We thus introduce an exposure-specific funding shortfall rate, ρ_{ji} , reflecting the maturity structure of the wholesale funding *bank i* receives from *bank j*. Then, the funding

shortfall *bank i* faces when a subset of banks $(\mathcal{Y} \cup \mathcal{D}) \subset \mathcal{Z}$, withdraw funding can be expressed:

$$\text{Funding Withdrawals: } \sum_{j \in (\mathcal{Y} \cup \mathcal{D})} \rho_{ji} x_{ji}, \quad \forall i \in \mathcal{Z}, \text{ where } \rho_{ji} \in [0,1] \quad (11)$$

Since multiple funding withdrawal calls are made in this framework including those that are based on optimization by banks under liquidity and leverage distress, banks consider total funding shortfalls through culmination of events:

$$\text{Funding Shortfalls: } \tau'_i = \tau_i^0 + \sum_{j \in (\mathcal{Y} \cup \mathcal{D})} \rho_{ji} x_{ji}, \quad \forall i \in \mathcal{Z}, \text{ where } \rho_{ji} \in [0,1] \quad (12)$$

For banks under liquidity distress, the funding shortfalls add to their liquidity replenishment needs:

$$\text{Liquidity Needs: } \eta'_i = \eta_i + \sum_{j \in (\mathcal{Y} \cup \mathcal{D})} \rho_{ji} x_{ji} \quad \forall i \in \mathcal{R} \quad (13)$$

On the flipside, these funds contribute towards liquidity surplus of the withdrawing banks:

$$\text{Liquidity Surplus: } \gamma'_h = \gamma_h + \sum_{i \in \mathcal{Z}} \rho_{hi} x_{hi} \quad \forall h \in (\mathcal{Y} \cup \mathcal{D}) \quad (14)$$

Moreover, if these banks happen to be simultaneously under liquidity distress, they reduce their liquidity replenishment needs:

$$\text{Liquidity Needs: } \eta''_h = \eta'_h - \sum_{i \in \mathcal{Z}} \rho_{hi} x_{hi} \quad \forall h \in \mathcal{R} \cap (\mathcal{Y} \cup \mathcal{D}) \quad (15)$$

Until now, other banks played a passive role as distressed banks defaulted on their obligations and/or withdrew funding from them. It is assumed that banks have some, albeit limited, foresight or given asymmetric information they adopt precautionary hoardings. They pre-emptively withdraw short term funding (or do not rollover funding) from banks that are under solvency or leverage distress $(\mathcal{D} \cup \mathcal{L}) \subset \mathcal{Z}$. Then, the funding shortfall faced by *bank i* when all banks withdraw funding from it can be expressed:

$$\sum_{j \in \mathcal{Z}} \rho_{ji} x_{ji}, \quad \forall i \in (\mathcal{D} \cup \mathcal{L}), \text{ where } \rho_{ji} \in [0,1] \quad (16)$$

This increases their total funding shortfall as:

$$\text{Funding Shortfalls: } \tau''_i = \tau'_i + \sum_{j \in \mathcal{Z}} \rho_{ji} x_{ji}, \quad \forall i \in (\mathcal{D} \cup \mathcal{L}) \not\in (\mathcal{Y} \cup \mathcal{D}) \quad (17)$$

$$\text{where } \tau'_i = \tau_i^0 + \sum_{j \in (\mathcal{Y} \cup \mathcal{D})} \rho_{ji} x_{ji}, \quad \forall i \in \mathcal{Z}, \quad \rho_{ji} \in [0,1]$$

Also, adding to the replenishment needs, if these banks are simultaneously facing liquidity distress:

$$\text{Liquidity Needs: } \eta_i^{iv} = \eta_i''' + \sum_{j \in \mathcal{Z}} \rho_{ji} x_{ji} \quad \forall i \in \mathcal{R} \cap (\mathcal{D} \cup \mathcal{L}) \quad (18)$$

On the flipside, these funds contribute towards liquidity surplus of the withdrawing banks:

$$\text{Liquidity Surplus: } \gamma_i''' = \gamma_i'' + \sum_{h \in \mathcal{D} \cup \mathcal{L}} \rho_{ih} x_{ih} \quad \forall i \in \mathcal{Z} \quad (19)$$

While decreasing the liquidity replenishment needs:

$$\text{Liquidity Needs: } \eta_i^v = \eta_i^{iv} - \sum_{h \in \mathcal{D} \cup \mathcal{L}} \rho_{ih} x_{ih} \quad \forall i \in \mathcal{R} \quad (20)$$

Having updated their information sets based on the default and distress related shocks, next, banks that are under leverage distress make an optimizing decision to bring their leverage to an acceptable level. In this setup, we assume that deleveraging happens through reducing the balance sheet, rather than raising capital. Effectively, banks trim their assets by prioritizing: (first) using liquidity surplus; (second) selling off HQLA pledged to the central bank; and (third) withdrawing funding from their large exposure counterparts, all while reducing their liabilities by equal amounts. The first and second choices affect the internal balance sheet dynamics of a bank while the third option involves a decision that will impact the liquidity, and potentially solvency of other banks. In order to derive the leveraged bank's optimal decision, we define a new variable that captures the aggregate of remaining short-term claims from all counterparts that *bank i* can potentially withdraw:

$$\text{Remaining Short Term Claims: } \pi_i = \sum_{j \in \mathcal{Z}} \rho_{ij} x_{ij} \quad \forall i \in \mathcal{L} \quad (21)$$

The other remaining variable needed for the optimization decision relates to the amount of HQLA pledged to the central bank for funding needs defined as β_i for *bank i*. Then, *bank i* determines the usage of the three options mentioned above as a function of its total funding shortfall, deleveraging needs, liquidity surplus, pledged HQLA to the central bank, and potentially withdrawable counterparty claims. Starting with the liquidity surplus:

$$\gamma_i^{iv} = \begin{cases} \max\{0, \gamma_i''' - \min\{(\beta_i^0 - \varphi_i'), \tau_i''\}\}, & \text{if } \tau_i'' \leq \beta_i^0 + \pi_i \\ 0, & \text{otherwise} \end{cases} \quad \forall i \in \mathcal{L} \quad (22)$$

Then, the change in the amount of HQLA pledged to the central bank is determined as follows:

$$\beta_i' = \begin{cases} \max\{0, \beta_i^0 + \tau_i'' - \varphi_i'\}, & \text{if } \tau_i'' \leq \beta_i^0 + \pi_i \\ \max\{0, \beta_i^0 + \gamma_i^{iv} + \pi_i - \varphi_i'\}, & \text{otherwise} \end{cases} \quad \forall i \in \mathcal{L} \quad (23)$$

Finally, *bank i* determines its withdrawal rate, ω_i , the portion of short-term claims that it finds optimal to withdraw equally from each counterparty:

$$\omega_i = \begin{cases} \min \left\{ 1, \max \left\{ 0, \frac{\max\{\varphi'_i - \beta_i^0, \tau''_i\} - \gamma''_i}{\pi_i} \right\} \right\}, & \text{if } \tau''_i \leq \beta_i^0 + \pi_i \\ 1, & \text{otherwise} \end{cases} \quad \forall i \in \mathcal{L} \quad (24)$$

As a result, the total funding shortfall of other banks, *bank j*, that face withdrawals from leverage-distressed banks increase proportional to the withdrawal rate:

$$\tau'''_j = \tau''_j + \sum_{i \in \mathcal{L}} \omega_i \rho_{ij} x_{ij}, \quad \forall j \in \mathcal{Z} \quad (25)$$

For liquidity-distressed banks, their replenishment needs would also increase similarly:

$$\eta^{v'}_j = \eta^v_j + \sum_{i \in \mathcal{L}} \omega_i \rho_{ij} x_{ij} \quad \forall j \in \mathcal{R} \quad (26)$$

Last in the chain, liquidity-distressed banks face the same set of choices leverage-distressed banks do though their information set differs slightly. Liquidity-distressed banks make their optimal decisions based an updated information set on own replenishment needs, total funding shortfalls, liquidity surplus, pledged HQLA to central bank and potentially withdrawable counterparty claims. The total amount of potentially withdrawable counterparty claims available to *bank i* is updated as follows:

$$\pi_i = \sum_{j \in \mathcal{Z}} \rho_{ij} x_{ij} \quad \forall i \in \mathcal{R} \quad (27)$$

They determine how the liquidity surplus changes in response as follows:

$$\gamma^v_i = \max\{0, \gamma^{v'}_i - \tau'''_i, \gamma^{v'}_i - \tau'''_i + \min\{\eta^{v'}_i, \pi_i\}\} \quad \forall i \in \mathcal{R} \quad (28)$$

Then, the change in the amount of HQLA pledged to the central bank is determined as follows:

$$\beta''_i = \beta'_i + \min\{\tau'''_i, \gamma^{v'}_i + \pi_i\} \quad \forall i \in \mathcal{R} \quad (29)$$

Finally, *bank i* determines its withdrawal rate, ω_i , the portion of short-term claims that it finds optimal to withdraw equally from each counterparty:

$$\omega_i = \min \left\{ 1, \max \left\{ 0, \frac{\eta^{v'}_i}{\pi_i} \right\} \right\} \quad \forall i \in \mathcal{R} \quad (30)$$

As a result, total funding shortfall of other banks, *bank j*, that face withdrawals from leverage-distressed banks increase proportional to the withdrawal rate:

$$\tau_j^{v'} = \tau_j^{v''} + \sum_{i \in \mathcal{R}} \omega_i \rho_{ij} x_{ij}, \quad \forall j \in \mathcal{Z} \quad (31)$$

This concludes all funding shocks that could take place in a single round.

A bank is pushed toward a fire sale when its funding shortfall exceeds surplus liquidity available to it. At this point, all banks consolidate their positions based on a series of liquidity shocks and determine whether their positions imply a fire-sale and if so how much. The amount of remaining assets available to the bank, θ_i , 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, this costly deleveraging amounts to the sale of assets:

$$\max \left\{ 0, \min \left\{ \theta_i, \frac{1}{1-\delta_i} (\tau_i^{v'} - \gamma_i^v) \right\} \right\} \quad \forall i \in \mathcal{Z}, \text{ where } \delta_i \in [0,1] \quad (32)$$

In addition to the earlier credit shock, the losses due to the fire sale are absorbed fully by *bank i's* capital:

$$c_i' = c_i^0 - \sum_{j \in \mathcal{Y}} \lambda_{ij} x_{ij} - \delta_i * \max \left\{ 0, \min \left\{ \theta_i, \frac{1}{1-\delta_i} (\tau_i^{v'} - \gamma_i^v) \right\} \right\} \quad \forall i \in \mathcal{Z} \quad (33)$$

The firesales lead to a contraction in *bank i's* assets:

$$a_i' = a_i^0 + \sum_{j \in \mathcal{Y}} (1 - \lambda_{ij}) x_{ij} - \max \left\{ 0, \min \left\{ \theta_i, \frac{1}{1-\delta_i} (\tau_i^{v'} - \gamma_i^v) \right\} \right\} \quad \forall i \in \mathcal{Z} \quad (34)$$

The other variables are also updated based on how *bank i* met the total funding shortfalls:

$$\gamma_i^{v''} = \max \{ 0, \gamma_i^v - \tau_j^{v'} \} \quad \forall i \in \mathcal{Z} \quad (35)$$

$$\beta_i^{v'''} = \beta_i^{v''} + \min \{ \tau_i^{v'}, \gamma_i^{v''} \} \quad \forall i \in \mathcal{Z} \quad (36)$$

$$\theta_i' = \max \left\{ 0, \min \left\{ \theta_i^0, \theta_i^0 - \frac{(\tau_i^{v'} - \gamma_i^v)}{1-\delta_i} \right\} \right\} \quad \forall i \in \mathcal{Z} \quad (37)$$

These last capital and liquidity positions of all banks are compared against the specific thresholds in order to determine whether any new banks face distress and/or default condition(s). If there are new banks, the exercise will continue to another round. Otherwise, the contagion cycle terminates and all the relevant outputs are generated.

In the end, the algorithm mechanics works in the following way. At the outset of the exercise, the event or the combination of events underlying the scenario is prescribed. The initial round

is triggered by these events. At the end of the round, the solvency, liquidity or leverage positions of the banks are reevaluated to determine whether the contagion has caused additional distresses or defaults in the network. If so, the exercise continues to the next round and this cycle continues until there are no new distresses or defaults in the system. Moreover, capital depletion as well as liquidity tightening continue even after a bank experiences default. This allows us to capture the full extent of contagion as well as its self-inflicting aspect as the defaults can take place in a range and due to different dynamics.

4. Results

4.1 Main Findings

In this section we unveil the outcome of the A-CoMap methodology by presenting contagion and vulnerability indexes conditional to an initial default event for 2830 consolidated banking groups¹⁵. As long as the international coverage of the interbank network (extra-EA banks) is relevant in capturing the cross-border dimension of contagion potential (Covi et al., 2019), the composition of the network is key in assessing amplification effects arising from the structure of the banking system. Precisely, the inclusion of euro area LSIs matters for assessing the transmission of domestic shocks to euro area SIs, which, in turn may reverberate further across institutions and borders. Hence, we jointly model them together with international spillovers to study the complex interactions of a domestic network within a multi-country perspective.

We start by reporting the breakdown of contagion potential by type of institutions (*Table 3*), i.e. the share of losses each category of banks induces and experiences from the other groups of banks. GSIBs are those banks that induce most losses to the global banking system, almost 31.9% of the total. Moreover, shocks coming from non-euro area banks are the most detrimental for EAGSIBs, respectively 17.5% from GSIBs and 8.6% from OSIBs so as confirming the finding previously discussed. Next, euro area significant institutions account for 23.3% of total induced losses, EAGSIB banks for 22.4%, non-euro area banks other than GSIB for almost 12.4%, and less significant institutions for 10%. Hence, LSIs direct contribution to overall contagion is non-negligible although limited, especially given that

¹⁵ The results are based on the bank-specific and exposure-specific calibration of the model parameters following Covi et al. (2019) and they are reported in **Appendix A**. In **Appendix B** a bank-specific breakdown of the results is provided.

