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Macroprudential capital buffers in heterogeneous banking networks: Insights from an ABM with liquidity crises

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Macroprudential capital buffers in heterogeneous banking networks. Insights from an ABM with liquidity crises.

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Abstract

To date, macroprudential policy inspired by the Basel III package is applied irrespective of the network characteristics of the banking system. We study how the implementation of macroprudential policy in the form of additional capital requirements conditional to systemic-risk measures of banks should regard the degree of heterogeneity of financial networks. We adopt a multi-agent approach describing an artificial economy with households, firms, and banks in which occasional liquidity crises emerge. We shape the configuration of the financial network to generate two polar worlds: one is characterized by few banks who lend most of the credit to the real sector while borrowing interbank liquidity. The other shows a higher degree of homogeneity. We focus on a capital buffer for SII and two buffers built on measures of systemic impact and vulnerability. The research suggests that the criteria for the identification of systemic-important banks may change with the network heterogeneity. Thus, capital buffers should be calibrated on the heterogeneity of the financial networks to stabilize the system, otherwise they may be ineffective. Therefore, we argue that prudential regulation should account for the characteristics of the banking networks and tune macroprudential tools accordingly.

Keywords: *agent-based model, capital requirements, capital buffers, financial networks, macroprudential policy, systemic-risk.*

JEL classification: *C63, D85, E44, G01, G21.*

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1. Introduction

The purpose of ensuring the stability of the banking system can be pursued with prudential instruments (capital ratios, liquidity buffers, etc.) and structural instruments. The style of intervention of the supervisory authorities in the wake of the financial crisis has sought to optimise the mix of micro- and macro-prudential solutions and conditioning of the market form in which banking agents operate. Unlike the theoretical reference models of regulation prevailing in the 1970s and 1980s *(Stigler et al., 1983)*, which favoured solutions oriented towards collusive oligopoly *(Stigler, 1964)* in order to make the banking system stable, the current models try to intervene in one direction with instruments oriented to level the playing field, creating incentives to competitive environments. Despite this, the financial crisis has shown that the potential for contagion between financial institutions in crisis has been fuelled especially when it has been powered by entities that are particularly interconnected with others. This characteristic, combined with the size and nature of the original risk factors, required a number of regulatory proposals aimed at reducing the probability of systemically associated failure events. The most relevant and commented on in the literature were the capital buffers, some of which were applied crosswise and homogeneously to banks (conservation and countercyclical buffers) and others differentiated by type of banks (G-SIFIs buffers). But there are also measures that are in fact of a structural nature, such as those contained in the Bank Recovery & Resolution Directive (BRRD) and in particular in the recovery and resolution plans, which are oriented to contain the growth in size and by production lines of banks. The current regulatory framework has therefore introduced a mix of prudential and structural tools *(Gabbi and Sironi, 2015)* raising numerous questions that are not always resolved with regard to the effectiveness and ability to achieve the objectives of banking supervision, especially the macro purpose to minimize the systemic risk. The debate on systemic risk and on the most effective supervisory tools intersects with the process of diversification of banks and more generally on the trend that can be observed of systems that tend more or less to heterogeneity among the actors that are part of them. This debate explores numerous implications: from stability to efficiency, from innovation orientation to corporate governance.

The issue of how banks' heterogeneity affects the stability of the financial system has been extensively discussed in the literature. Banks can be heterogeneous along several dimensions such as size *(Iori et al., 2006)*, connectivity *(Amini et al., 2016)*, connectivity and asset holdings *(Caccioli et al., 2012)*, default probabilities *(Lenzu and Tedeschi, 2012)*, shocks, size and connectivity *(Loepfe et al., 2013)*. A concise review of the literature about the implication of banks' heterogeneity can be found in *Chinazzi and Fagiolo (2013)*. A strand in the literature exploring the role of heterogeneity to which *Wagner (2008)* and *Beale et al. (2011)* are key contributors, focuses on the effect of correlations in banks' portfolios returns. The main insight in this context is that when market players diversify their portfolios, banks' risk exposures become similar and the system as a whole tends to a higher degree of homogeneity. In this case banks become individually less risky, but systemic risk increases. Similar conclusions are derived by, *Acharya (2009), Acharya and Yorulmazer (2008)* and *Moore and Zhou (2013)* who, to mitigate the potential systemic effect of excessive portfolio diversification, propose a correlation-based capital adequacy requirement, increasing, not only in the individual risk of a bank, but also in the correlations of a bank's portfolio returns with those of other banks in the economy. However, when homogeneity refers, not to the composition of banks' portfolios, but to banks' size and risk appetite *Iori et al. (2006)* show that increasing heterogeneity destabilizes the system. In fact switching from a situation where all banks have a similar size of deposits to another where the distribution of deposits across banks is more uneven leads to systemic instability when interbank connectivity increases. One policy implication that suggests itself is that interbank lending relationships be confined to banks that share similar characteristics. The findings of *Caccioli et al. (2012)* reinforce this insight. Building on the seminal model of *Gai and Kapadia (2010)*, they study the probability of contagion in a financial network model which accounts for banks' heterogeneous degree and balance sheet size. The main results is that the extent of contagion is limited when banks are homogeneous in size and degree. Conversely, when banks show heterogeneity along these dimensions, and connectivity is high, the probability of contagion conditional to the failure of the bank with the biggest balance sheet is higher than the probability associated to the default of the most interconnected banks. This entails that imposing additional capital buffers to big banks may be more effective than targeting the most interconnected ones. Similar policy implications are also discussed in *Loepfe et al. (2013)*.

The contribution of the current paper is to assess the effectiveness of macro prudential measures in a context that may have a more or less diversified market environment. In particular, the main research question of the paper is whether prudential measures aimed at calibrating capital in the face of banking losses can be more or less effective when the actors in the banking system tend to be more or less heterogeneous with each other. Specifically, we aim to identify the capacity of the different criteria for the application of capital ratios to minimize the risk of contagion when bank heterogeneity is given in terms of banks' size and degree in the banking network. A fundamental role in our model is played by the interbank market. It is a source of funding that is in itself a safety net. This source of liquidity is preferred by banks to central bank refinancing both for signaling reasons and because the interbank market is not collateralized, unlike central bank facilities. If the financial dynamics that is evident in the interbank market synthesizes the funding liquidity risk and related contagion, the second protection factor is that represented by capital, which is the element on which the international regulatory framework is based, since the Basel Accord of 1988. In our model, when a bank's equity capital is negative (i.e. when the value of assets is lower than the value of liabilities) bankruptcy occurs. Then its shareholders bail-in by injecting sufficient new capital to reach the minimum ratios. To simulate the impact of different capitalization measures in different banking market contexts, we conduct counterfactual policy experiments in an agent-based model (ABM) of the economy. The original model *(Gurgone et al., 2018)* is expanded to allow banks to use systemic risk measures to determine their capital requirements and to modify the heterogeneity of the banking network, where moving towards a more homogeneous system grows the similarity of banks' portfolios and so risk diversification. Moreover, the original model produces risk correlation in banks' portfolios since these are exposed to the firm sector, whose profitability changes along the business cycle.

In our study, we compare standard regulatory measures based on risk weighted assets with the capital needed to ensure the resilience of banks in the event of losses based on systemic risk measures. The scores are calculated using three different risk assessment methods:
(i) EBA method for identifying the degree of exposure to contagion risk. The method assigns a score to each institution calculated on the basis of three elements: size, importance, interconnection.
(ii) A second criterion is a systemic impact algorithm, called DebtRank *(Battiston et al., 2012)*. It is a metric based on the nature of the network representing the banking system, in particular on the relationship between banks-firms and interbank exposures. In this case, the capital buffers of the individual node (which is the individual bank) are determined on the basis of the systemic impact derived from the ranking generated by the DebtRank.
(iii) The third criterion applied in our model is always derived from the DebtRank algorithm, but instead of measuring the impact we take into account the vulnerability of a bank measured by the relative capital loss induced by the forced default of other individual banks. The financial distress is defined as the relative change in shareholders' equity.
The shocks that can lead to bank failure are numerous and our paper simulates shocks transmitted by firms when the profitability of borrowers of funds is not sufficient to repay bank debts; shocks that can be generated in the interbank market due to lack of liquidity; finally, shocks driven by deleveraging when distressed banks liquidate their assets on the market. We assess the different roles of these channels of risk propagation in the cases of high or low heterogeneity in the banking industry. By simulating low and high heterogeneity market models within the agent based model we identify the probability of losses, defaults of financial and non-financial firms, and contagion and their response to capital requirements determined via different policy measures. Our approach presents some similarities with *Poledna et al. (2017)*. They employ a macroeconomic agent-based model to compare the effectiveness of Basel III capital surcharges with a tax on systemic risk. The last turns out to be the best policy since it can shape the topology of the interbank reducing systemic-risk. Instead, we keep the Basel's bucketing approach, and we extend it to other systemic-risk assessment methods when the banking system is more or less heterogeneous.