LSIs, in terms of units, are almost 88% of the banking sector. To what may concern the loss absorption or vulnerability, we can notice that 15.6% of the total losses of the system is experienced by LSIs, of which 7% as direct impact from SIs. These incoming and outgoing contagion spillovers imply primarily that SIs' contagion is amplified indirectly via the LSI network with substantial heterogeneity across banks.

Table 3: Contagion Matrix

TYPES	EAGSIB	SI	LSI	GSIB	OSIB	ToT
EAGSIB	8.0	8.7	3.4	2.2	0.1	22.4
SI	5.7	5.9	7.0	4.0	0.7	23.3
LSI	1.9	3.9	1.8	2.0	0.4	10.0
GSIB	17.5	8.0	2.6	3.7	0.1	31.9
OSIB	8.6	2.6	0.8	0.3	0.1	12.4
ToT	41.8	29.1	15.6	12.2	1.4	100

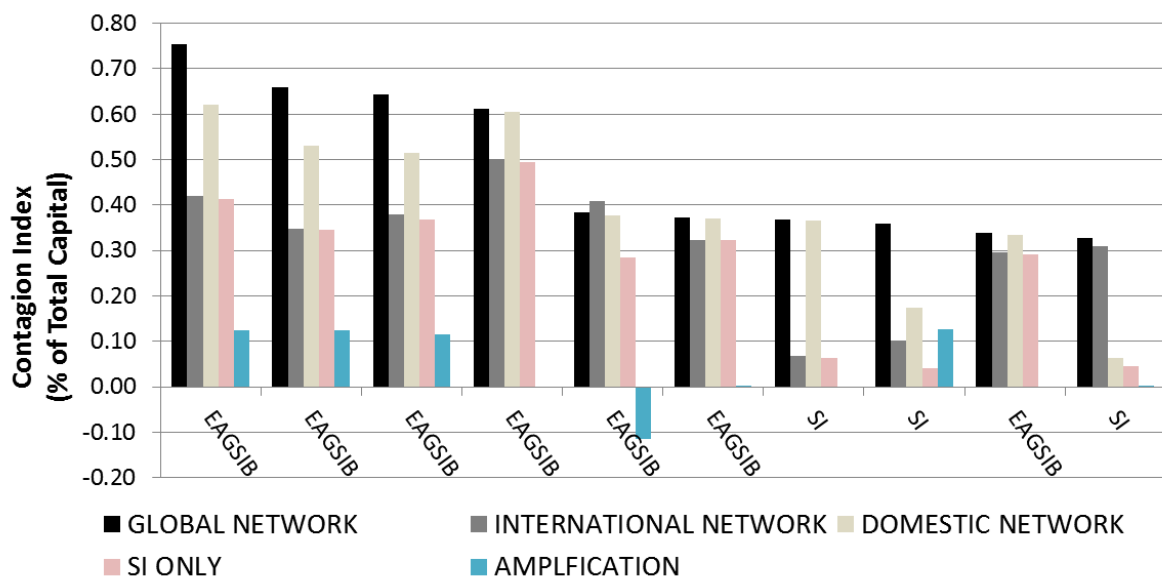
Note: Note: Each row reports the share of losses induced by each bank category in % of total losses. Columns identify the share of losses experienced by each bank category in % of total losses. The share of experienced losses of GSIBs and OSIBs banks are small given the limited exposure coverage.

In this respect, **Figure 2** compares contagion potential among the top-10 euro area banks across three network structures, respectively the “global network” reporting the baseline estimates for the complete interbank bank market, the “international network” composed by only large domestic and non-euro area banks (excluding the LSI sample), and a “domestic network” composed by only domestic euro area banks (excluding international banks). For comparative purposes, we present the contagion index at global scale (not only limited to euro area losses) for which we keep the denominator fixed equal to the amount of capital of the full system.

Overall, we see some important patterns underlining the added value of modelling these three dimensions jointly: SIs, LSIs and international banks. First of all, the losses induced by the top-10 euro area banks in the “global network” are 52% higher than those reported for the “international network”, and 22% higher than those computed from the domestic network alone. Hence, most of the amplification effects are generated from within the domestic network since it is quite unlikely that an SI default would trigger additional failures in the international network, while it is more likely that an SI default would trigger second round effects in the domestic network.

Moreover, it is clearly visible the presence of heterogeneity in terms of contagion potential among the top-10 banks across network structures. By comparing the domestic network and the international network with the network composed by SI only, we can notice respectively the importance of banks' exposures via-a-vis LSIs and non-euro area banks. For instance, by including the “domestic network” the contagion potential of two SIs increases by a factor of 5 and 4 respectively relatively to the “SI network”. Although the limited coverage of non-euro area banks' exposures, there is also a bank in the top-10 that is sensibly more exposed towards non-euro area banks than within the domestic network. In the end, by comparing amplification effects due to the interaction of the domestic network with the international network, we can see that contagion potential is not additive, thereby confirming the presence of non-linearities arising from the composition of the network. Remarkably, the interaction among network structures may also lead to a reduction of contagion potential. This is due to the fact that liquidity hoarding behaviors may increase the resilience of weak nodes, thereby reducing domino effects in the system. The following section will dig deeper into this modelling feature.

Figure 2: Contagion Risk Contribution of Network Coverage



Note: Contagion Index refers to total capital losses to all banks in percent of entire banking system's total capital.

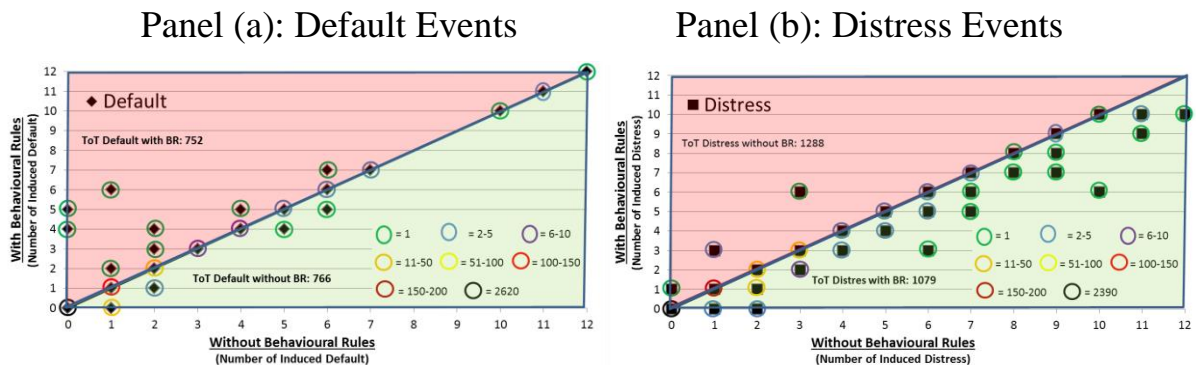
4.3 Impact of Market Reaction to Contagion

The adaptive CoMap model presented in this paper imposes certain behavioral rules determining how banks react to shocks. The framework allows to study whether

precautionary and hoarding behaviors of banks in times of financial market distress may lead to amplified or mitigated effects. In order to assess these effects, we run a counterfactual exercise without modelling liquidity hoarding behaviors conditional to the realization of a distress event. This is similar to assume that banks have only partial information on counterparty risk, and they are not able to act preemptively. **Figure 3** summarizes the findings by reporting for each exercise respectively the total number of default and distress events across all simulations, respectively Panels (a) and Panel (b).¹⁶

Overall, when we include liquidity hoarding behaviors, the number of defaults and distress events decrease by 14 and 209 units, respectively. This implies that allowing banks to withdraw the short-term part of the exposures when a counterparty is in distress is a powerful mechanism in mitigating contagion. Nevertheless, heterogeneous effects are present, and in some simulations liquidity hoarding behaviors increase the level of stress to some nodes in the network. Overall, the mitigating effects seem to outweigh the amplifying ones.

Figure 3: Impact of Behavioral Rules



Note: X-axis reports number of default/distress events with the model including behavioral rules, while Y-axis reports the number of default/distress events with the model without behavioral rules. At each point of the X-axis there may be one or multiple events taking place.

¹⁶ Unique number of default/distress events refers to the fact that banks may be simultaneously defaulting or being in distress due to multiple distress conditions taking place. For instance a bank may be in solvency and liquidity distress at the same time. If this is the case, we avoid double-counting and we consider only one distress event.

4.4 Assessing the Trade-off Between Rising Capital Requirements and Capital Buffers

In this section we aim to test whether a capital surcharge affecting minimum capital requirements (MCR) is more effective in curbing contagion than a capital surcharge affecting capital buffer requirements (CBR). According to our knowledge, this is the first attempt in the literature of banking regulation which tries to quantify this effect. This is possible within our methodological framework since a breach of minimum capital requirements lead to different reaction than a breach of the capital buffers.

The exercise consists in three counterfactual exercises assuming a homogeneous increase across all banks in the sample of, respectively minimum capital requirements (MCR – Exercise 1) and capital buffer requirements (CBR – Exercise 2). Then we also compare these outcomes with a counterfactual exercise assuming an equal split among the two requirements summing to the capital surcharge (MIX – Exercise 3). In the end, the same amount of the capital surcharge is added to the capital base so as to assume that banks target a constant capital surplus (ks) relatively to the threshold affected whether it is the default threshold (c^{DF}) or the distress threshold (c^{DS}), i.e a constant distant to the threshold. These assumptions lead to equation (39) and equation (40)¹⁷.

Exercise 1, in which the capital surcharge is applied to minimum capital requirements, implies that banks have a constant distant to the default threshold (c_0^{DF}) used throughout the paper, i.e. a capital surplus (ks_1^{DF}) above the default threshold equal to ks_0^{DF} . Nevertheless, the distant from the distress threshold (c_0^{DS}) increases up to (ks_1^{DS}) making banks less likely to get into distress relative to the baseline results. Contrary, Exercise 2, in which the capital surcharge is applied to capital buffer requirements, implies that banks have a constant distant to the distress threshold (c_0^{DS}) used throughout the paper, i.e. a capital surplus (ks_2^{DS}) above the distress threshold equal to ks_0^{DS} . Nevertheless, the distant from the default threshold (c_0^{DF}) increases up to (ks_2^{DS}) making banks less likely to get into default relative to the baseline results. In the end, Exercise 3 lies between the two exercises, with banks having a larger distant to both the default (c_0^{DF}) and distress (c_0^{DS}) thresholds than in the baseline case. We need to note that an increased capital base would affect also the distant to the leverage distress and

¹⁷ See **Appendix D** for a mathematical derivation.

default thresholds, making a bank less likely to get into leverage distress or default. However, this effect is common across all exercises¹⁸.

$$ks_2^{DF} > ks_3^{DF} > ks_1^{DF} = ks_0^{DF} \quad (39)$$

$$\text{where: } ks_1^{DF} = k_0 - c_0^{DF} \equiv ks_0^{DF} ; ks_3^{DF} = ks_1^{DF} + \frac{1}{2}CS ; ks_2^{DF} = ks_1^{DF} + CS$$

$$ks_1^{DS} > ks_3^{DS} > ks_2^{DS} = ks_0^{DS} \quad (40)$$

$$\text{where: } ks_2^{DS} = k_0 - c_0^{DS} \equiv ks_0^{DS} ; ks_3^{DS} = ks_2^{DS} + \frac{1}{2}CS ; ks_1^{DS} = ks_2^{DS} + CS;$$

Figure 4 presents the average number of default and distress events across all simulations for all three exercises. As we can see the overall estimates reflect the inequalities described in equation (39) and equation (40). Exercise 1, in which banks target a constant distant to minimum capital requirements, experience almost no change in the average number of default per simulation relative to the baseline, while a strong decrease in the average number of distress events. The opposite outcome is visible for Exercise 2, when banks target a constant distant from the distress threshold. The average number of default strongly decreases, whereas the average number of distress events increase due to the fact that now it is more difficult for banks to breach the default threshold, and more banks would lie in the distress zone. In the end, Exercise 3 shows that, for both types of event, the average decreases, lying between the estimates of Exercise 1 and Exercise 2. Notably, these results hold across different level of capital surcharges. Overall, the policy mix, according to these two metrics, average number of default and distress events, seems to be the most effective and also Pareto efficient outcome. However, since distress and default events are a discrete variables taking value 0 or 1, we provide the same comparison for a continuous variable such average losses across simulations, and check whether results may differ.

Panel (a) of **Figure 5** shows that average losses across all simulations decrease linearly, however differently among policies depending on the capital surcharge applied. For instance, a capital surcharge of 0.25% of RWA seems to be more effective in reducing average losses when applied to capital buffers relative to the policy mix and also to minimum capital requirements. Nevertheless, when the capital surcharge of 0.5% is applied, we find that higher capital requirements would reduce average contagion more than a capital surcharge

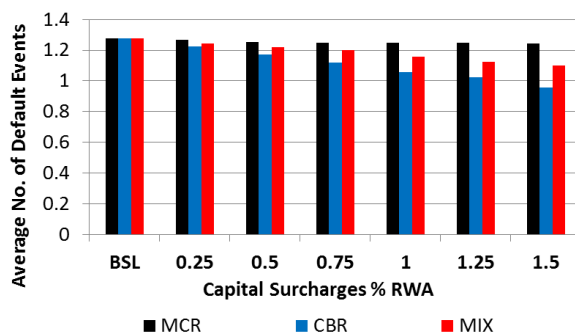
¹⁸ The amplification effects due to leverage distress/default events may be visible in the tail of the distribution, whereas they don't play an important role for the mean of distribution. By checking only default and distress events due to solvency, results do not change.

applied to capital buffer requirements, and even more relative to the policy mix. Interestingly, the policy mix which lies in between the two by construction, and therefore should be closer to the results of a capital surcharge applied to minimum capital buffers, is the least effective among the three.