The main findings reveal that the effectiveness of macroprudential capital buffers depends on the degree of heterogeneity of the banking network, hence the best policy changes in different settings.
We observe that a more homogeneous banking system, and specifically the interbank network, leads to more stability regardless of the macroprudential policy implemented. When banks are homogeneous in deposits, the interbank market maximizes risk diversification, whose benefits exceed the drawbacks of risk spreading. At the same time, the homogeneity of banks in terms of assets lowers knock-out effects and therefore reduces the probability of contagion or extreme events.
Moreover, the characteristics of systemic-important banks modify switching to a more homogeneous network. While it is advisable to apply additional capital surcharges to the largest banks in terms of assets under high heterogeneity, the key characteristics of systemic-banks under low heterogeneity are the size of liabilities

jointly with interbank interconnectedness. Applying such network-contingent policies permits the reduction of the frequency of extreme events and, ultimately, to enhance financial stability.

The rest of this paper is organized as follows: Section 2 describes the modelling framework, distress dynamics, systemic-risk measures and macro-prudential policies. Section 3 goes through the results of the simulations and the policy experiments. Discussion and Conclusion are in Sections 4 and 5.

2. The model

In this section we provide an overview of the macroeconomic model and a detailed description of the behavior of banks. The reader is referred to section A.1 in the Appendix for further details about the model. The structure of the model builds on an amended version of the agent-based-model (ABM) in *Gurgone et al. (2018)*, though the financial sector has been further developed.

2.1. Overview

The economy is populated by three main groups of agents: households $hh = \{1,\ 2, \dots,\ N^H\}$, firm $ff = \{1,\ 2, \dots,\ N^F\}$ and banks $bb = \{1,\ 2, \dots,\ N^B\}$. Moreover, the economy includes a government, a central bank and a special agency. All these entities have their own balance sheet and obey to behavioral rules. Agents interact in different markets: firms and households meet on markets for goods and labor, firms borrow from banks on the credit market, banks exchange liquidity in the interbank market. The government makes transfer payments to the household sector while keeping the public debt at a steady level. The CB generates liquidity by buying government bills and providing advances to those banks that require them; it furthermore holds banks' reserve deposits in its reserve account. Households work and buy consumption goods by spending their disposable income. In the labor market, households are represented by unions in their wage negotiations with firms, while on the capital market, they own firms and banks, receiving a share of profits as part of their asset income. Firms borrow from banks to pay their wage bills in advance, hire workers, produce and sell their output on the goods market. The banking sector provides credit to firms, subject to regulatory constraints. In each period banks try to anticipate their liquidity needs and access the interbank market as lenders or borrowers. If a bank cannot secure the demanded liquidity or it is insolvent, it sells part of its illiquid assets at a discount to the special agency that acts as a liquidator. The assets in the agency's portfolio are held to maturity, while profits or losses are transferred to the Central Bank.

2.2. Networks

There co-exist static and dynamic networks. The first type is generated before the beginning of simulations and it is kept unchanged. It describes the time-invariant connections of depositors and shareholders with banks. Conversely, link formation in firms-banks and interbank networks is not constrained by any pre-determined structure but settled by a matching mechanism. *In toto*, static and dynamic networks form a multilayer network, where households, firms, and banks are interconnected.

We aim to represent high and low heterogeneity worlds. In the first world we call *interbank lenders* those banks having many depositors but few lending opportunities toward firms. The principal activity of interbank lenders is lending to other banks, thus they have low interbank in-degree and form the peripheral part of the interbank network. Their size in terms of net worth is negatively correlated with the degree in the deposits networks. At the opposite, we call *credit lenders* those banks with high out-degree in the credit market that have few links with depositors but are densely connected in the interbank network, being the core. They borrow funds from the peripheral banks and their size is positively correlated with their degree in the firm-bank credit market. The low heterogeneity world is a flattened version of the other one. Banks are more homogeneous in the number of depositors, lending opportunities, net worth and the interbank network does not show a core-periphery structure anymore.

The remainder of this section presents the formation algorithm of static networks. Links formation in dynamic networks is described by the matching mechanisms in Section 2.3. Fig. 1 shows the distribution of banks' out-degrees. Baseline statistics are in A.3.

2.2.1 Heterogenous world

Depositors' networks A preferential attachment algorithm controls the formation of the *bipartite* static graphs that describe the connections of depositors and banks. Since both households and firms have deposits, two different networks are needed. We employ the same fitness measure to ensure that the normalized total degrees of banks are similar in both cases. At each step τ a household (firm) i enters the algorithm and connects to a randomly chosen bank b with a probability $p^d_{ib,\tau}$. This depends on the number of b's links ($degree^d_{b,\tau}$), which is updated at each iteration, a randomly assigned fitness measure ($fitness^d_b$), and a constant (a^d).

$$p^d_{ib,\tau} = \frac{degree^d_{b,\tau} fitness^d_b + a^d}{\sum_b \left(degree^d_{b,\tau} fitness^d_b + a^d\right)} \qquad where\ i = \{h,\ f\} \tag{1}$$

Each household (firm) can have at most one link, namely she keeps her deposits in one bank only. The algorithm is repeated until everyone is connected to a bank so that the total degree of the network is equal to the number of depositors.

Pseudo-credit network The firms-banks credit network is determined endogenously through a preferential attachment mechanism as in Eq. (12) in Section 2.3.1. The attachment probability depends on banks' total degree in a static network called *pseudo-credit network*. The pseudo-credit network is generated by the same preferential attachment mechanism of Eq. (1), but the fitness measure is the inverse of $fitness^d_b$ normalized by its sum so that the total degree is negatively correlated with the number of links in the deposits networks. Moreover, when a new link is created firms do not exit from the algorithm but meet the next bank in the list until the total number of links exceeds an integer $link^{max}$.

$$fitness^c_b = \frac{\sum_b fitness^d_b}{fitness^d_b}$$

This creates a guideline for the attachment mechanism where the probability to connect to a firm is negatively correlated with the number of depositors.

Shareholders' network The bipartite shareholders' network determines the identity of shareholders of firms and banks. Despite our simplified framework does not provide precise treatment for equity shares, shareholders receive dividend payments from the banks to which they are connected and will bail them in contingent upon bankruptcy. The number of shareholders of firms and banks is a positive function of the mutual connections in the pseudo-credit network. In other words, we assume that the larger the degree of firms (or banks), the larger the number of shareholders. This roughly reflects the idea that the most interconnected agents are those with the best lending or borrowing opportunities. Therefore, they have larger net worth and thus more shareholders. The probability that a node h connects to a firm (bank) j is a function of j's degree in the pseudo-credit network ($degree^c_j$) and a constant (a^s). The algorithm is repeated 5 times. At each repetition, h can connect to any j conditional on the attachment probabilities. We do not restrict the maximum links of households to banks and firms so that each i can be connected to more than one node.

$$p^s_{hj} = \frac{degree^c_j + a^s}{\sum_j \left(degree^c_j + a^s\right)}, \quad j = \{f,\ b\} \tag{2}$$

2.2.2 Homogeneous world

Low network heterogeneity is achieved by changing the attachment mechanisms. Depositors' and pseudo-credit networks are generated with a simple mechanism described in Table 1. The algorithm for shareholders' network is unchanged.

Depositors' network	Pseudo-credit network
(i) Form a list of households (or firms).	(i) Form a list of firms.
(ii) Each element i in the list is sequentially assigned to a random bank.	(ii) Each element i in the list is sequentially assigned to a random bank.
(iii) i is removed from the list.	(iii) i is not removed from the list.
(iv) Stop only when all elements are matched to a bank.	(iv) Stop after 5 iterations of all elements in the list.

Table 1: Generating algorithms of depositors' and pseudo-credit networks.

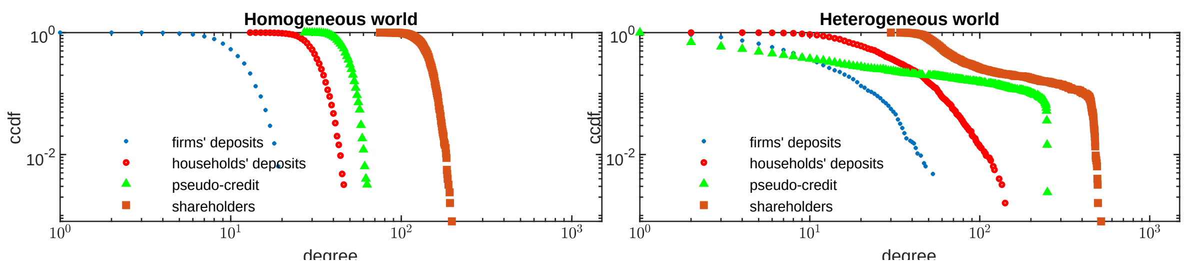


Figure 1: Loglog complementary cumulative distribution function (ccdf) of banks' total degree for low *(left)* and high *(right)* network heterogeneity.

2.3. Banks

Banks play simultaneously in the credit and interbank markets by lending to firms and trading liquidity. The overall amount of money in the system is fixed. It means that money is exogenous, although studying the system under endogenous creation of money would be an avenue for future research. Lending to the real sector is financed out of short-term liabilities, namely deposits of households and firms, or interbank funds. In case liquidity is not immediately available from these sources we assume that banks sell assets in a special market at the price determined in Eq. (20). The asset side of banks' balance sheet consists of loans to firms (L), interbank lending (I^l), highly liquid assets or liquidity (R). Liabilities are deposits of households and firms (Dep), and interbank loans (I^b). Table 2 reports the composition of the balance sheets of banks and firms.