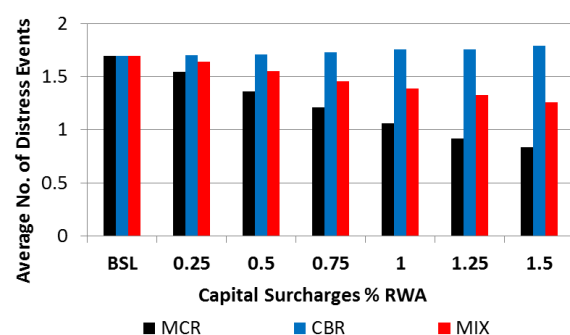
This finding emphasizes how heterogeneity in terms of banks' balance sheet characteristics and the specificity of the network structure jointly modelled may produce non-linear interactions among shocks. Similar heterogeneity in the results is visible when the 0.75% capital surcharge is applied. In fact, at this point, the surcharge applied to capital buffer requirements become more effective than the capital surcharge applied to minimum capital requirements, while the policy mix remains still the least effective option. For capital surcharges equal to 1% of RWAs, we notice a trend inversion, and both capital buffer requirements and the policy mix become more effective than the minimum capital requirements surcharge, although the former is still more effective than the latter. However, for levels of capital surcharge above 1% of RWA, the policy mix becomes the most effective tool. This result shows how the impact of capital surcharge may have very heterogeneous effects depending on the starting condition of the banking sector, i.e. the distant of the banking sector from the distress and default thresholds.

Figure 4: Average Default and Distress Events Across Capital Surcharges

Panel (a): All Average Sample Default Events



Panel (b): All Sample Average Distress Events

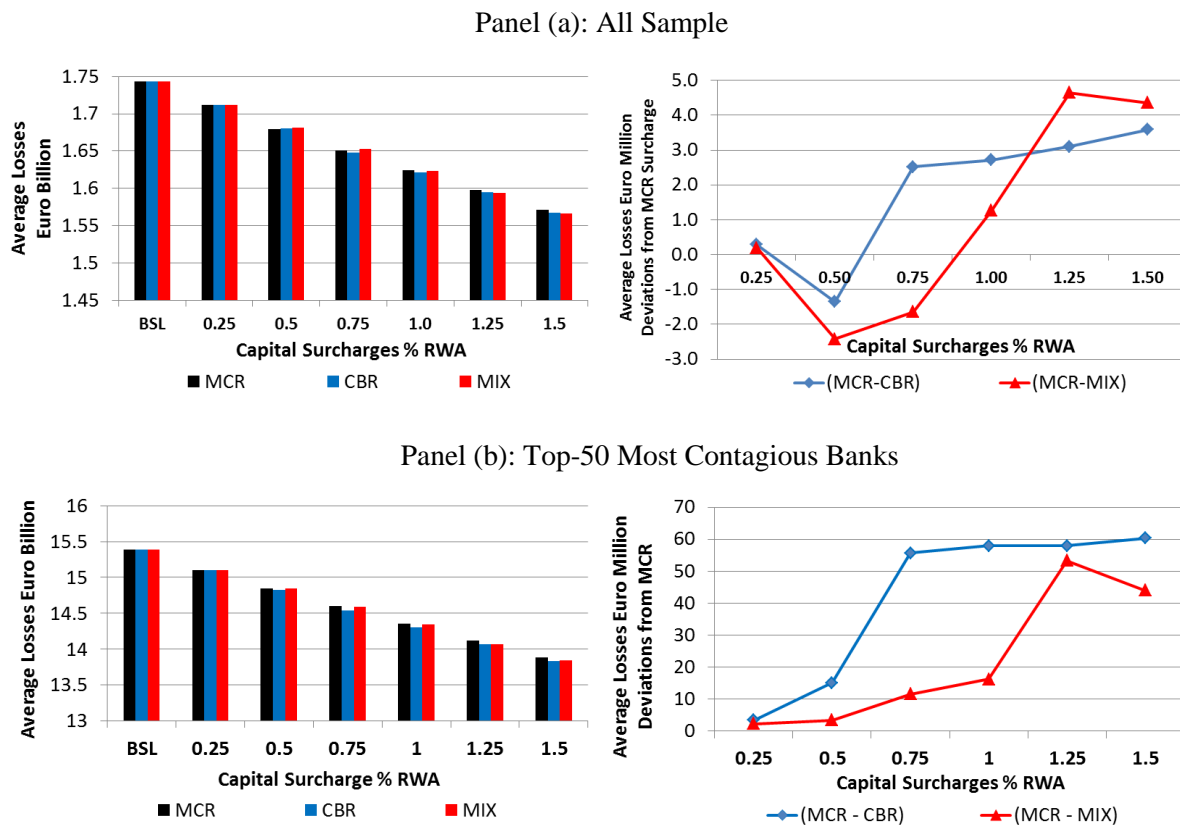


Note: The counterfactual analysis assumes a homogeneous increase across all banks in the sample of, respectively Minimum Capital Requirements (MCR), Capital Buffer Requirements (CBR), and an equal split among the two summing to the capital surcharge (MIX). The same amount of the capital surcharge is added to the capital base. Baseline estimates (BSL) refer to the results presented in the previous sections based on the baseline calibration of the model parameters reported in the appendix A.

Moreover, Panel (b) of *Figure 5* shows that when we consider only tail-events, approximated by those simulations in which a top-50 bank default in terms of contagion index is assumed, we see that a capital surcharge applied to buffer requirements is on average the most effective policy option. This result holds even if we limit the sample to the top-30 or to the top-10 most

contagious banks. Nevertheless, this is not the most effective outcome at bank-specific level, since among the top-30 banks, there are two cases (at 1.5% of capital surcharge) in which an increase in minimum capital requirements would further improve the resilience of the system conditional to that bank defaulting.

Figure 5: Average Losses, and Deviations from Minimum Capital Requirements



Note: The counterfactual analysis assumes a homogeneous increase across all banks in the sample of, respectively Minimum Capital Requirements (MCR), Capital Buffer Requirements (CBR), and an equal split among the two summing to the capital surcharge (MIX). The same amount of the capital surcharge is added to the capital base. Baseline estimates (BSL) refer to the results presented in the previous sections based on the baseline calibration of the model parameters reported in the appendix A. Deviations measure the difference between average loss computed by applying the capital surcharge to minimum capital requirement and to capital buffer requirements, or vis-à-vis the policy mix

Overall, given our modelling framework, an increase in the capital buffer requirements tend to be more effective than an increase in the minimum capital requirements or the so defined policy mix. This result is driven by the fact that capital buffers may be interpreted like a fire-wall. When a bank breaches it, the security signal is transmitted to the other banks in the network, which act and reduce their short-term exposures vis-à-vis the vulnerable and potentially contagious entity. The breach of capital buffer requirements, by providing private information to the public, triggers liquidity hoarding behaviors which, reshape the networks

structure, and, on average, tend to reduce the negative externalities a vulnerable node may further produce.

4.5 Too Many Too Fail and Multiple Distress Events

Differently from the previous sections, which focus on the impact of an idiosyncratic shock to a bank assuming its default, this section studies the contagion propagation due to a system-wide shock aiming at studying the too-many-too-fail issue. Two exercises are performed: i) a multiple default scenario of LSIs to reconstruct whether and to what extent simultaneous small shocks may replicate the default of a large bank; ii) a multiple distress scenario.

Regarding the first exercise, the shock assumes the default of the top-LSI banks following the ranking based on the baseline contagion estimates.¹⁹ In order to compare the magnitude of the initial shock, **Figure 6** reports the number of LSIs shocked and the percentage of capital depletion relative to the average capital of the most contagious EAGSIB dividing it in buckets of 10% up to 100%. Since LSI banks are domestically-oriented banks, we compare estimates of the euro area-based contagion index.

It is important to note that assuming multiple default events reduces in decrements the impact among banks. This is driven by the fact that, in a given jurisdiction, if more banks are exogenously assumed to be in default there are fewer banks that can potentially experience defaults as a result. This is true for domestic banks such as LSI which are mainly exposed to the domestic market.²⁰

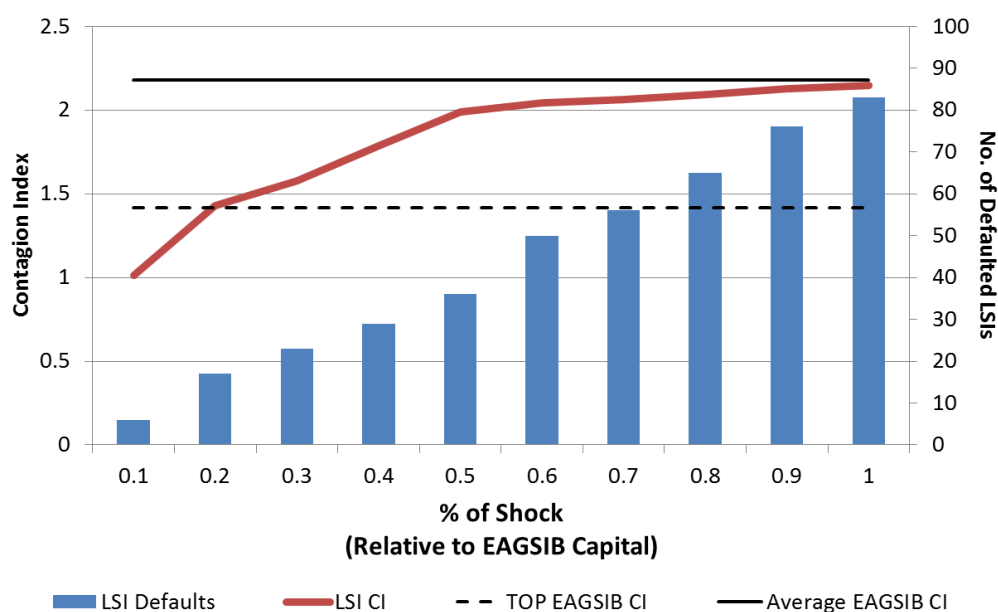
Overall, we can see from **Figure 6** that shocking the Top-6 most contagious LSI banks, which accounts for almost 10% of the average of EAGSIBs' capital, produces a quite relevant impact, almost 40% of the one produced by the most contagious EAGSIB, and 2/3 of the EAGSIBs' average contagion index. Definitely, size matters, but only up to a certain

¹⁹ This assumption imposes that the capital base falls below the default threshold. This capital loss is not used for the calculation of the contagion index as in any other exercise.

²⁰ For instance, scenario "shock = 10%" assumes 6 LSI banks defaulting. The sum of their capital base is equivalent to 10% of the most contagious EAGSIB. However, scenario "shock 100%" assumes 83 LSI defaulting thereby the possible number of banks defaulting is reduced. This is likely the case, since when we look at scenario "shock 50%" 36 banks trigger almost the same number of defaults of the scenario with 83 assumed defaults. There is a clear trade-off between the shock assumption and the comparability of the results. The initial assumption affects the network structure to a point that results may not be comparable anymore. This threshold for this exercise is around the 50% shock.

point. There is a network effect driven by the heterogeneity of banks' characteristics and the topology of the network for which a similar shock may produce four times its impact. In fact, when the top-30 most contagious LSI banks default simultaneously (shock 40%), they show a contagion potential 25% higher than the EAGSIBs' average. In the end, when the top-82 LSIs default simultaneously, that is a shock equivalent to 100% of the capital of the most contagious EAGSIB, the shock is able to replicate the very same effect.

Figure 6: Too Many Too Fail



Note: Contagion Index refers to capital losses to all euro area banks in percent of entire euro area banking system's total capital. The shock is calculated in % of the capital of the EAGSIB. The initial shock resembles the default of the most contagious LSI given the baseline estimates of the contagion index.

Regarding the second exercise, we shock to distress the most contagious euro area banks following the ranking based on the baseline contagion estimates. The combination of shocks (11) assumes that all top-11 euro area banks go into distress simultaneously, and then we perform additional scenarios by reducing the size of the initial shock by one bank at each time. For instance, scenario (2) assumes the simultaneous distress of the two most contagious euro area banks. Moreover, in order to show how heterogeneity of shocks may matter we provide estimates also for combination in reverse ordering from the least contagious bank among the top-11 banks (2R).

In this respect, **Figure 7** reports the initial shock in percent of the capital of the total banking system. The initial shock assumes that banks would deplete their capital base up to breaching

the distress threshold, i.e. their highest capital buffer²¹. The solvency distress assumption triggers behavioral responses from banks. The initial shocked banks would hoard liquidity from the system for precautionary reasons, while market reactions would imply that the non-affected banks would reduce their exposure amount by the short-term part, which is calculated according to the exposure-specific funding shortfall.

The key outcome of this exercise is to study how hoarding behaviors due to contagion and uncertainty connected to distressed banks may lead to non-negligible cascade effects. The attempt is to show how a much milder scenario than a default event may trigger contagion via the funding channel. It is important to note that for this exercise assuming multiple distress events does not reduce in decrements the impact among banks since shocked banks may still move from a solvency distress stance into a solvency, liquidity or leverage default situation.

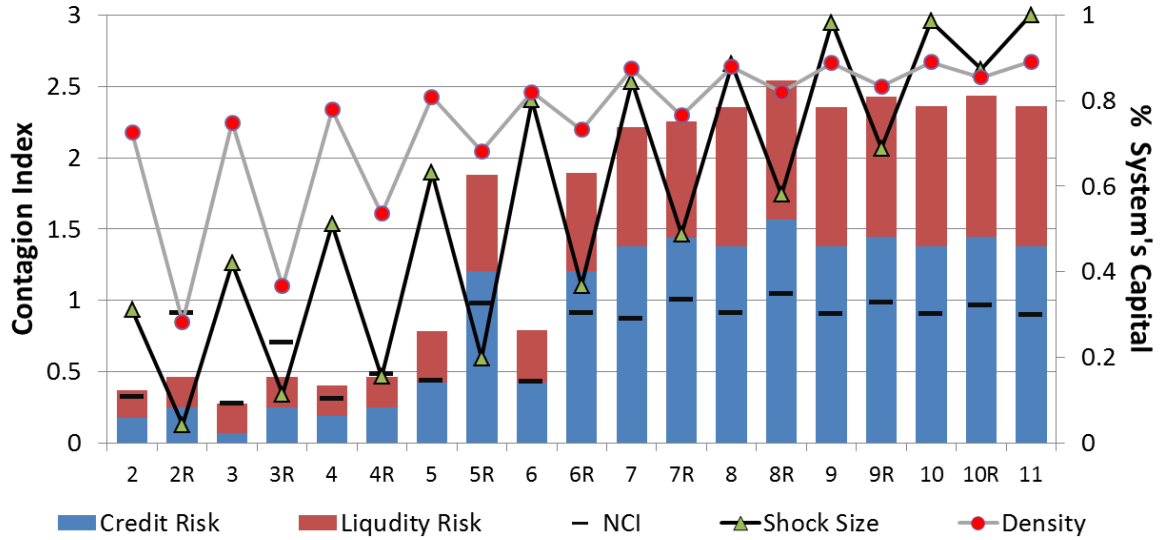
Figure 7 shows that multiple distress events have a relevant contagion potential, especially liquidity risk accounts for a large part of the contagion index, on average 45% across the various exercises. In the baseline estimates for a default event funding risk accounted on average for 7% of the total CI index. Moreover, for some scenarios, such as (2), (3) and (4) that is a simultaneous distress shock to respectively top-2, top-3 and top-4 most contagious banks, losses due to funding risk outweigh those from credit risk. This is the clear impact of hoarding behaviors in the interbank network, since the top-4 banks are also those that are the main liquidity providers to the network.

Another interesting finding is that the relative size of the shock approximated by the capital of the shocked banks matter relatively less than the concentration of portfolios. In fact the latter is crucial in determining the level of contagion. Scenarios based on the reverse ordering (R), that is, with relatively smaller size banks, show relatively to its peer scenario with the same amount of banks shocked, a higher level of contagion and a lower density. A low density refers to the part of the network affected from the shock. For instance, scenario (2R) has a density equal to 28%, relative to scenario (2) which affects almost 80% of the network's nodes. Hence, when the shock has a low density the very same banks in the network face cumulative losses, producing non-negligible amplification effects due to

²¹ For simplicity we assume a solvency distress scenario. Changing the shock to a liquidity or leverage distress event would change the overall dynamics.

cascade defaults. In fact, the neighboring contagion indexes (NCI) in the scenario with low density (R), are always higher, than the NCI computed for the baseline Scenario (without R).

Figure 7: Multiple Distress Events



Note: the ratio between the full capital base of the banks involved and the total banking system's capital approximates the shock size. Nonetheless, the actual capital depletion assumed is much smaller than the full capital base. We do this since it is easier to compare the actual size of the banks affected, preferring it to the relative size of the shocks. The X-axis reports the number of banks that have been set to distress. For instance, when $x=2$ we refer to the shock involving the most contagious banks among the top-11 banks, whereas when $x=2R$, it refers to the shock involving the least contagious banks of the top-11 most contagious banks. Contagion index report the losses induced to euro area banks as share of euro area banking system's capital. NCI refers to the neighbouring contagion index, that is, induced losses divided by the capital of the affected banks (right hand side Y axis). Density captures the share of the nodes affected (right hand side Y axis).

4.6 Heterogeneous and Non-linear Effects

Changes in the estimation of liquidity and solvency parameters may lead to both heterogeneous and non-linear effects for the bank-specific contagion and vulnerability measures. This section aims at testing whether the results are sensible to this variation and if interactions among parameters may lead to non-linear effects. In this respect, the identification of each parameter threshold is important to assess whether additional cascade effects would be triggered, and in case they are, how relevant it is.

Figure 8 shows the heterogeneous effects to a simultaneous variation of all liquidity parameters (funding shortfall, discount rate and pool of assets), to a change in all solvency parameters (LGD and distress threshold), and to a simultaneous change of both types of parameter. All parameters are gradually increased in steps of 10% up to 50%, with the exception of the funding shortfall, the discount rate and the distress threshold which are constructed with a slightly modified rule. In fact, the funding shortfall parameter has been

modified by increasing the minimum threshold. All exposures with a funding shortfall below the threshold were shifted up to the threshold. This was implemented to avoid some parameters from becoming larger than 1 for some exposures. The discount rate presents the same issue. To overcome this, we set linear increases with half of the percentage points displayed in the chart. Regarding the distress threshold, to avoid becoming larger than the capital base, we set up an upper limit equal to the capital base minus 0.1%. Finally, the liquidity buffer and the pool of assets face a negative variation and not a positive one, as all other parameters.

Findings show that heterogeneous contagion effects to simultaneous changes in liquidity parameters are clearly visible when parameters are increased by at least 40%-50%. The vulnerability index presents similar features. Contrary, results are much more sensible to simultaneous variations in solvency parameters. Already at 20%, banks tend to shift upwards, while above the 40% threshold they tend to produce homogenous levels of contagion and vulnerability. When we look at contemporaneous variations in liquidity and solvency parameters, we see that some banks may induce a higher level of contagion in the single solvency scenario than in the combined one. At a threshold lower than or equal to 40%, the average contagion index seems to be higher in the single solvency scenario than in the combined one. This because a higher funding shortfall parameter leads to higher amount of funding withdrawals and in turn to a lower amount of losses when a solvency default takes place. However, when the threshold shifts up to 50%, many banks tend to induce higher losses in the combined scenario than in the solvency. From a vulnerability perspective, the combined scenario tends to maintain heterogeneity in the vulnerability scores, at least more than in the case of the contagion index. Variations of single parameters are reported in *Appendix C*.

Figure 9 aims at disentangling the non-linearities due to changes in the parameter thresholds. The non-linear effects in this modelling framework are a function of the number of cascade defaults produced in the system. The average effect across the top-50 banks is so reported for both the contagion and vulnerability indexes.

We see that single variations in liquidity parameters do not lead to non-linear effects.²² Moreover, the effects are quite mild even by stretching the parameters up to 50%. However, when we perform simultaneous variations, we can see that some non-linearities appear above the 45% threshold. This is more evident when we look at the vulnerability index, which shows the beginning of non-linear effects around the 25% threshold.

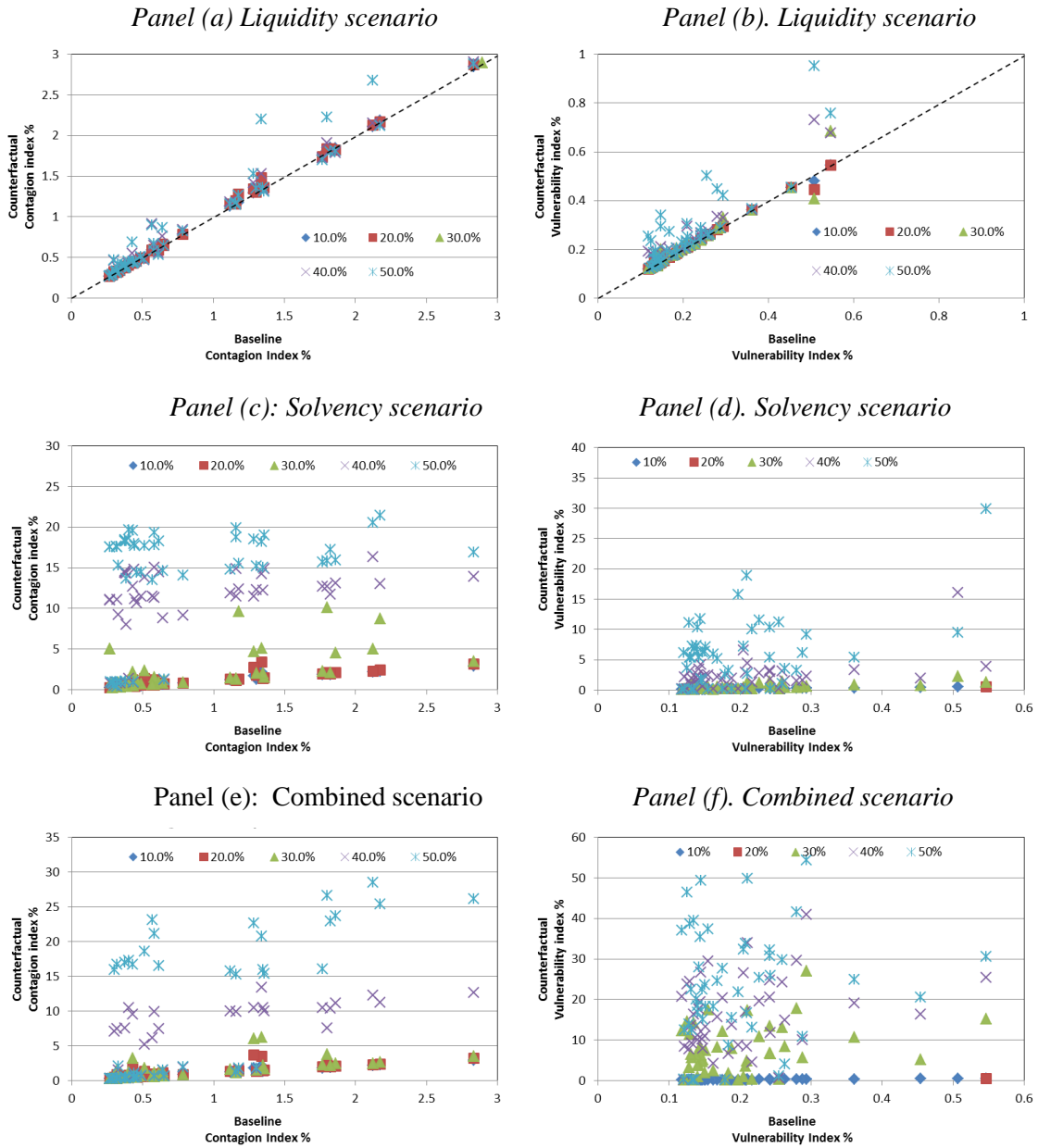
Contrary variations in solvency parameters tend to produce stronger effects than variations in isolation of liquidity parameters, and when combined the effects become clearly non-linear. Every 10% increases above the 30% threshold, the contagion index increase by almost a factor of 3. This result holds also for the average vulnerability index of the top-50 banks.

Last, when we combine variations in solvency and liquidity parameters the contagion index increases faster, just above the 25% threshold, and the non-linear effects become much stronger. The CI index calculated on a 35% threshold is close to 6% for only variations in solvency parameters, and it reaches 17% when the liquidity ones are interacted. The average vulnerability index of the top-50 banks for a 35% threshold increase even more, by almost a factor of 8 due to the interaction with liquidity parameters.

Overall, results seem to be robust for a range of parameters within a 25% variation. Above this threshold, the effects become extremely non-linear, producing many more cascade defaults relative to the baseline estimates. This potential source of non-linearities may place the accent on how shifts in parameters may be correlated, and if they tend to endogenously vary in the same dangerous directions. This would give a realistic prediction of the level of distress an adverse shock may produce.

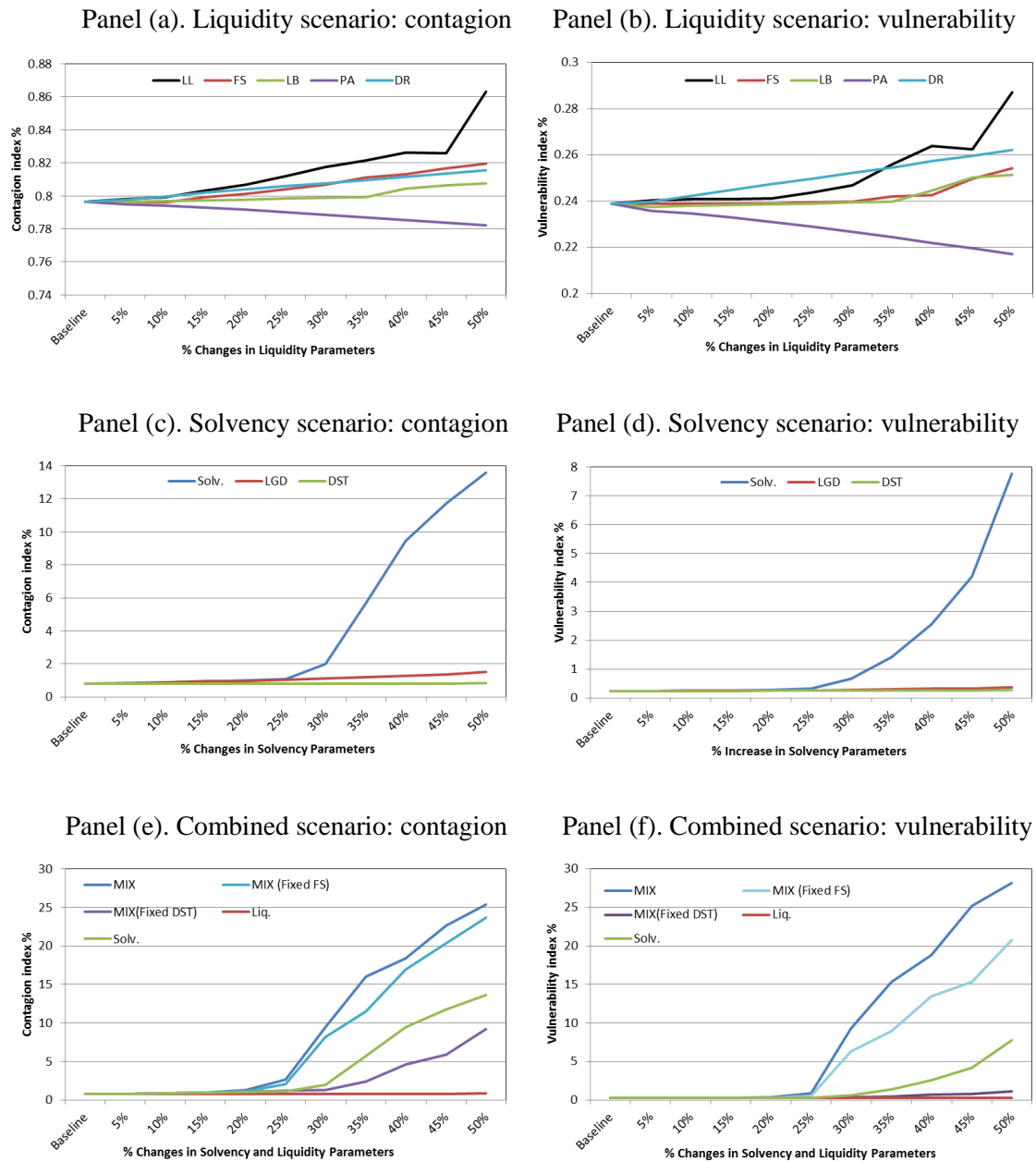
²² The only exception is for the liquidity buffer (see **Appendix C**).