Banks		Firms	
Assets	Liabilities	Assets	Liabilities
L	Dep	Dep	L
I^l	I^b		
R			
	nw^B		nw^F

Table 2: Balance sheets of banks (left) and firms (right). Loans to firms (L), interbank lending (I^l), liquidity (R), deposits (Dep), interbank borrowing (I^b).

The net worth of bank b at time t is defined according to

$$nw^B_{b,t} = R_{b,t} + L_{b,t} + I^l_{b,t} - Dep_{b,t} - I^b_{b,t}. \tag{3}$$

Banks comply with a standard minimum capital requirement so that net worth must be greater or equal than a fraction $\frac{1}{\lambda}$ of risk-weighted-assets (RWA). Assuming that liquidity R is riskless, $RWA_{b,t} \equiv \omega_1 L_{b,t} + \omega_2 I^l_{b,t}$.

$$nw^B_{b,t} \geq \frac{1}{\lambda} RWA_{b,t} \tag{4}$$

Gross profits Π^B are given by the difference between interest inflows and outflows, where r^L is the rate paid to deposits on Central Banks' account, the subscript k indicates the residual maturity of loans to firms, r^{ib} is the interest rate on interbank lending, and r^D is the deposit rate to households or banks. If profits are positive, these are subject to taxes at the rate of θ^B. Then the fixed share δ^B is distributed to shareholders.

$$\Pi^B_{b,t} = R_{h,t-1} r^L + \sum_{j=1}^{J} L_{bj,t-k_j} r^f_{bj,t-k_j} + \sum_{q=1}^{Q} I^l_{bq,t-1} r^{ib}_{bq,t-1} - D_{b,t-1} r^D - \sum_{z=1}^{Z} I^b_{bz,t-1} r^{ib}_{bz,t-1} \tag{5}$$

The net worth of bank b updates with the retained profits minus the losses from exposures to firms and banks, and operating costs c increasing with the bank's size.

$$\Delta nw^B_{b,t} = (1-\theta^B)(1-\delta^B)\Pi^B_{b,t} - \sum_{j=1}^{J} loss^F_{t,bj} - \sum_{q=1}^{Q} loss^B_{t,bq} - c(nw^B_{b,t-1})^2 \tag{6}$$

Recovery rates The effective loss on a generic asset a_{bi} owed by i to b is $a_{bi}(1-\varphi_i)$, where φ is the recovery rate. All of i's creditors can recover $\varphi_i = \frac{\mathcal{A}_i}{\mathcal{L}_i}$, *i.e.* the ratio of borrower's assets ($\mathcal{A}_i = \sum_i a_i$) to liabilities ($\mathcal{L}_i$). However, the nominal value of illiquid assets is not immediately convertible in cash and must first be liquidated to compensate creditors. We denote the liquidation value of the banks' assets $\mathcal{A}^{liq}_i$, where $\mathcal{A}^{liq}_i \leq \mathcal{A}_i$. The actual recovery rate can be written as:

$$\varphi_{ib} \equiv \frac{\mathcal{A}^{liq}_i}{\mathcal{L}_i}$$

Furthermore, we assume that there is a pecking order of creditors, so that they are not equal from the viewpoint of bankruptcy law: the most guaranteed are depositors and then banks with interbank loans. For instance, those creditors who claim interbank loans towards the defaulted bank i recover the part of i's assets left after the other creditors have been compensated. The recovery rate is expressed as

$$\varphi_i = \max\left(0,\ \frac{\mathcal{A}^{liq}_i - Dep_i}{\mathcal{L}_i - Dep_i}\right). \tag{7}$$

It is worth noticing that *loss given default* is $LGD \equiv 1 - \varphi$, so that the net worth of creditor b updates as $nw^B_{b,t} = nw^B_{b,t-1} - LGD_{ib,t} a_{bi,t}$.

2.3.1 Credit market

Firms and banks meet in the credit market, where the former demand credit to anticipate the wage bill, while the latter allocate the supply of credit as determined by Eq. (8). The maturity of loans is randomly extracted by a discrete uniform distribution $\mathcal{U}(\underline{d},\ \bar{d})$.

The maximum credit that can be lent to firms is constrained by minimum capital requirements in (4).

$$L^s_{b,t+1} = \frac{\lambda}{\omega_1} nw^B_{b,t} - \frac{\omega_1}{\omega_2} I^l_{b,t} - L_{b,t} \tag{8}$$

All banks assign the same default probability ρ^f to a firm j, which depends on its desired leverage rate - that is demanded credit to net worth ratio ℓ, where ℓ^*, v^f, and u^f are calibration parameters.[1]

$$\rho^f_{b,t} = u^f \ \exp\left[v^f\left(\frac{\ell_j}{\ell^*} - 1\right)\right] \tag{9}$$

Bank b sets the interest rate to j depending on her cost of funds (cf) and default probabilities.

$$r^f_{bj,t} = \frac{1 + cf_{b,t}}{1 - \rho^f_{bj,t}} - 1 \tag{10}$$

where $cf_{b,t}$ is bank's cost of funds. It depends on the composition of liabilities, with $w^s_{b,t}$ representing the share of each source of liquidity (deposits, interbank borrowing) over total liabilities.

$$cf_{b,t} = w^D_{b,t} r^D + w^I_{b,t} r^b_{t-k,b} \quad s = \{Dep,\ I^b\} \tag{11}$$

Matching in the credit market Links in the firms-banks credit network form endogenously following a preferential attachment mechanism with probabilistic switching. At the opening of the credit market firms demanding loans are sorted by their ascending default probabilities and matched one-by-one with a bank. This is chosen by sampling with replacement among those with positive credit supply. Sampling weights ν depend on banks' share of the total degree in the pseudo-credit network, which is negatively correlated with the number of depositors (see Section 2.2).

$$\nu_b = \frac{degree_b}{\sum_b degree_b}$$

The probability that a firm j switches to the candidate partner b and cuts the links with her previous lender k is regulated by (12) where ν_0 is a midpoint constant.

$$p^{switch}_{jb} = \frac{1}{1 + \exp\left[-\kappa(\nu_b - \nu_k - \nu_0)\right]} \tag{12}$$

The algorithm is repeated for all banks in the list until the credit demand of firm j is exhausted; the loan supply of banks goes to zero; after j meets the last bank in her list. If there is no previous lender k, j is matched with b.

2.3.2 Interbank market

Banks participate in the interbank market to protect themselves against the risk of running out of funding. This is achieved by setting aside a buffer of liquidity large enough to run bank activities without incurring shortages. If such target cannot be reached, illiquid assets (loans to firms) are sold. Differently from *Gurgone et al. (2018)*, where the Central Bank always acts as the lender of last resort, we assume that banks prefer to retrieve liquidity in the market rather than borrowing from the discount window of the Central Bank. This would signal their riskiness in that cannot access other sources of funding exposing them to the stigma of peers, as documented in *Armantier et al. (2015)*. The liquidation process is detailed in 2.4 where the asset price is determined by Eq. (20). In case a bank needs to sell a sizable quantity of assets, liquidation could depress the final price and determine the deterioration of its balance sheet.

Since the primary source of bank funding is deposits, the interbank market takes place when there are endogenous changes in deposits, that is three times within one iteration of the model. At each market session banks try to anticipate how much liquidity they need to avoid shortages until the closing of the market and form a *liquidity target*. In the end, the market closes and banks settle their positions. The timeline of the market unfolding is represented in Figure 2.

[1] The price of consumption goods is set by firms via a mark-up on the unitary cost of output, which includes the labor and credit cost. As the wage rate and the mark-up rule is equal across all firms, the cost of credit affects the chances of firms to sell the production in the competitive goods market. Thus, high leveraged firms pay a greater rate on loans. Their final goods are comparatively more expansive and are subject to greater losses than those less leveraged. Therefore, the assessment of firms' default probability is simply expressed as a function of the leverage rate.

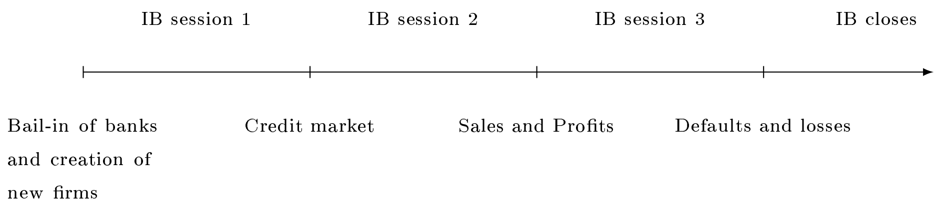


Figure 2: Timeline of the interbank market (IB). Source: *Gurgone et al. (2018)*

Bank b needs to borrow additional liquidity if the inequality (13) is not satisfied otherwise b offers the positive difference in the interbank market.

The left-hand-side is the liquidity held at the CB net of the compulsory reserves. At the right-hand-side $liq^{tag} = \beta(out^E - in^E)$ represents the liquidity buffer, which depends on the difference between expected cash outflows and inflows during one period.

$$R_{h,t} - rrDep_{h,t} \geq liq^{tag}_{b,t} \tag{13}$$

The expected cash outflows are given by the sum of the payment of interest rates on deposits, the expected cost of interbank borrowing, and the expected roll-over of existing loans to firms. Expected values are denoted by superscript E and are computed by an exponential weighted average of past values. The expected cash inflows are the sum of interest payments on loans by the subset of firms j, plus the principal of loans that will be paid back at the end of t by borrowers V weighted by their default probabilities, plus the interest paid by the CB on reserves.

The interbank demand and supply are obtained from (13). Demand is specified in Eq. (14).

$$I^d_{b,t} = liq^{tag}_{b,t} - (R_{b,t} - rrDep_{b,t}) \tag{14}$$

As with loan supply, the supply of interbank funds in (15) is constrained by the minimum regulatory capital requirements.

$$I^s_{b,t} = \min\left(R_{b,t} - rrDep_{b,t} - liq^{tag}_{b,t}, \quad \frac{\lambda}{\omega_2} nw^B_{b,t} - \frac{\omega_1}{\omega_2}\sum_{j\in J} L_{bj,t-k} - \sum_{z\in Z} I^l_{bz,t-k}\right) \tag{15}$$

The interbank reservation rate r^{ask} is the minimum rate at which banks are willing to lend interbank funds. It is adjusted for the default probability of the counterparty, ρ^{ib}. For a hypothetical borrower z it is

$$r^{res}_{bz,t} = \frac{1 + r^L}{1 - \rho^{ib}_{bz,t}} - 1. \tag{16}$$

The default probability computed by a potential lender b for a bank z is a function of its observed financial leverage, namely the total exposures to equity ratio lev^{ib}, where lev^*, v^{ib}, and u^{ib} are calibration parameters.

$$\rho^{ib}_{z,t} = u^{ib} \ \exp\left[v^{ib}\left(\frac{lev_z}{lev^*} - 1\right)\right] \tag{17}$$

Matching in the interbank market Interbank borrowers enter randomly one-by-one and are assigned to a random candidate lender. Lenders' ask price is the reservation rate r^{res} from (16). Trading is only possible above it. Borrowers do not know at what rate they could be charged so they bid taking as a reference the mid-corridor between the minimum and maximum rates in the system. These are set by the central bank and correspond to the rate paid on excess funds r^L and the rate offered by the discount windows for emergency refinancing operations r^H. The bid rate of borrowers is formed as a mark-up over the mid-corridor.

$$r^{bid}_{z,t} = \frac{r^H + r^L}{2}(1 + \varepsilon_{z,t}) \qquad \text{with } r^{bid}_{z,t} \in [r^L,\ r^H] \tag{18}$$

The mark-up is increased if there is unfilled demand and decreased otherwise without exceeding the boundaries of the corridor.

$$\varepsilon_{z,\tau+1} = \begin{cases} \varepsilon_{z,\tau} + \gamma & if\ I^d_{z,\tau} > I^b_{z,\tau} \text{ and } r^{bid}_{z,\tau} \leq r^H \\ \varepsilon_{z,\tau} - \gamma & if\ I^d_{z,\tau} = I^b_{z,\tau} \text{ and } r^{bid}_{z,\tau} \geq r^L \end{cases}$$

where $\tau = \{1, \dots, n^\tau\}$ is the ordinal number of borrowing attempts within each execution of the interbank market. Any interbank transaction takes place if $r^{bid}_z \geq r^{res}_{bz}$ at $r^{ib}_{bz,t} = r^{bid}_{z,t}$.

2.3.3 Risk management

Banks resort to risk management strategies to mitigate the losses from systematic risk.

At the loan level, banks diversify credit risk by limiting the maximum exposures to firms based on the estimated default probabilities ρ^f and a maximum equity loss per loan ζ. We follow *Assenza et al. (2015)* so that the maximum amount of outstanding loans to firm j is

$$L^{max}_{bj,t} \equiv L_{bj,t} \leq \frac{\zeta nw^B_{b,t}}{\rho^f_{j,t}}.$$

At the aggregate level, the risk management strategy is operated by setting a maximum portfolio to equity ratio depending on perceived risk. Banks set a target leverage ratio in terms of assets over equity that changes depending on their risk tolerance. The last is determined by a VaR level estimated on returns to risky assets. We employ a parametric VaR at $\alpha = 0.99$ and assume that mean returns and volatility follow a normal distribution.

$$VaR^\alpha_t(L + I^l) \leq nw^B_t \Rightarrow \frac{L + I^l}{nw^B_t} \leq \frac{1}{VaR^\alpha} \tag{19}$$

Therefore, banks will manage the total credit supply to comply with Eq. (19) so that the leverage ratio does not exceed $\frac{1}{VaR^\alpha}$.

2.3.4 Recapitalization

When the net worth of a bank is negative it declares bankruptcy. Its assets are liquidated and distributed to creditors as described at the beginning of Section 2.3 so that the net worth equals zero. The only elements left on the balance-sheet are deposits and a corresponding amount of R on the asset side. The bank stays out of business for a minimum of $timer^B$ periods or until it can be recapitalized by its shareholders, so it is not replaced by another one but receives fresh capital. The new capital is paid by banks' shareholders proportionally to their number, where the shareholders of a bank are those households that receive dividends from it. The assumption is consistent with the construction of shareholders' network presented in Section 2.2, *i.e.* banks with a larger number of connections with firms have more shareholders than the other. Thus, those that can achieve a large size in terms of assets and net-worth have a larger number of shareholders ready to bail-in by injecting new capital. If the new capital of those banks that have more lending opportunities (the total degree in the pseudo-credit network) is not enough, they could fall into bankruptcy in the aftermath of re-capitalization due to the sharp growing exposure to the firms' sector. The new capital, $\phi\sqrt{N^{sh}_b}$ is therefore proportional to the number of shareholders of bank b.

2.4. Distress dynamics

Distress propagates through balance sheets when agents go out of business. The dynamics is illustrated in Figure 3. We distinguish between two sources of distress: systematic and illiquid. The systematic source starts with the deterioration of firms' balance sheets. It operates in every simulation producing a recurring pattern of defaults and losses. Instead, the illiquid source is activated infrequently but produces liquidity crises with high losses and longer bankruptcy chains. It comes into play when the deterioration of banks' balance sheets leads to a shortage of liquidity and consequently to assets liquidation.

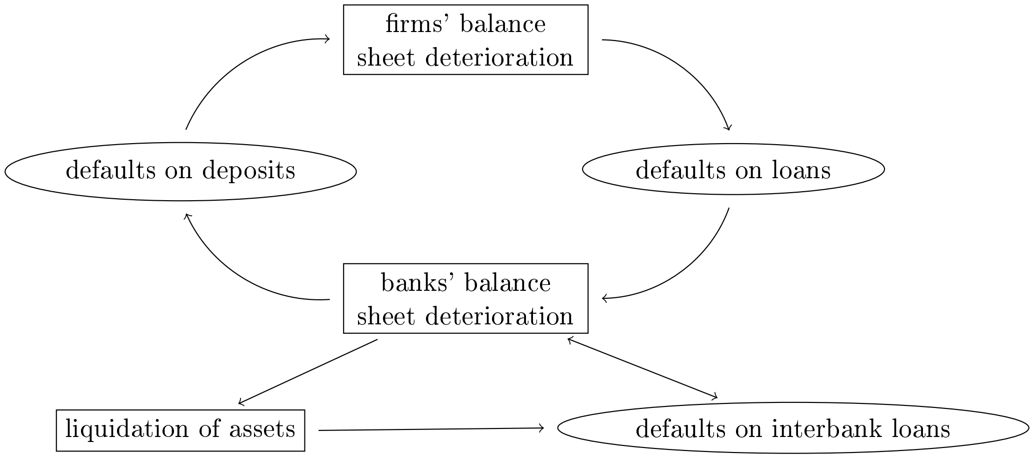


Figure 3: Distress is transmitted from firms to banks through credit market, from banks to banks in interbank market and from banks to firms through banks' liabilities.

Systematic It is connected to the model's dynamics that produces cyclical fluctuations. Distress originates in the firms' sector, and then it is transmitted to banks. In good times, when unemployment is low, there is upward pressure on prices following a rise in nominal wages. At some point, firms' revenues from the goods market are not enough to repay loans hence some of them go into default. Shocks propagate from firms to banks, within the interbank market and from banks to firms.[2]

Illiquid The second origin is related to rationing in the interbank market: the supply of liquidity is subject to the risk-management strategy of banks, which adjusts it to respond to a fall in returns. In a downturn, the outstanding stock of loans and credit demand by firms do not decrease simultaneously with supply. Although total credit supply is revised downwards, those lenders that have experienced negligible losses keep on lending to firms and substitute other banks that have temporarily limited their exposures. This has a twofold effect: it raises the liquidity demand of these lenders and increases their leverage ratios. Combining reduced interbank supply and sustained demand of some lenders may bring about rationing. Albeit such circumstances do not arise in every computer simulation, in a limited number of cases it gives rise to a liquidity crisis where a bank is forced to liquidate its assets to retrieve liquidity. This may determine bankruptcy followed by the propagation of distress to interbank creditors and further rounds of contagion. A representative run of the model is shown in Figure 4, which displays simulations of total production, and demand and supply of interbank funds. Liquidity crises arise occasionally from the rationing on the interbank market.