Figure 8: Heterogeneous Effects due to Changes in Model Parameters



Note: the funding shortfall parameter has been modified by increasing the minimum threshold. All exposures with a funding shortfall below the threshold were shifted up to the threshold. Regarding the discount rate, we set linear increases with half of the percentage points displayed in the chart. Regarding the distress threshold, we set up an upper limit equal to the capital base minus 0.1%. All outliers of the vulnerability index higher than 60% have been omitted for comparative purposes. Finally, the liquidity buffer and the pool of assets face a negative variation and not a positive one as all other parameters.

Figure 9: Non-linear Effects due to Changes in Model Parameters



Note: It is reported the average effect across the top-50 banks. Scenario (LL) refers to the combined liquidity scenario; (FS) refers to variations in the funding shortfall; (LB) refers to variation in the liquidity buffer; (PA) refers to variations in the pool of assets; (DR) refers to variations in the discount rate; (LGD) refers to variations in the loss given default; (DST) refers to variations in the distress threshold; (MIX) refers to the combined scenario between solvency and liquidity parameters; (MIX fixed FS) refers to the combined scenario by keeping fixed the funding shortfall; (MIX fixed DST) refers to the combined scenario by keeping fixed the distress threshold.

Conclusion

The paper has investigated how precautionary banks' behaviours may amplify or mitigate contagion within the global banking network. In this respect, an adaptive contagion mapping methodology (A-CoMap) has been developed to model banks' reactions to solvency, liquidity, and leverage distress events. The key mechanism at work allows banks to withdraw short-term funding from other banks that are in distress, while exposed through their long-term claims, which remain contractually binding. Hence, banks may reduce their exposures to the detriment of increasing the likelihood that the bank in distress ends up defaulting, thereby triggering credit risk losses equal to the amount of unsecured funded amounts to its funding counterparts.

The key finding from such behaviours is that the overall number of distress and default events is reduced. However, this is only true in average, and it may be higher or lower on a case-by-case basis. Clearly, banks' heterogeneity play a paramount role in driving the results in one direction or the other.

Additionally, thanks to the comprehensive network structure covering bilateral linkages among domestic banks and between domestic and international banks, we have built a contagion matrix identifying the distribution of losses across five types of banks: EAGSIB, SI, LSI, GSIB, OSIB. GSIB banks are the most contagious within the euro area banking network, while EAGSIB are the most vulnerable, respectively those banks that induce and experience most losses in the euro area interbank network. Moreover, we have for the first time assessed how the two dimensions, domestic versus international, are intertwined. In fact, we have shown how a contagion index computed only on one of these dimensions, that is without considering the LSI sample or the international sample of banks, may be drastically underestimated for specific players.

Further, we have shown how the baseline results are robust to the parameters calibration. Stretching the parameters values by 20% tends to only slightly change the average level of the contagion and vulnerability indexes. Hence, heterogeneity of banks is present because of the given network structure. Moreover, we have proved that increasing the level of parameters above 40% tends to create the opposite effect, all banks become quite homogeneous in terms of induced contagion. Complementary to this exercise, we have brought clear evidence of non-linearities in loss amplification. Tipping points emerge clearly from stretching the parameters in isolation, however remarkable non-linear amplification effects are the result of the interaction among the liquidity and solvency dimensions. Hence,

the interaction between liquidity and solvency parameters leads to lower tipping points, make it more likely to generate this non-linear effect driven by higher amplification ratios. This implies that the inclusion of additional channels of contagion is crucial in assessing properly the nature of these non-linear features.

Next, we assess for the first time the different effects in terms of system's resilience of rising a bank's minimum capital requirements relative to rising its capital buffer requirements. The results emphasize that the optimum in terms of contagion mitigation is a function of the capital surcharge. Depending on its amount and the banking system's distance to the default and distress thresholds, an increase in minimum capital requirements may be more beneficial than rising the capital buffers, or a mix between the two. Moreover, we show that also in this exercise there is evidence of heterogeneous impact across banks, since rising capital buffers among the top-50 banks seems to be on average optimal. Nevertheless, at a bank-specific level, in two cases among the top-50 defaults the system will be better-off by rising minimum capital requirements.

In the end, by running counterfactual exercises, we have shown how the too-many-too fail issue is actually as relevant as the too-big-too fail one. Small simultaneous domestic default shocks to the LSI sample may induce relevant contagion effects to the euro area banking system. This result highlights how domestic shocks may not be a negligible source of systemic risk in a so interconnected system.

Finally, we relax the trigger event assumption to assess the contagion level due to a distress event. In this respect, the initial shock does not produce credit risk losses, but sets in motion liquidity dynamics which may lead to cascade liquidity defaults and in turn a relevant level of contagion. What we notice is that the level of induced losses depends on the combination of simultaneous distress events assumed. Complementarity and concentration of portfolios on a few entities are important network characteristics in determining contagion effects due to distress events.

Having strengthened the analytical framework with the inclusion of the remaining players in the euro area banking system also motivates further research questions and areas. One of the important questions to ask, particularly relevant for policy-makers in the euro area, is how a systemic risk fund can prevent potential contagion losses to the system. Our adaptive CoMap model can be a reasonable starting point to fully incorporate central planners and various incentive mechanisms to analyse cost-benefit trade-offs of a systemic risks fund and what would be the suitable size and expected contribution from financial entities into such fund.

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Appendix A

1. Exposure-Specific Loss Given Default and Funding Shortfall

One key insight from our network of large exposures is that we can disentangle the collateral amount pledged for each exposure. Hence, we are able to derive as shown in equation (38) an exposure-specific loss-given-default ($\lambda_{i,j}$) between *bank i* and *counterparty j* as the ratio between the unsecured amount or net exposure (NE) over the total gross exposure amount (GE). Non-reporting banks in the sample are assumed to have a uniform LGD equal to the average $\bar{\lambda}$ across all reporting banks. On the one hand, (Panel a) depicts the distribution of $\lambda_{i,j}$ which shows two consistent fat-tails and a mean (red line) equal to 50%. Exposures with an LGD close to 0 are fully secured, while exposures close to 1 are those fully unsecured for which equity exposures represent a relevant share. On the other hand, Panel (b) reports the amount of short-term funding as share of total funding, i.e. our funding shortfall parameter ($\rho_{i,j}$) as shown in equation (39). In this regard, short-term is defined as an exposure with maturity below one month. This is to be consistent with the liquidity coverage ratio which assumes a 30-day distress scenario for determining the minimum HQLA buffer.

$$\lambda_{i,j} = \frac{NE_{i,j}}{GE_{i,j}} = LGD_{i,j} \quad (38)$$

$$\rho_{i,j} = \frac{GE_{i,j < 30days}}{GE_{i,j}} \quad (39)$$

2. Liquidity Surplus

The liquidity surplus is directly derived from the liquidity coverage ratio and consists of the difference between the LCR's numerator and denominator.²³ Hence, the liquidity surplus (γ_i) refers to the stock of HQLAs (LB_i) above the net funding outflows (NLO_i) over a 30-day liquidity distress scenario. (Panel c) reports the surplus as share of banks' total assets. The average of the sample is close to 7.5% which is used for approximating the missing LCRs for some international banks.²⁴ The liquidity surplus may be used to obtain liquidity from the central bank in exchange for collateral, or to deleverage if the bank is in leverage distress.

$$LCR: \frac{LB_i}{NLO_i} > 1 \xrightarrow{yields} LB_i > NLO_i \xrightarrow{yields} \gamma_i \equiv LB_i - NLO_i > 0 \quad (40)$$

²³ The numerator, as of 2018, needs to be larger than 100% of the denominator.

²⁴ Furthermore, if a bank is currently facing a transition period to achieve the 100% LCR ratio, whenever $NLO_i > LB_i$, in order to be conservative we set $\gamma_i = 0$.

3. Fire Sales Discount Rate and Pool of Assets

Modelling fire sales via cross-holding of assets a' la Cont and Schaanning (2017) requires granular-asset class information for all banks in the network. At the ECB such information is available only for the top-20 euro area banks leaving most of the sample uncovered. In this respect, we prioritize having a common approach for all banks in the sample and thus we construct and use bank-specific parameters to approximate a fire sales event. As previously described, if a bank is leverage or liquidity constrained, it is forced to respectively sell and pledge part of its surplus of HQLA assets. In this respect, we assume that no discount rate is applied on the sales of the HQLAs consistently with the assumption on pledging them to the central bank in exchange for liquidity. However, in case the surplus of HQLAs (γ_i) is depleted, the bank may sell at a discount rate from its pool of financial non-HQLA assets to obtain additional liquidity.²⁵ Hence, we calibrate the rate at which banks are forced to discount their assets as they react to a funding shortfall.

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 (41) 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 non-HQLA assets available for sale (θ_i). Therefore the δ_i coefficient 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 ($\bar{\delta}_E$). The average haircut ($\bar{\delta}_j$) for each asset class is based on the latest ECB's guidelines on haircuts.²⁶ 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%.

$$\delta_i = \sum_j^N \frac{\bar{\delta}_j A_j}{A_j} = \frac{\bar{\delta}_{CB} CB_i + \bar{\delta}_{ABS} ABS_i + \bar{\delta}_{GG} GG_i + \bar{\delta}_{FC} FC_i + \bar{\delta}_{NFC} NFC_i + \bar{\delta}_E E_i}{UNCBEA_i} \quad (41)$$

²⁵ We do not allow banks to sell part of their loan portfolios.

²⁶ 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>

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 as based on balance sheet categories. (Panels d and e) 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 62.5%, whereas the pool of non-central bank eligible assets is left skewed, with a mean centered around 10% of total assets.

4. Solvency Distress/Default Threshold

A key assumption to model banks' reactions is the definition of default (c_i^{DF}) and distress (c_i^{DS}) thresholds. On the one hand, a default event is triggered when the bank experiences a breach to its minimum requirements defined as the sum of minimum Tier1 capital (MC) equal to 6% of RWAs and the bank-specific Pillar 2 requirement (P2R) set by the supervisor (Equation 42). On the other hand, a distress event is triggered when the bank faces a breach in its level of capital buffer defined as the sum of the default threshold (c_i^{DF}), the capital conservation buffer (CCoB) ranging between 1.875% and 2.5% CET1 capital, a bank-specific buffer, which is the higher among the Systemic Risk Buffer (SRB), GSII and OSII buffers, and a counter-cyclical capital buffer requirement (CCyB).²⁷ Overall, 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).²⁸ When the bank breaches 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, hence in distress. **Figure A.1** (Panels g and h) show the sample distribution of both thresholds.

$$\text{Default Threshold} \equiv c_i^{DF} = (MC_i + P2R_i) \quad (42)$$

$$\text{Distress Threshold} \equiv c_i^{DS} = [c_i^{DF} + CCoB_i + \max(SRB_i, GSII_i, OSII_i) + CCyB_i] \quad (43)$$

²⁷ Depending on the extent to which the jurisdiction where the bank is located has fully or only partially phased in the end-2019 requirement.

²⁸ As stated in the Bank Recovery and Resolution Directive (BRRD), 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 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).

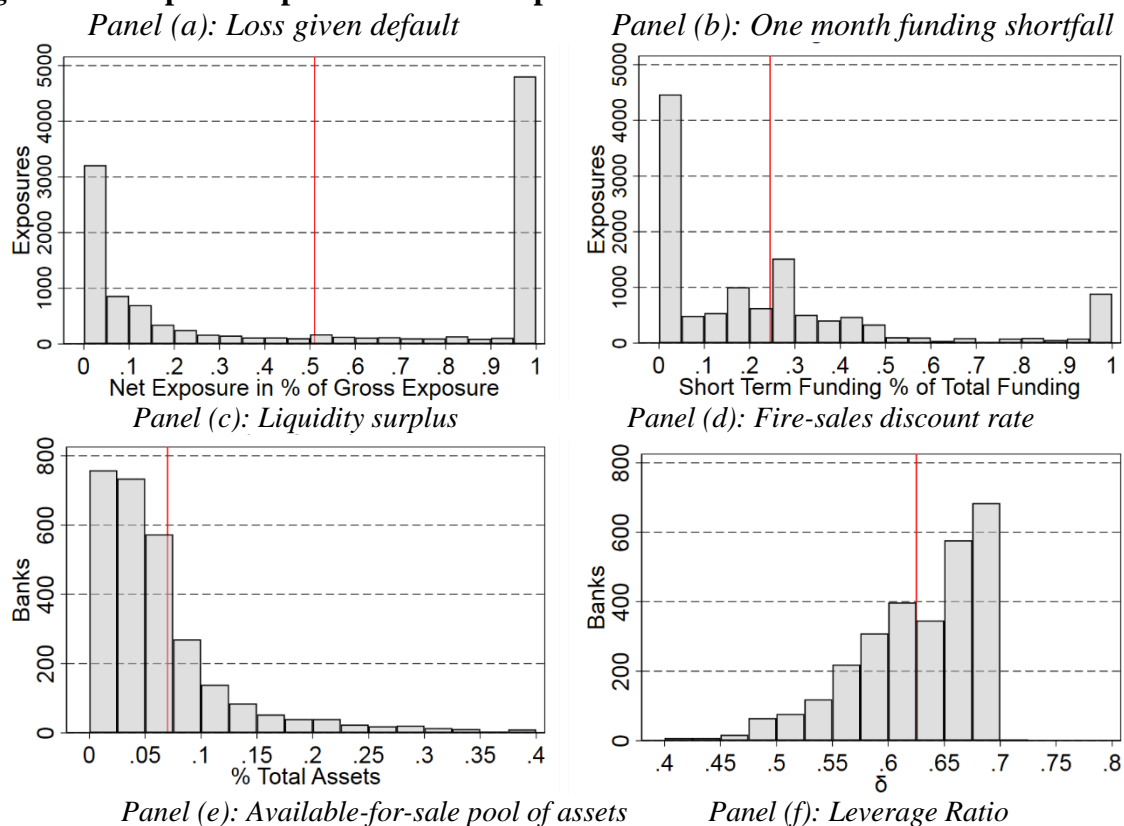
5. Leverage ratio

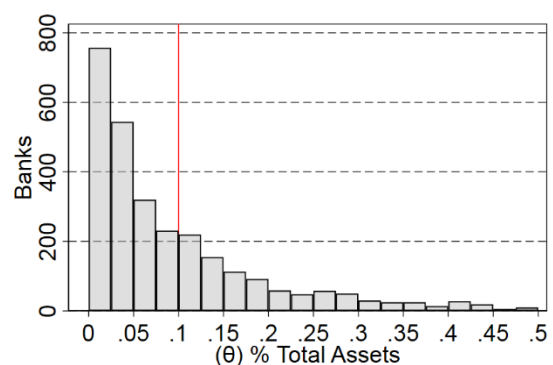
The Basel Committee on Banking Supervision (BCBS) decided to make the provisional 3.0% leverage ratio a binding minimum requirement from 2018 onwards. Banks may therefore face a trade-off between investing in RWAs and expanding their balance sheet towards less risky assets since the leverage ratio may become binding. In this regard, it is important to track banks' leverage dynamics through the system and assess how this target threshold may affect the spread of contagion. We so define in Equation (44) leverage as the ratio between Tier 1 capital and total assets which must be at any time higher than 3%, otherwise the bank is considered in leverage distress. We also consider that a bank may be in default due to an extremely high leverage when it is below 1%.