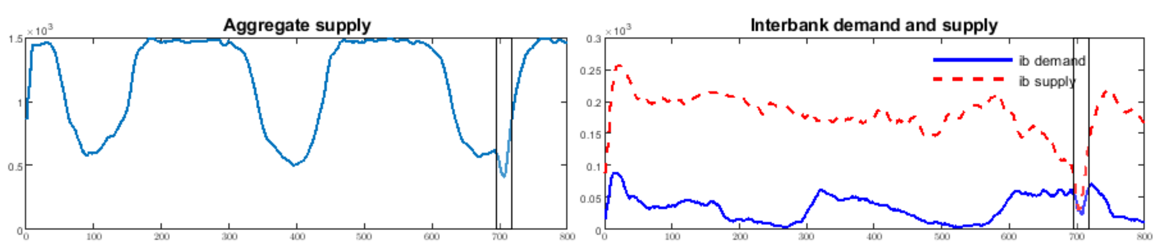


Figure 4: Representative simulations of aggregate supply and interbank demand and supply. A liquidity crisis occurs around $t = 700$. A default cascade follows the liquidation of assets of the illiquid bank. This causes a credit crunch and consequently a slump in aggregate supply.

Liquidation of assets Banks liquidate assets (loans to firms) in two cases: when they run out of liquidity, as explained above, and when they default to repay creditors. The role of liquidator is operated by a special

[2]If the net worth of a bank is negative, it defaults on its liabilities including the deposits of firms and households. A deposit guarantee scheme is not implemented.

agency that buys the assets of bank b at price p

$$p_\tau = p_{\tau-1}\left(1 - \frac{\Delta q_{b,\tau}}{q_t}\frac{1}{\epsilon}\right) \tag{20}$$

where $\Delta q_{b,\tau}$ is the quantity of loans that bank b needs to liquidate,[3] ϵ is the asset price elasticity, q_t is the total quantity of loans in period t. Banks that need liquidity enter the market in a random order marked by τ, so that the first one sells at p_1, the second at p_2 and so on; we assume that at the end of each unit of time the initial asset price is set again at $p_0 = 1$. The assets purchased by the agency are then kept until maturity. Profits and losses realized by the agency are transferred to the government so that money is not subtracted to the stock-flow consistent system.

2.5. Systemic capital buffers

The banking sector is regulated through capital requirements. As mentioned in Section 2.3, all financial institutions must comply with minimum capital requirements that correspond to a fixed ratio of RWA. In this section we introduce another supplementary requirement that adds up to minimum capital requirements. This is an additional capital surcharge that we call "*Systemic Capital Buffer*" (SCB) as it is based on a systemic-risk assessment of banks. Moreover, we implement three types of SCBs, which differ from each other depending on how systemic-risk is measured. The first type of surcharge is the well-known buffer for systemically important financial institutions and addresses high-impact banks.[4] The second one is addressed to the same target (high-impact financial institutions), but systemic-importance is assessed differently. The third capital buffer shares the same methodology of the second but aims to measure the systemic vulnerability of banks. Following the technical classification of the ESRB, the last pair falls within the so-called systemic-risk buffer (SyRB), while the first is a buffer for O-SII.[5] In any case, when capital falls short of the regulatory target, banks decrease their credit supply and retain dividends until they comply with the regulation.

Score-based capital buffers How we assign SCBs relies on scores. Banks are subject to an assessment of their systemic importance that we can think of being conducted by a financial authority and whose outcome is quantified by a score. Before introducing the details about systemic-risk assessment, we discuss how capital buffers are assigned to banks based on their score.

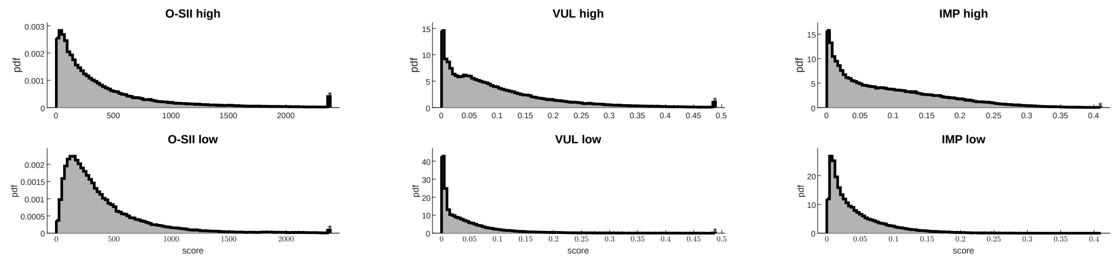
[3] Banks first determine their liquidity need, then compute the fair value of their portfolio loan by loan. Next they determine Δq taking into account Eq. (20). Lastly, they choose which loans should be liquidated to reach their objective.
The loans for sale are evaluated at their fair market value by discounting cash flows:

$$L_{bj}^{fv} = \frac{L_{bj}(1 + Mr^f)(1 - \rho_j^f)}{\underline{r}^M}$$

where $L_{b,j}$ is the book value of the loan of bank b to firm j, M is the residual maturity, r^f is the interest rate on the loan, ρ^f is the default probability of firm j, and $\underline{r}$ is the risk-free rate.

[4] We refer to the capital buffer for other (domestic) systemically important institutions (O-SII) absent any cross-jurisdictional activity of banks in our framework.

[5] *"The systemic risk buffer (SyRB) aims to address systemic-risks of a long-term, non-cyclical nature that are not covered by the Capital Requirements Regulation"* (ESRB, `https://www.esrb.europa.eu/national_policy/systemic/html/index.en.html`). European financial authorities are free to define the SyRB as long as it does not interfere with any other capital requirements. This translates into different scopes and many ways to define the SyRB.



(a) (b) (c)

Figure 5: Distribution of systemic-risk scores under high *(top)* and low *(bottom)* heterogeneity computed with the methods: EBA *(a)*, DebtRank vulnerability *(b)*, DebtRank impact *(c)*. All distributions show positive skewness and right tails, which are longer under high heterogeneity.

Scores of banks are classified into five categorical buckets or classes, as showed in Table 3. Each bucket corresponds to an interval determined on the distribution of scores resulting from simulations without capital buffers, which is low or high heterogeneity and risk-weighted adjusted capital requirements. In other words, we first simulate the model to obtain the distribution of scores (see Figure 5) under a given type of systemic-risk assessment but without activating SCBs. After that, we divide the distribution into intervals and assign intervals to buckets, where each bucket corresponds to a given interquantile range as reported in the second column of Table 3. Buckets are linked to capital buffers that add on minimum capital requirements. The method for selecting the score quantiles assigned to capital buffers is discussed in Section A.5. When SCBs are activated, Eq. (4) is substituted by

$$nw_{b,t}^{B} \geq \left(\frac{1}{\lambda} + \eta_{b,t}\right) RWA_{b,t} \tag{4a}$$

where η is the value of the SCB based on a 12 periods moving average of the score.

Class	Score quantiles	Capital buffer as % of RWA
5	$[q_4,\ +\infty]$	3.0% CET1
4	$[q_3,\ q_4)$	2.5% CET1
3	$[q_2,\ q_3)$	2.0% CET1
2	$[q_1,\ q_2)$	1.5% CET1
1	$[q_0,\ q_1)$	1.0% CET1

Table 3: Determination of capital buffers. Scores are classified in intervals based on selected quantiles (q).

Systemic-risk assessment Scores are computed with three different risk-assessment methods: (i) "EBA method" for the identification of O-SII; (ii) DebtRank algorithm measuring systemic impact; (iii) DebtRank algorithm measuring systemic vulnerability.

i) Additional capital buffers for systemic-important institutions (SII) have been architected with the idea to reduce the impact that the failure of a SII might have on financial stability. They are specifically addressed to institutions that are *"too-big-to-fail"* or *"too-interconnected-to-fail"*. To determine capital buffers we adapt the guidelines of EBA (European Banking Authority) to our model. The method assigns a score to each institution computed as a weighted average of three evaluation criteria (size, importance, interconnectedness). Table 4 reports the indicators, weights, and the model variables for each criterion.
ii) In line with the aim of capital buffers for SIIs, we provide an alternative method to measure the impact of banks. It is based on DebtRank *(Battiston et al., 2012)*, a network algorithm inspired by feedback-centrality that evaluates the importance of a node (bank) in the interbank and firm-bank credit networks. Therefore, capital buffers based on systemic impact are derived from a score computed with *DebtRank*.
The algorithm forces the default of banks one-by-one and, for each defaulted bank, measures the relative equity loss of the financial system, i.e. the ratio of total equity (firms plus banks) after and

Criterion	Indicators	Variables	Weight
Size	Total assets	$(L_b+I_b^l+R_b)/\sum(L_b+I_b^l+R_b)$	33.33%
Importance	Private sector deposits	$Dep_b/\sum Dep_b$	16.66%
	Private sector loans	$L_b/\sum L_b$	16.66%
Interconnectedness	Intra-financial system assets	$I^l/\sum I_b^l$	16.66%
	Intra-financial system liabilities	$I_b^b/\sum I_b^b$	16.66%
Complexity	N.A. in the model		

Table 4: Scoring system for the identification of O-SIIs.

before the default. This ratio represents the impact that the defaulted bank has on the system. Banks' score is the mean of the impact ratio computed 500 times per bank. Scores are then employed for the determination of capital buffers utilizing of the bucketing mechanism presented in Table 3. More details about DebtRank are in Appendix A.2.

iii) Also, capital buffers based on systemic individual vulnerability are derived from a score computed via *DebtRank*. However, rather than measuring the impact, we account for the relative equity loss induced by forcing the defaults of banks one-by-one. The relative equity loss h represents the financial distress and is defined as the change in equity at the end of one iteration (T) to the initial equity. It is between 0 and 1: 0 corresponds to no losses, while 1 is bankruptcy.

$$h_{b,T} \equiv \frac{nw_{b,T}^B - nw_{b,0}^B}{nw_{b,0}^B} \tag{21}$$

To be more clear, suppose we are interested in the relative equity loss of bank b. Then we force the default of all other banks, one-by-one. As for case (ii), the algorithm is iterated 500 times per bank. At the end of each iteration we record $h_{b,T}$ and after all iterations we have a $500 \times (N^b - 1)$ array containing the relative equity loss of b. The systemic vulnerability score is the average $h_{b,T}$ across all observations.