As we can see banks from (Panel f), leverage ratio ranges between 3.5% and 60%, with an average close to 10%.

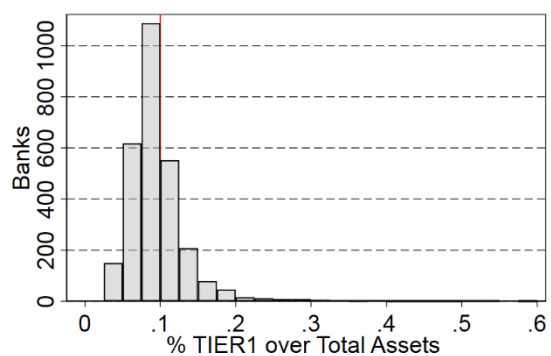
$$\text{Leverage Ratio} \equiv LR_i = \frac{\text{Tier1 Capital}_i}{\text{Total Assets}_i} > 3\% \quad (44)$$

Figure A.1: Exposure-specific and Bank-specific Calibrated Model Parameters

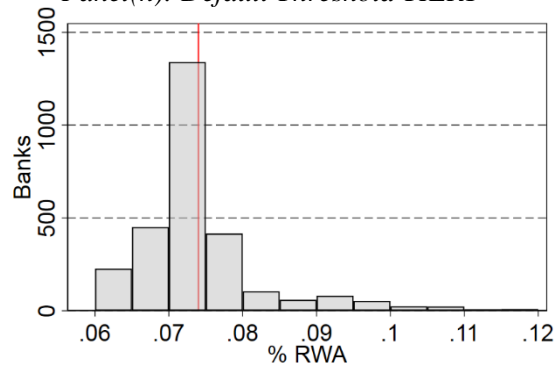
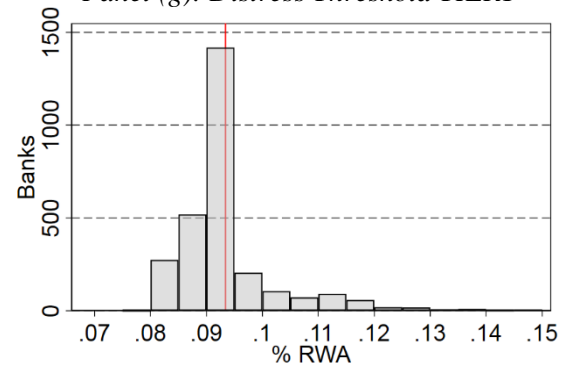




Panel (g): Distress Threshold TIER1



Panel(h): Default Threshold TIER1



Source: COREP Supervisory Data (Templates: C.01-C.03, C.28.00, C.30, C.67.00.a, C.72.00.a); FINREP Supervisory Data (Templates F.01, F32.01); and Bankscope.

Appendix B – Breakdown of Main results

Table B.1 reports the top-50 default events ranked in terms of contagion index (CI) to the euro area banking system. The hypothetical default event of one bank among the top-10 depletes almost 1.8% of the euro area banking system's Tier 1 capital, approximately EUR 47 billion.²⁹ The CI index of the most contagious bank is larger by a factor of 11 than the least contagious bank among the top-50 banks, and even among the top-10 most contagious banks remarkable differences exist.

International spillovers seem to be pronounced even if the domestic network of less-significant institutions comes into play. In fact, in terms of contagion, there is an almost equal split between EA and extra-EA banking groups. 24 extra-EA banking groups occupy the top-50, whereas 5 out of 10 the top-10, and the most contagious bank is a foreign institution.

In terms of channels underlying contagion, losses due to credit risk dominate those due to funding risk via fire sales by a factor respectively of 14 among the top-10 banks, and by a factor of 20 among the top-50. This finding emphasizes that the top contagious banks are the central liquidity providers of the network, and a failure among them would trigger liquidity hoarding behaviors and fire sales losses.

An innovative feature of the CoMap methodology is the neighboring contagion index (NCI). In fact, it remarkably differs from the standard CI by taking into account the density of loss propagation. The lower the density the higher is the NCI, implying that the amount of losses is quite concentrated across few banks. For instance, bank 49 and bank 43, which are at the bottom of the top-50 shows the highest NCI because they affect respectively only 2% and 3% of the total banking sector. Moving now to the top-10, we can clearly notice that extra-EA banks show an NCI always higher than EA banks. This is due to the fact that extra-EA banks have always a lower density than EA banks, they affect, in average, fewer nodes than EA banks do. Moreover, the share of losses is unevenly distributed across its direct and indirect connected counterparts, if we decompose the NCI on a bank-to-bank basis³⁰. Overall, a high NCI represents (i) a bank highly exposed to a relatively closed domestic network, or (ii) it might be an extra-EA bank strongly exposed to the core of the euro area banking sector. The

²⁹ The capital of the triggering bank is not included in the CI index calculation.

³⁰ For confidentiality reasons we cannot share results based on this level of granularity.

latter pattern comes from the structure of the dataset since we miss bilateral linkages among extra-EA banks, thereby reducing on average the number of directly and indirectly connected components.

When it comes to the nature of default/distress events (contagion level), solvency defaults are more likely to be induced than liquidity or leverage defaults. In comparison, liquidity distress events are more likely to be induced than a solvency or leverage distress events. Hence, a bank with a higher share of induced liquidity default/distress events than solvency/leverage distress events may be identifiable as a liquidity provider in the network, otherwise a liquidity drainer. In the end, some entities may trigger much more default/distress events relatively to their CI ranking. This is due to the fact that these banks are central entities within the domestic network of LSIs. Hence, small-medium domestic banks play an important role of contagion amplifier. This finding highlights the relevance of considering the network of EA significant and less-significant institutions in its entirety since some SIs are more exposed to the LSI sample than to other SI and global banks. Neglecting this topologic feature of the network may strongly underestimate cascade effects and banks' contribution to euro area systemic risk.

This finding brings to the forefront the relevance of the interconnectedness literature based on bilateral exposures and bank balance-sheet based methodologies to study systemic risk since approaches based on market data, for which data on small-medium entities are not available, cannot capture this contagion and amplification channel. This channel of contagion is further investigated in section 4.2 to study if and under which conditions small shocks to the periphery of the network may provoke system-wide losses.

Another modelling feature we want to assess it's the degree of amplification an exogenous default event may determine. Hence, we report the number of rounds the algorithm faces before converging as well as the ratio between direct and indirect losses. The average number of rounds is close to 3, with some banks inducing distresses or defaults up to fifth round after the initial shock hit the system. This implies that in every round there has been at least one default or distress event leading to additional dynamics and possible losses in subsequent rounds. Hence, we calculate the contribution of amplification effects to a bank's systemic importance. On average, 33% of losses among the top-10 banks are induced due to other banks' subsequent distress or default events. This finding has relevant policy-bearings. By avoiding contagion to further entities, the amount of losses induced by banks with a high

amplification ratio would be strongly reduced, therefore thwarting an idiosyncratic shock from becoming a system-wide one.

Table B.1: Contagion Measures

Contagion			EURO AREA LOSSES			GLOBAL		Defaults				Distress				Amplification		Sacrifice Ratio		
Rank	Country	Type	CI	CI CR	CI FU	NCI	Density	ToT	Solv.	Liq.	Lev.	ToT	Solv.	Liq.	Lev.	Rounds	Ratio	G	EA	N
1	XEA	GSIB	2.84	2.75	0.09	2.46	37.68	4	3	1	2	10	5	6	3	4	0.3	1.2	1.1	0.1
2	EA	EAGSIB	2.18	1.99	0.19	1.19	63.57	14	12	12	4	23	13	11	7	3	0.3	3.3	2.7	1.1
3	EA	EAGSIB	2.12	2.12	0.00	0.95	64.59	15	15	0	7	17	7	11	9	3	0.1	1.5	1.5	0.5
4	EA	EAGSIB	1.86	1.65	0.21	1.01	65.26	12	12	1	5	20	9	12	9	3	0.5	3.5	2.8	1.0
5	XEA	GSIB	1.83	1.66	0.17	1.86	33.69	2	1	1	0	5	4	1	0	3	0.4	2.5	2.0	0.1
6	EA	EAGSIB	1.80	1.72	0.08	1.02	63.46	7	7	1	0	9	5	4	2	3	0.5	4.0	3.2	1.5
7	XEA	GSIB	1.77	1.56	0.21	2.04	29.06	1	1	1	0	3	1	2	1	2	0.4	2.3	2.0	0.0
8	XEA	GSIB	1.36	1.18	0.18	1.45	33.85	4	3	1	1	9	3	6	4	4	0.6	4.4	3.5	0.2
9	XEA	GSIB	1.35	1.35	0.00	1.61	24.10	1	1	0	0	1	0	1	0	3	0.0	0.7	0.7	0.0
10	EA	EAGSIB	1.34	1.21	0.13	0.67	57.89	28	23	5	12	33	12	22	17	4	0.3	2.0	2.0	0.7
AVERAGE TOP 10			1.84	1.72	0.12	1.42	47.31	8.8	7.8	1.30	3.10	13.0	5.9	7.6	5.20	3.20	0.33	2.54	2.15	0.52
11	EA	EAGSIB	1.30	1.29	0.01	0.75	49.41	11	11	1	1	12	6	6	5	3	0.0	1.1	1.1	0.3
12	EA	SI	1.28	1.28	0.00	0.78	47.15	56	55	12	6	108	91	19	17	4	0.0	5.4	5.3	5.1
13	EA	EAGSIB	1.18	1.18	0.00	0.63	54.11	11	10	0	5	14	6	10	9	4	0.0	5.3	5.2	2.7
14	XEA	GSIB	1.16	1.02	0.14	1.64	26.77	2	2	0	1	4	1	3	1	3	0.7	3.5	2.6	0.2
15	XEA	GSIB	1.16	1.16	0.00	0.97	35.12	3	1	12	0	6	4	2	2	3	0.0	0.9	0.9	0.0
16	XEA	GSIB	1.12	1.01	0.11	2.07	20.81	1	1	0	0	1	0	1	0	2	0.7	0.9	0.7	0.1
17	EA	SI	0.79	0.79	0.00	0.80	31.81	13	12	1	7	17	8	10	8	5	0.1	2.0	1.8	1.0
18	XEA	GSIB	0.65	0.65	0.00	0.95	19.68	0	0	0	0	0	0	0	0	1	0.0	3.0	3.0	0.0
19	EA	SI	0.64	0.63	0.01	0.47	38.82	134	132	3	58	125	31	94	86	4	0.2	34.7	34.7	34.5
20	EA	SI	0.61	0.40	0.21	1.29	27.98	2	1	1	1	3	0	3	2	3	1.2	26.3	12.8	0.3
21	XEA	GSIB	0.58	0.58	0.00	1.24	13.45	0	0	0	0	1	0	1	0	2	0.0	1.0	1.0	0.0
22	EA	EAGSIB	0.58	0.58	0.00	0.32	53.09	7	6	1	0	9	6	4	2	3	0.0	1.7	1.7	0.9
23	EA	SI	0.56	0.56	0.01	0.42	40.45	5	4	12	0	7	5	2	1	3	0.1	0.9	0.9	0.3
24	EA	SI	0.51	0.36	0.15	0.30	54.30	10	9	12	4	10	4	6	4	4	0.6	2.7	2.4	0.1
25	XEA	GSIB	0.49	0.49	0.00	0.72	19.51	1	1	0	1	2	0	2	2	3	0.0	1.0	1.0	0.0
26	XEA	GSIB	0.46	0.46	0.00	1.24	10.57	0	0	0	0	0	0	0	0	1	0.0	1.0	1.0	0.0
27	XEA	OSIB	0.44	0.44	0.00	0.91	14.19	0	0	0	0	0	0	0	0	1	0.0	0.2	0.2	0.0
28	EA	SI	0.44	0.44	0.00	0.40	31.48	11	10	1	4	14	6	9	6	4	0.2	1.0	1.0	0.7
29	XEA	GSIB	0.43	0.43	0.00	0.39	31.61	0	0	0	0	3	3	0	0	2	0.0	0.3	0.3	0.0
30	EA	SI	0.43	0.43	0.00	0.26	47.26	6	6	0	2	6	4	3	3	3	0.0	3.1	3.1	2.6
31	EA	SI	0.40	0.40	0.00	0.36	31.75	0	0	0	0	8	7	1	1	3	0.0	4.4	4.4	4.3
32	XEA	GSIB	0.38	0.38	0.00	0.63	17.69	1	0	1	0	1	0	1	0	2	0.0	0.2	0.2	0.0
33	EA	SI	0.38	0.38	0.00	0.64	16.97	0	0	0	0	0	0	0	0	1	0.0	5.1	5.1	4.4
34	XEA	GSIB	0.38	0.38	0.00	0.93	12.42	1	1	0	0	0	0	0	0	2	0.0	0.1	0.1	0.0
35	EA	EAGSIB	0.38	0.38	0.00	0.17	63.92	4	4	0	1	5	3	2	2	3	0.0	0.4	0.4	0.0
36	XEA	GSIB	0.37	0.37	0.00	0.53	20.47	1	1	0	0	0	0	0	0	2	0.0	0.1	0.1	0.0
37	EA	SI	0.37	0.37	0.00	0.21	50.74	2	2	0	0	10	7	3	3	3	0.0	0.7	0.7	0.1
38	XEA	GSIB	0.34	0.34	0.00	0.91	11.25	1	1	0	0	0	0	0	0	2	0.0	0.1	0.1	0.0
39	EA	SI	0.33	0.33	0.00	0.36	26.17	1	1	0	0	0	0	0	0	2	0.0	8.1	8.1	7.9
40	XEA	OSIB	0.32	0.32	0.00	0.72	12.68	0	0	0	0	3	1	2	1	3	0.0	0.7	0.7	0.0
41	EA	SI	0.32	0.32	0.00	0.47	19.38	3	3	0	0	1	0	1	1	3	0.0	1.5	1.5	1.0
42	EA	SI	0.32	0.32	0.00	0.39	24.80	1	0	0	1	2	1	1	1	2	0.0	15.2	14.4	5.0
43	XEA	OSIB	0.31	0.31	0.00	2.94	3.05	0	0	0	0	0	0	0	0	1	0.0	1.5	1.5	0.0
44	EA	SI	0.30	0.26	0.04	1.06	19.88	1	1	0	0	3	1	2	1	2	15.0	21.0	8.5	3.5
45	EA	LSI	0.29	0.29	0.00	0.39	37.31	0	0	0	0	0	0	0	0	2	0.0	53.8	30.5	1.8
46	XEA	GSIB	0.28	0.28	0.00	0.81	10.02	0	0	0	0	0	0	0	0	1	0.0	0.1	0.1	0.0
47	XEA	OSIB	0.27	0.27	0.00	1.80	4.37	0	0	0	0	0	0	0	0	1	0.0	4.0	4.0	0.0
48	XEA	OSIB	0.27	0.27	0.00	0.78	9.86	0	0	0	0	2	2	0	0	2	0.0	4.0	4.0	0.0
49	XEA	OSIB	0.27	0.27	0.00	3.65	2.08	1	1	0	0	0	0	0	0	2	0.0	3.8	3.8	0.0
50	EA	LSI	0.26	0.26	0.00	2.00	3.75	62	61	1	31	55	13	42	38	5	0.3	52.8	52.8	52.8
AVERAGE TOP 50			0.80	0.76	0.04	1.01	30.8	8.8	8.3	0.6	3.1	11.2	5.4	6.1	5.0	2.7	0.45	5.9	4.8	2.7