3. Results

Results are obtained from simulations of the model in Matlab. We run 1000 Monte-Carlo iterations of the model for each type of systemic capital buffer under high and low heterogeneity. The time length of one simulation is 800 periods, from which we eliminate the transient time of 300 periods. The seed of the pseudo-random number generator takes different values for every Monte-Carlo iteration so that the realization of random variables is not repeating itself. It produces random variations in the network structures as well.

3.1. Heterogeneity

The first set of results summarized in Figure 6 shows the effects of changing the heterogeneity in network structures. The first two complementary cumulative distribution functions (ccdfs) from the left refer to the degree distributions of banks, which is the distribution of links from banks to firms (bank lending) and from banks to banks (interbank borrowing). The high and low heterogeneity curves move away as the values on the horizontal axes increase. Changing the network structures produces the expected effect, viz. higher degrees are observed in the heterogeneous world. Though the degree distribution is dissimilar, it should be noted that it is not perfectly homogeneous under low heterogeneity as the matching mechanisms operating in credit and interbank markets generate dynamic networks deviating from uniformity. The same result applies to the size distribution of banks measured by net worth (which is also highly correlated to assets and balance sheet size), but no differences are displayed for the net worth of firms. The last is presumably due to the lack of assumptions about banks' efficiency to channel funds and/or the ability of banks in solving asymmetric information. The third graph on the right of Figure 6 displays the similarity between banks' portfolios under low and high heterogeneity. We expect that the networks generation process leads to a polarization in the core business of banks under high heterogeneity, *i.e.* the portfolios of interbank and credit lenders are dissimilar. We measure portfolio similarity by a *Generalized Jaccard index*. The index is defined as

$$Jacc_{b,k} = \frac{\sum_{s=1}^{S} \min\left(\Psi_{b,s},\ \Psi_{b,s}\right)}{\sum_{s=1}^{S} \max\left(\Psi_{b,s},\ \Psi_{b,s}\right)}$$

for the portfolios of banks b and k, where S is the total number of assets and $\Psi_{b,s}$ is the share of asset s in b's portfolio, such that $\sum_{s=1}^{S} \Psi_{b,s} = 1$. Under our assumptions $S = 3$, since there are three types of assets: loans to firms, interbank loans, and liquidity. The Jaccard index gives a value in the interval $[0, 1]$, where the maximum similarity is achieved at 1 and the minimum at 0.

The distribution of the average values of $Jacc$ reveals that dissimilarity is more marked when heterogeneity is high as the corresponding distribution is located below the homogeneous one (at its left on the histogram). The two distributions cross in the right part of the diagram. Such puzzling behavior is however limited to a marginal part of the data as it turns out from the histogram. Despite it is difficult to provide the right causal explanation, we suggest that, due to the greater number of defaults and losses with high heterogeneity, similarity may be higher in periods around banks' default.

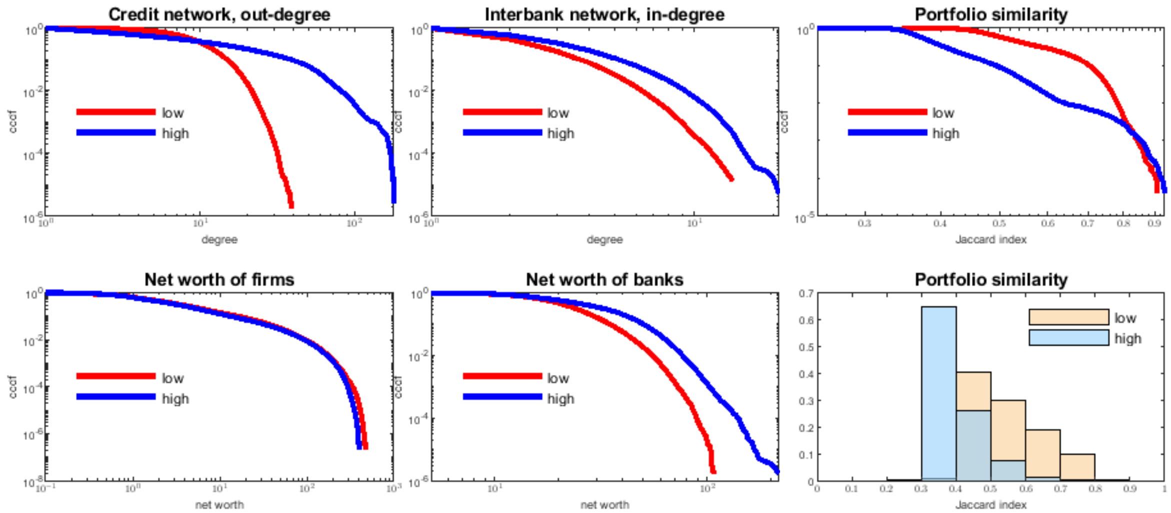


Figure 6: Distribution of degree, net worth, and Jaccard similarity under low (red) and high (blue) heterogeneity. The ccdfs are in log-log scale.

Figures 7 and 8 visualize the structures of interbank and credit networks. These are directed and dynamic graphs accounting for all the transactions that occurred throughout two representative simulations for low and high heterogeneity. The size of nodes is adjusted for the weighted degree of banks (or firms), so that the largest nodes depict the biggest interbank borrowers in Figures 7a and 7b, and those banks most involved in lending to firms in Figures 8a and 8c. The difference between high and low heterogeneity is visually clear for banks, whereas the variation in firms' borrowing is negligible (Figures 8b, 8d).
A visual inspection of the interbank network under low heterogeneity reveals immediately that all banks are similar in terms of borrowing, in contrast with the heterogeneous case. Network statistics in Table 5 confirm the visual analysis: the homogeneous network is denser and more clustered with low maximum centrality. On the other side, the heterogeneous graph is less interconnected, shows a weak disassortative mixing, and a higher maximum betweenness centrality: few banks borrow most interbank liquidity.
The subfigures (a) to (d) in Figure 8 highlight lending to firms (left) and borrowing from banks (right). While firms' borrowing does not show a wide variation, the variance in bank lending changes remarkably from low ($CV < 1$) to high ($CV > 1$). In other words, lending to firms is operated by a few big banks with high heterogeneity (Figure 8c) At the same time, the total intermediated credit is similar in the two cases.

In summary, we check that the assumptions about network structures in Section 2.2 produce the desired outcomes when applied to the full model. We find that they lead to different degree distributions, dissimilar portfolios, and net worth of banks. Moreover, network inspection confirms that two groups of banks emerge under high heterogeneity, one specialized in lending to firms and the other in interbank lending. In addition to these results, cross-correlations between network and market variables are in A.3.

(a) low (b) high

Figure 7: Interbank network under low (a) and high (b) heterogeneity at the end of a representative simulation. The size of nodes represents weighted in-degree (number of incoming links weighted by the amount borrowed). The thickness of edges shows the link weight in terms of borrowing between pairs of nodes. The network diagrams are plotted with Gephi using the Force Atlas algorithm.

Statistics	Low heterogeneity (a)	High heterogeneity (b)
Average degree	24.00	11.80
Average path length	1.04	1.29
Clustering	0.96	0.62
Density	0.96	0.49
Assortativity	-0.06	-0.12
Betweenness centrality (max)	1.26	19.37

Table 5: Descriptive network statistics for subfigures 7b and 7a.

(a) low (b) low

(c) high (d) high

Figure 8: Bimodal firms-banks network of the credit market. Banks are the blue nodes, firms are the red nodes. The size of the blue nodes shows the weighted out-degree (number of outgoing links weighted by the amount lent) of banks under low (a) and high heterogeneity (c). In the same way, the size of red nodes shows the weighted in-degree of firms (number of incoming links weighted by the amount borrowed) under low (b) and high heterogeneity (d). The network diagrams are plotted with Gephi using the Geo Layout.

Statistics	Low heterogeneity (a, b)	High heterogeneity (c, d)
CV out-degree (banks' lending)	0.462	1.487
CV in-degree (firms' borrowing)	1.102	1.211
Avg ratio	1.003	1
Density	0.061	0.048

Table 6: Descriptive network statistics are reported in Table (c), where *CV* are the coefficients of variation of weighted out (in)-degrees, *Avg ratio* is the ratio of average weighted-degree to the average weighted-degree in the high heterogeneity case (*Avg ratio* for out and in-weighted degrees is identical). *Avg ratio* close to one under low heterogeneity means that the total credit lent by banks to firms is similar in the two cases.