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 euro area 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.

Nevertheless, a high amplification ratio is not enough to justify such an intervention. A euro area macroprudential supervisor needs a complementary perspective to assess pragmatically the cost-return tradeoff of saving the bank. Hence, it needs to look at the EA sacrifice ratio indicator. In fact, this metric, when it is higher than 1, indicates that the cost of recapitalizing the initial bank defaulting up to its full capital base is lower than the costs induced to the system if it fails. In this way we are able to capture, as widely discussed in the systemic risk

literature, those entities which are too interconnected to fail (Battiston et al., 2012). These two measures, sacrifice ratio and amplification ratio, may be positive correlated, though not always. If a bank's induced losses are due to first round effects, the amplification ratio may be smaller than 1 but the sacrifice ratio may still suggest a positive return from the intervention. This ratio may also be presented from a national or a global perspective. In fact, there may be cases for which an intervention is justified on a euro area scale but not nationally since the potential losses induced to the domestic banking system are lower than the cost of recapitalizing the bank.

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 a global scale.

The banks with the 50 highest vulnerability scores are all from within the euro area and belong to the sample of less-significant institutions. 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.

The most vulnerable bank experiences on average 2% of capital depletion given any other bank default in the system. The average for the top-50 is close 0.24%, double than the average of the full sample, and half of the average of the top-10 most vulnerable banks. Four-Fifth of the losses is due to credit risk, while one-fifth to liquidity risk, the latter mostly concentrated in few entities.

In terms of experienced default events, solvency risk is the primary cause, followed by leverage defaults (leverage below 1.5%) and liquidity defaults events which are much lower. Contrary, liquidity distress events are more likely to be triggered, with an average among the top-50 12 times higher than solvency distress events and 20% higher than leverage distress events. Notably, among banks defaulting due to solvency, on average among the top-50 only 25% of the cases are previously in a solvency distress situation. This outlines that on average a default event and subsequent cascade effects are usually deep enough to directly breach minimum capital requirements and deplete within the same round all the capital buffers. This leads to important policy implications that will be further assessed with counterfactual exercises in the macroprudential section.

In the end, we 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, 83% of the losses are provoked from within the euro area, although some banks are more exposed to risks outside the euro area. This ratio also holds across the full sample of banks.

Table B.2: Vulnerability Measures

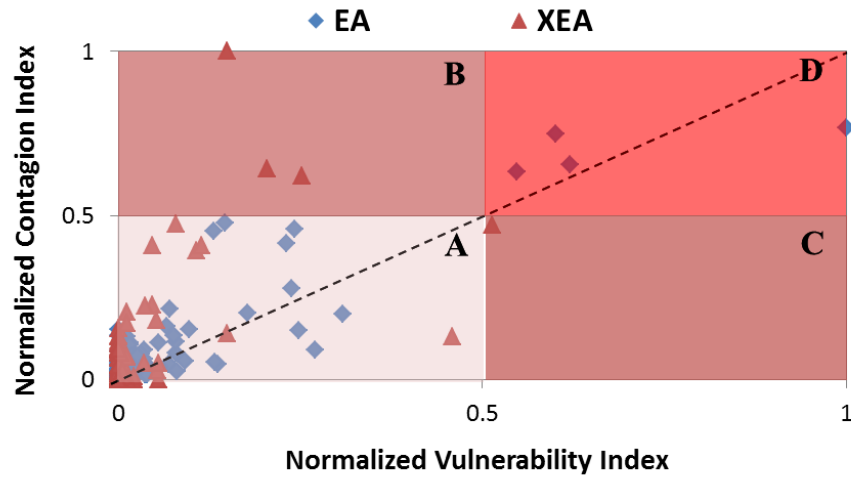
Vulnerability		GLOBAL LOSSES			Defaults				Distress				Amplification	Contribution	EURO AREA LOSSES		
RANK	Type	VI	VICR	VIFU	ToT	Solv.	Liq.	Lev.	ToT	Solv.	Liq.	Lev.	Ratio	Own_J	VI	VICR	VIFU
1	LSI	2.04	0.00	2.04	11	11	3	0	11	0	11	0	0.0	0.57	0.99	0.00	0.99
2	LSI	0.55	0.55	0.00	9	8	0	9	15	0	15	9	0.9	18.28	0.41	0.41	0.00
3	LSI	0.51	0.00	0.51	1	1	1	0	1	0	1	0	0.0	0.00	0.55	0.00	0.55
4	LSI	0.45	0.45	0.00	14	14	0	12	16	0	16	15	0.0	2.95	0.32	0.32	0.00
5	LSI	0.36	0.36	0.00	8	8	0	8	9	1	8	8	0.1	1.67	0.35	0.35	0.00
6	LSI	0.29	0.29	0.00	7	7	0	7	7	0	7	7	0.6	2.10	0.32	0.32	0.00
7	LSI	0.29	0.29	0.00	6	6	0	1	6	3	3	3	0.0	13.65	0.30	0.30	0.00
8	LSI	0.28	0.28	0.00	6	6	0	3	6	1	5	4	1.0	1.97	0.30	0.30	0.00
9	LSI	0.26	0.26	0.00	5	5	0	3	8	1	7	5	0.0	0.00	0.19	0.19	0.00
10	LSI	0.26	0.26	0.00	6	6	1	4	4	0	4	4	2.4	1.86	0.28	0.28	0.00
AVERAGE TOP 10		0.53	0.27	0.26	7.3	7.2	0.5	4.7	8.3	0.6	7.7	5.5	0.5	4.3	0.40	0.25	0.14
11	LSI	0.26	0.26	0.00	7	7	0	5	8	0	8	8	0.0	6.55	0.23	0.23	0.00
12	LSI	0.24	0.24	0.00	2	0	0	2	15	0	15	14	0.0	0.18	0.25	0.25	0.00
13	LSI	0.24	0.24	0.00	4	4	0	1	4	0	4	4	1.4	1.70	0.26	0.26	0.00
14	LSI	0.24	0.24	0.00	7	7	0	7	8	0	8	8	2.5	1.73	0.26	0.26	0.00
15	LSI	0.23	0.23	0.00	6	6	0	4	6	0	6	4	2.1	1.62	0.24	0.24	0.00
16	LSI	0.22	0.22	0.00	2	2	0	0	2	2	0	0	0.0	0.22	0.19	0.19	0.00
17	LSI	0.21	0.16	0.05	5	5	2	5	7	1	7	6	0.9	1.51	0.23	0.18	0.05
18	LSI	0.21	0.21	0.00	6	6	0	1	4	1	3	1	0.2	0.07	0.10	0.10	0.00
19	LSI	0.21	0.21	0.00	0	0	0	0	1	0	1	1	0.0	0.34	0.22	0.22	0.00
20	LSI	0.21	0.21	0.00	1	1	0	1	3	2	1	1	0.0	0.26	0.18	0.18	0.00
21	LSI	0.19	0.19	0.00	6	6	0	5	6	0	6	6	0.0	1.03	0.21	0.21	0.00
22	LSI	0.18	0.18	0.00	7	7	0	1	3	0	3	2	0.0	10.33	0.20	0.20	0.00
23	LSI	0.18	0.18	0.00	0	0	0	0	1	0	1	1	1.6	0.08	0.18	0.18	0.00
24	LSI	0.18	0.18	0.00	4	4	0	1	1	0	1	1	0.0	1.39	0.17	0.17	0.00
25	LSI	0.17	0.17	0.00	3	3	0	3	6	3	3	3	0.5	1.26	0.19	0.19	0.00
26	LSI	0.16	0.16	0.00	3	3	0	1	3	0	3	3	0.2	1.14	0.18	0.18	0.00
27	LSI	0.16	0.16	0.00	4	4	0	0	1	1	0	0	0.0	4.93	0.17	0.17	0.00
28	LSI	0.15	0.15	0.00	4	4	0	4	4	0	4	4	0.4	1.11	0.17	0.17	0.00
29	LSI	0.15	0.15	0.00	4	4	0	2	4	0	4	4	0.0	5.55	0.16	0.16	0.00
30	LSI	0.15	0.15	0.00	1	0	0	1	5	0	5	5	0.0	0.15	0.11	0.11	0.00
31	LSI	0.15	0.15	0.00	0	0	0	0	3	3	0	0	2.4	0.47	0.14	0.14	0.00
32	LSI	0.15	0.15	0.00	9	9	0	2	8	0	8	8	0.3	0.92	0.16	0.16	0.00
33	LSI	0.15	0.15	0.00	3	3	0	0	1	1	0	0	0.0	0.24	0.16	0.16	0.00
34	LSI	0.14	0.14	0.00	0	0	0	0	5	5	0	0	0.0	0.39	0.10	0.10	0.00
35	LSI	0.14	0.14	0.00	1	1	0	0	5	4	1	1	0.0	0.04	0.06	0.06	0.00
36	LSI	0.14	0.14	0.00	1	1	0	0	0	0	0	0	1.0	0.92	0.14	0.14	0.00
37	LSI	0.14	0.14	0.00	2	2	0	0	12	12	0	0	0.0	0.11	0.12	0.12	0.00
38	LSI	0.14	0.14	0.00	0	0	0	0	0	0	0	0	1.8	0.99	0.15	0.15	0.00
39	LSI	0.14	0.14	0.00	4	4	0	1	1	0	1	1	0.0	0.33	0.09	0.09	0.00
40	LSI	0.14	0.14	0.00	2	2	0	1	3	1	2	2	0.0	0.59	0.15	0.15	0.00
41	LSI	0.13	0.13	0.00	3	3	0	1	2	0	2	2	0.0	0.00	0.08	0.08	0.00
42	LSI	0.13	0.08	0.05	3	3	3	1	3	0	3	3	1.0	3.75	0.13	0.08	0.06
43	LSI	0.13	0.13	0.00	0	0	0	0	2	2	0	0	0.1	0.94	0.14	0.14	0.00
44	LSI	0.13	0.13	0.00	3	3	0	0	3	3	0	0	0.2	0.92	0.14	0.14	0.00
45	LSI	0.13	0.13	0.00	4	4	0	0	3	2	1	0	0.0	1.07	0.02	0.02	0.00
46	LSI	0.13	0.13	0.00	3	3	0	1	3	0	3	2	0.5	0.90	0.14	0.14	0.00
47	LSI	0.12	0.12	0.00	0	0	0	0	0	0	0	0	0.0	0.03	0.06	0.06	0.00
48	LSI	0.12	0.12	0.00	3	3	0	2	2	0	2	2	0.0	4.44	0.13	0.13	0.00
49	LSI	0.12	0.12	0.00	0	0	0	0	1	1	0	0	0.0	0.07	0.09	0.09	0.00
50	LSI	0.12	0.12	0.00	3	3	0	2	2	0	2	2	0.8	0.85	0.13	0.13	0.00
AVERAGE TOP 50		0.24	0.19	0.05	3.8	3.7	0.2	2.0	4.6	1.0	3.6	3.1	0.45	2.04	0.20	0.17	0.03

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 (VICR) and funding (VIFU) shocks. VI from Euro Area (VIEA) 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 the ratio of losses in subsequent rounds to losses in the immediate round. The results in this table are ranked by VI Global Scale.