3.2. Analysis of tails

The materialization of systemic-risk triggered by illiquidity or default cascades may give rise to high variability in the data generated by the model. Here we assess the effect of SCBs in reducing the outliers by looking at the tails of the distribution. Moreover, the whole data distribution gives an idea about the overall working of SCBs.

Figures 9 and 10 display the ccdfs in log-log plots. We add two vertical lines referred to the benchmark case (RWA) to mark the median (green line) and the boundary below which data are considered outliers (red line), namely points where $X > q_3 + 1.5(q_3 - q_1)$. Let us consider the results in the heterogeneous case first. When SCBs are activated, the ccdfs tend to stay below the benchmark for defaults and above for losses.[6] Moving towards the right-bottom corner, the number of available data points becomes scant, so the distribution of defaults becomes less accurate. The ccdfs of EBA and VUL for liquidation defaults and losses display better performance than RWA. In sum, we observe that the adoption of EBA and VUL in highly heterogeneous systems is beneficial to reduce the risk of illiquidity and mitigate the materialization of extreme events. Conversely, the effect of IMP is ambiguous in the tails and beneficial in the rest of the distribution.

We now turn to the analysis under low heterogeneity. Overall, the magnitude of defaults and losses, as measured on the horizontal axis, is lower than under high heterogeneity. The distributions of interbank and liquidation defaults show that EBA and VUL are no longer effective. This result is confirmed by the inspection of the corresponding subfigures for losses. IMP lowers the right tail of interbank defaults and losses, but the ccdfs for liquidations are close to the benchmark. These observations suggest that the advantage of imposing additional capital surcharges is limited under low heterogeneity, where IMP is marginally superior to EBA and VUL. For what concerns the distress transmitted by firms, results follow those under high heterogeneity though the distance between curves shrinks.

The study of tails shows that SCBs improve systemic stability under high heterogeneity but offer limited gains when the system tends to homogeneity. Deeper scrutiny reveals that some types of buffers work better or worse than others. The best results in the heterogeneous and homogeneous worlds are achieved by EBA and IMP, respectively. Also, in view of the results in Figure 11, there is little evidence about any deleterious effects of SCBs.

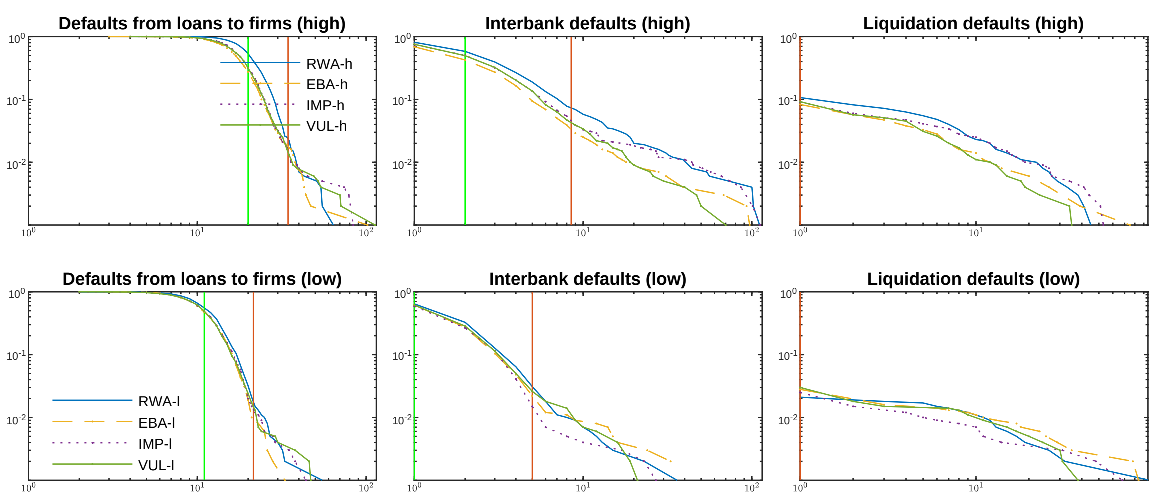


Figure 9: Ccdf of banks' defaults under high and low heterogeneity in log-log scale. The red vertical line is the limit beyond which the data are classified as outliers in the benchmark distribution (RWA), namely those points $X > q_3 + 1.5(q_3 - q_1)$. The vertical green line is the median of the benchmark distribution (RWA). The ccdfs are computed on the sum of defaults per Monte Carlo simulation.

[6] Losses from the firms' sector are connected to the total amount of credit and follow the logic of the model: SCBs reduce the defaults of banks from loans thus the credit supply of banks is not impaired as often as in the benchmark case. It ensures credit to firms, which can borrow more and rely less on their net worth to finance production. On the other hand, firms' leverage increases, and so the losses of banks.

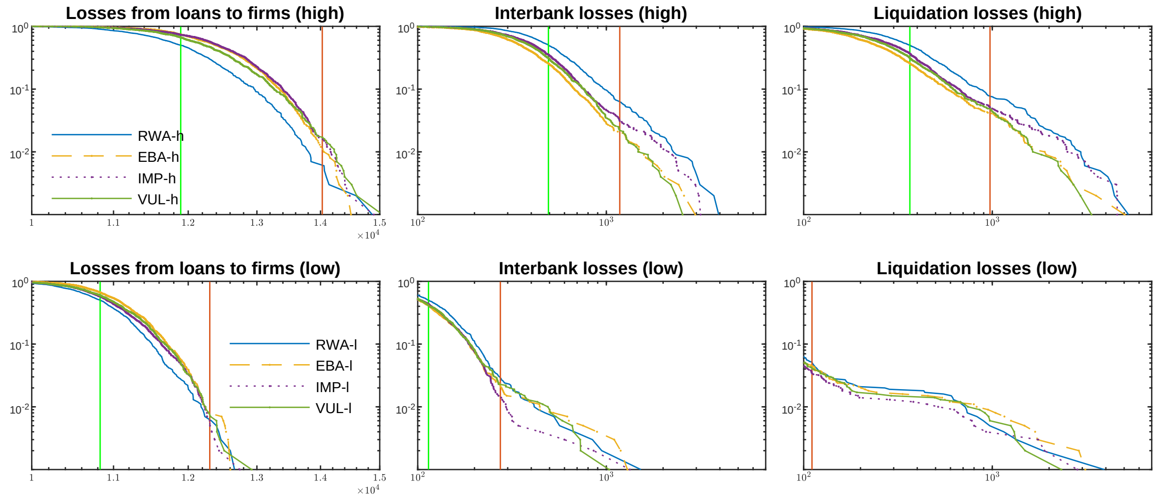


Figure 10: Ccdf of banks' losses under high and low heterogeneity in log-log scale. The red vertical line is the limit beyond which the data are classified outliers in the benchmark distribution (RWA), namely those points $X > q_3 + 1.5(q_3 - q_1)$. The vertical green line is the median of the benchmark distribution (RWA). The ccdfs are computed on the sum of losses per Monte Carlo simulation.

3.3. Reduction of extreme events

We aim to understand the effects of SCBs on financial stability. Therefore, here we compare the effectiveness of SCBs for their ability to stabilize the system by looking at large crises and systemic-events. Large crises can arise in model simulations, although they are not visible at every run. Then we look at the frequency of large events in our sample of Monte-Carlo simulations and visualize the results in Figure 11. We specify a definition of systemic event that adapt to our model and excludes confounding factors: We define "*systemic event*" those episodes in which the three following conditions are met together: *(i)* at least 25% of banks are defaulted or inactive waiting for recapitalization; *(ii)* there is a default cascade via the interbank market involving at least 15% of banks in a single unit of time; *(iii)* the losses of the banking sector are greater or equal than 5% of the maximum total equity throughout the simulation. Moreover, we account for defaults and losses in the ten periods following the systemic event to capture the distress that propagates indirectly to the balance sheets of agents following the model dynamics. The following abbreviations are employed henceforth: RWA is the benchmark case where banks are only required to have a capital greater or equal than a fraction of their risk-weighted assets. EBA refers to capital buffers for O-SII, IMP refers to buffers based on DebtRank impact, and VUL refers to those based on DebtRank vulnerability. Details about capital buffers are in Section 2.5. High and low heterogeneity are denoted respectively by h and l.

The first subfigure accounts for the frequency of systemic events. The first fact that stands out is the difference between high and low. The frequency of systemic events is much higher under heterogeneity. The second observation is about the effects of SCBs: they always decrease the frequency when heterogeneity is high compared to the benchmark, but the ranking is reversed when the system tends to homogeneity. IMP-l marginally improves financial stability, while EBA-l and VUL-l are ineffective. The last subfigure reports the frequency of those events when at least 25% of banks are in defaults at the same time, excluding those that are inactive waiting for recapitalization. The chart builds on a different and less strict criterion than the first one for systemic events, thus works as a control for the other results. The bars ranking is similar to the first subfigure and follows approximately the patterns displayed in the tails of distributions in Figure 9 for liquidation and interbank defaults.