Overall, **Figure A.2** combines information from both indexes, although here the vulnerability index is derived in absolute terms before being normalized. In this respect, this graph 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 quadrant (D) are

both highly contagious and vulnerable. These metrics provide a useful monitoring tool to assess threats to euro area financial stability due to interconnectedness.

Figure A.2: Systemic-Risk Map

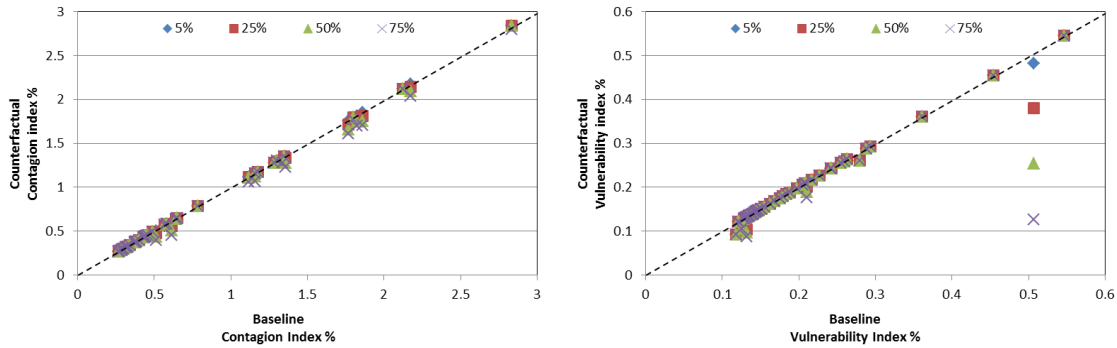


Note: Contagion and vulnerability indexes are normalized by dividing each index for the entity's maximum value. Vulnerability index is considered in absolute terms, i.e. the % of losses experienced is multiplied by the capital base.

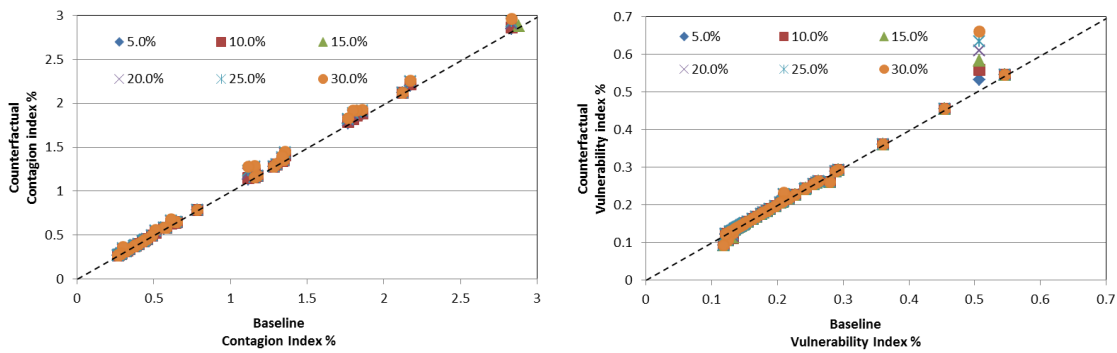
Appendix C

Figure A.3: Heterogeneous Effects due to Changes in Model Parameters

Panel (a) Pool of assets



Panel (b) Discount Rate



Panel (c) Distress Threshold

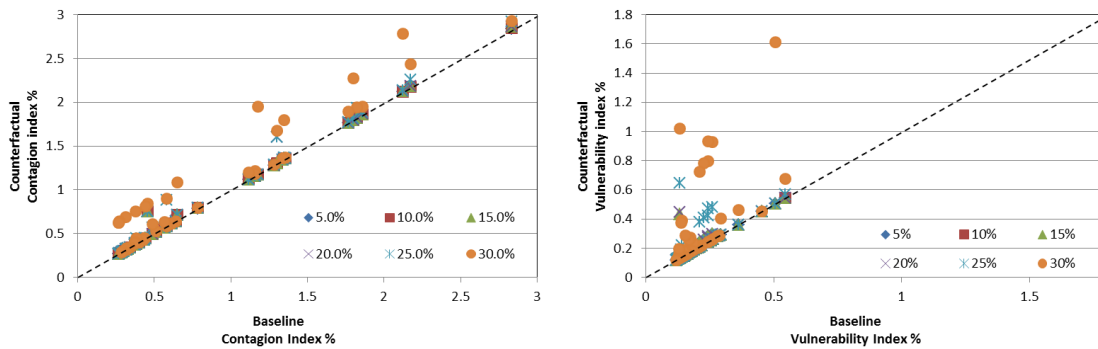
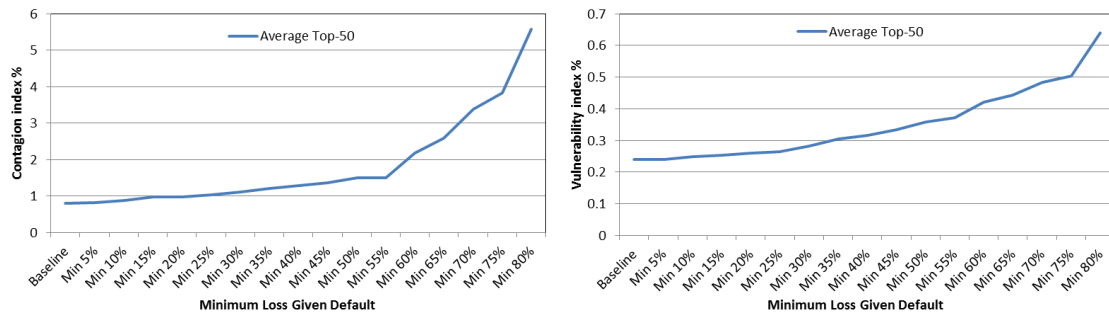
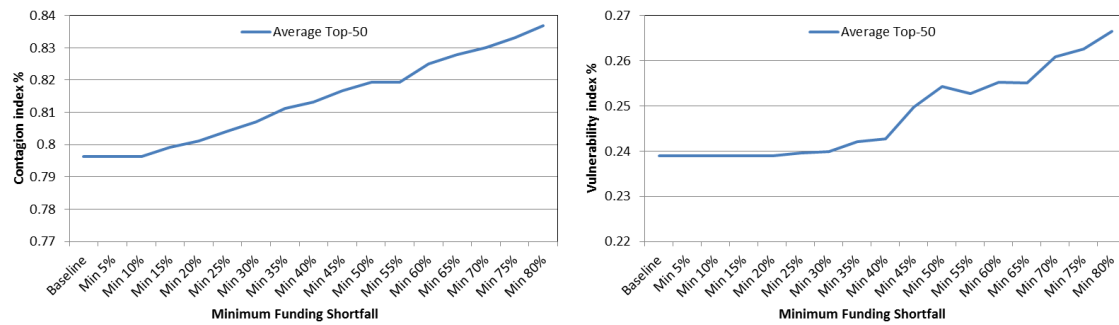


Figure A.4: Non-linear Effects due to Changes in Model Parameters

Panel (a) Loss Given Default



Panel (b) Funding Shortfall



Panel (c) Liquidity Surplus

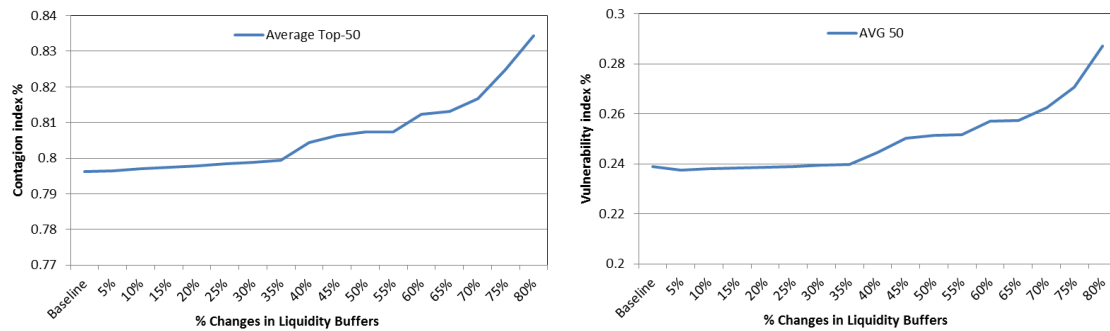
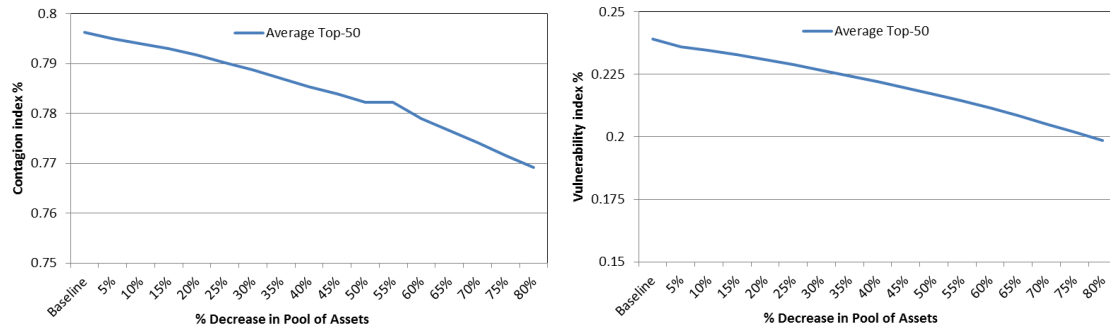
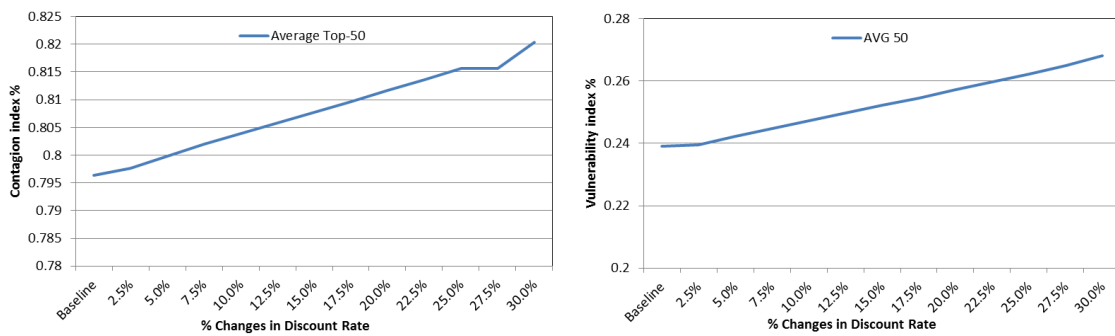


Figure A.5: Non-linear Effects due to Changes in Model Parameters

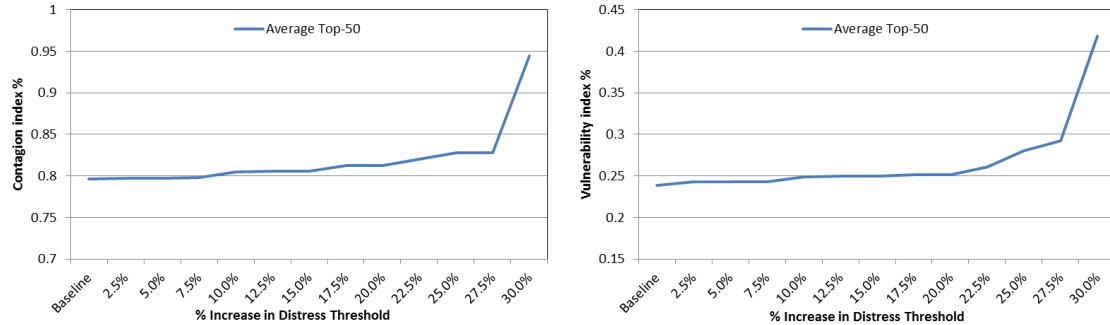
Panel (a) Pool of Assets



Panel (b) Discount Rate



Panel (c) Distress Threshold



Appendix D

Exercise 1 (MCR): $c_1^{DF} = c_0^{DF} + CS$; $c_1^{DS} = c_0^{DS}$; $k_1 = k_0 + CS$

Distant to the Default Threshold or Capital Surplus (ks_1^{DF}):

$$ks_1^{DF} = k_1 - c_1^{DF} = (k_0 + CS) - (c_0^{DF} + CS) = k_0 - c_0^{DF} \equiv ks_0^{DF}$$

$$ks_1^{DS} = k_1 - c_1^{DS} = (k_0 + CS) - c_0^{DS} > ks_0^{DS}$$

Exercise 2 (CBR): $c_2^{DS} = c_0^{DS} + CS$; $c_2^{DF} = c_0^{DF}$; $k_2 = k_0 + CS$

Distant to the Distress Threshold or Capital Surplus (ks_2^{DS}):

$$ks_2^{DS} = k_2 - c_2^{DS} = (k_0 + CS) - (c_0^{DS} + CS) = k_0 - c_0^{DS} \equiv ks_0^{DS}$$

$$ks_2^{DF} = k_2 - c_2^{DF} = (k_0 + CS) - c_0^{DF} > ks_0^{DF}$$

Exercise 3 (MIX): $c_3^{DF} = c_0^{DF} + \frac{1}{2}CS$; $c_3^{DS} = c_0^{DS} + \frac{1}{2}CS$; $k_3 = k_0 + CS$

Distant to Both Thresholds or Capital Surplus ($ks_3^{DF}; ks_3^{DS}$):

$$ks_3^{DF} = k_3 - c_3^{DF} = (k_0 + CS) - \left(c_0^{DF} + \frac{1}{2}CS\right) = k_0 - c_0^{DF} + \frac{1}{2}CS = ks_0^{DF} + \frac{1}{2}CS$$

$$ks_3^{DS} = k_3 - c_3^{DS} = (k_0 + CS) - \left(c_0^{DS} + \frac{1}{2}CS\right) = k_0 - c_0^{DS} + \frac{1}{2}CS \equiv ks_0^{DS} + \frac{1}{2}CS$$