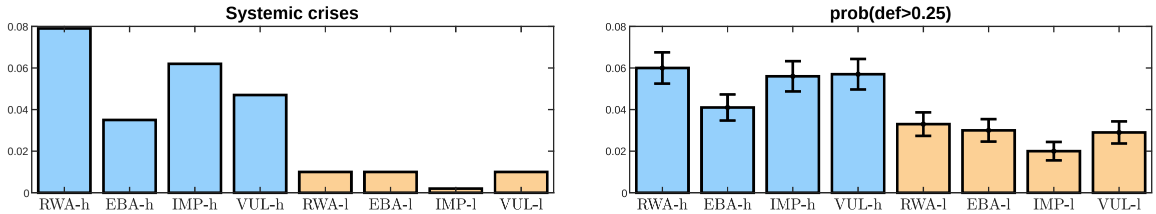


Figure 11: Frequency of systemic events (left) and default probability of banks (right) for high (light blue) and low (light red) heterogeneity. The bar chart on the right shows the frequency of events when at least 25% of banks go into default simultaneously. Error bars represent standard deviation.

A further comparison of SCBs is shown in Figure 12 that displays the number of simultaneous defaults in the interbank market. These are defined as those events when at least 15% of banks go bankrupt in a single unit of time due to interbank contagion. If SCBs are effective, we expect that they decrease the default probability of the most systemic banks, which subsequently reduces interbank contagion. The error bars in Figure 12 are consistent with the results from Figure 11: EBA reduces the length of simultaneous defaults the most under high heterogeneity but is the worst policy under low heterogeneity. IMP does the opposite.

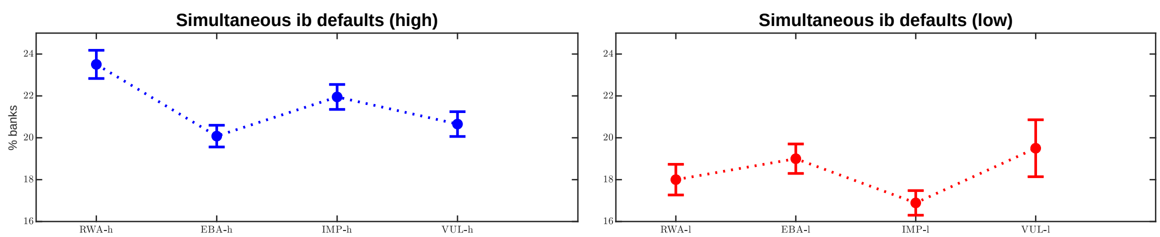


Figure 12: Average and standard error of the number of banks involved in simultaneous interbank defaults conditional on the default of at least 15% of banks at the same time. High heterogeneity (left, blue), low heterogeneity (right, red).

3.4. Regression analysis

In Table 7 we conduct simple least square regressions to disentangle the effect of banks' characteristics on the working of SCBs. We consider pooled cross-sectional data of individual banks generated in six simulations, one for each SCB under high and low heterogeneity. The response variable is the score deriving from the systemic-risk assessment of banks (see Section 2.5). The regressors include balance-sheet variables (net worth, deposits, loans to firms, interbank lending and borrowing) and network variables (number of incoming and outgoing links in the interbank network, number of links to firms in the credit market). For conducting the comparison, we normalize all scores between 0 and 100. It is worth noticing that scores are lower (Figure 5 and Table 8) shifting from high to low heterogeneity. So, normalization results in a greater magnitude of several coefficients under low heterogeneity. Taking it into account, the following analysis is general enough to apply in both cases. Anyway, the magnitude of the coefficients could be only compared either within high or low heterogeneity. Moreover, the objective of this section is not to conduct a precise econometric analysis of the data but to have a broad indication of what is most relevant for scores.

	EBA-h	IMP-h	VUL-h	EBA-l	IMP-l	VUL-l
Constant	0.305	8.894***	8.634***	-1.229***	4.080***	5.134***
	(0.309)	(0.776)	(0.487)	(0.457)	(0.474)	(0.290)
Net worth	0.042***	0.086***	-0.244***	0.069***	-0.056**	-0.283***
	(0.014)	(0.028)	(0.018)	(0.025)	(0.023)	(0.018)
Deposits	0.022***	0.079***	0.009***	0.019***	0.095***	0.001
	(0.002)	(0.006)	(0.003)	(0.002)	(0.004)	(0.001)
Loans to firms[a]	-	-	-	0.082***	0.052***	0.096***
				(0.005)	(0.009)	(0.005)
Ib borrowing	0.052***	0.085***	0.059***	0.126***	0.142***	0.019***
	(0.003)	(0.005)	(0.004)	(0.009)	(0.008)	(0.006)
Ib lending	0.039***	0.004	0.125***	0.146***	0.028***	0.158***
	(0.002)	(0.005)	(0.004)	(0.006)	(0.006)	(0.007)
Ib in-degree	-0.096	1.927***	1.110***	0.734***	1.286***	0.228
	(0.114)	(0.237)	(0.179)	(0.245)	(0.232)	(0.146)
Ib out-degree	-0.197**	1.967***	0.980***	0.208	2.277***	1.359***
	(0.086)	(0.262)	(0.193)	(0.185)	(0.207)	(0.163)
Credit out-degree	0.442***	-0.220***	0.000	0.684***	-0.282***	-0.046**
	(0.026)	(0.020)	(0.015)	(0.054)	(0.036)	(0.020)
R-squared	0.850	0.410	0.456	0.552	0.619	0.546
No. observations	10051	10188	10048	12346	12225	12185

Table 7: OLS regression results. Response variables are the systemic-risk scores. All scores are normalized between 0 and 100. HAC standard errors are reported in parenthesis. *, **, and *** indicate significance at the 90%, 95%, and 99% level, respectively.
[a] Omitted due to multicollinearity.

The previous picture differs for the IMP score. The regression points out that the score captures banks' impact on the financial network in terms of interconnectedness and liabilities. Every additional incoming or outgoing interbank link contributes to an increase in the score because a default would affect either interbank creditors or depositors. By the same token, deposits show a larger coefficient than in other regressions. Banks' net worth is presumably related to the score by the correlation with deposits and loans to firms. Remarkably, the credit out-degree coefficient suggests that lending concentration increases the score of IMP. In other words, *ceteris paribus* risk diversification is rewarded. Turning to VUL, the factors affecting its score are not surprising: the coefficients of net worth, lending banks, and interbank borrowing (reflecting loans to firms) clearly relate to vulnerability.

To understand the change in the effectiveness of SCBs between the two types of banking networks, it is essential to examine the cross-correlations of the regressors in Tables 9 and 10. The major change can be observed in the correlation between loans to firms and interbank borrowing. Moving towards a more homogeneous network, liquidity is distributed more uniformly across banks. It results that banks may lend to firms without resorting to the interbank market. Therefore, regulating banks based on asset size (EBA), especially loans, becomes less effective. IMP turns into the best policy since by explicitly accounting for liabilities and interconnections, it identifies and protects the most important nodes in the network.

To sum-up, the regression analysis shows that all scores reflect the design of the systemic-risk assessment methodology. The EBA score is sensitive to the elements on the banks' balance-sheet, in particular lending. The score of IMP accounts jointly for banks' interconnectedness and liabilities. The net worth and exposures of banks are the factors that determine vulnerability and mostly affect the score of VUL. Furthermore, switching from high to low heterogeneity changes the distribution of liquidity and the effectiveness of SCBs.

	mean	median	std	min	max
High heterogeneity					
Score EBA-h	410.304	211.835	534.400	0.157	4538.475
Score IMP-h	0.067	0.046	0.064	0.000	0.355
Score VUL-h	0.080	0.045	0.095	0.000	0.823
Net worth	27.495	23.426	16.639	0.000	112.654
Deposits	80.565	35.481	107.542	0.026	823.184
Loans to firms	49.746	9.406	84.235	0.000	613.495
Ib borrowing	36.390	0.000	80.323	0.000	762.513
Ib lending	36.385	14.343	56.709	0.000	577.230
Ib in-degree	0.880	0.000	1.563	0.000	13.000
Ib out-degree	0.880	1.000	0.889	0.000	7.000
Credit out-degree	9.973	3.000	15.155	0.000	90.000
Low heterogeneity					
Score EBA-l	399.912	290.621	362.138	2.751	3468.613
Score IMP-l	0.047	0.029	0.049	0.000	0.348
Score VUL-l	0.044	0.022	0.061	0.000	0.614
Net worth	21.340	19.252	11.362	0.000	82.493
Deposits	88.425	63.303	79.574	0.548	675.903
Loans to firms	45.292	27.823	51.911	0.000	445.944
Ib borrowing	13.400	0.000	37.545	0.000	476.611
Ib lending	13.400	0.000	28.827	0.000	467.053
Ib in-degree	0.461	0.000	1.001	0.000	10.000
Ib out-degree	0.461	0.000	0.713	0.000	6.000
Credit out-degree	8.772	8.000	4.874	0.000	30.000

Table 8: Summary statistics.

	nwb	dep	loan	ibb	ibl	ib in	ib out	cred out
nwb	1.000	0.466	0.397	0.242	0.357	0.162	0.139	0.269
dep	0.466	1.000	-0.087	-0.171	0.591	-0.247	0.378	-0.228
loan	0.397	-0.087	1.000	0.917	-0.232	0.780	-0.332	0.673
ibb	0.242	-0.171	0.917	1.000	-0.214	0.822	-0.314	0.604
ibl	0.357	0.591	-0.232	-0.214	1.000	-0.279	0.633	-0.308
ib in	0.162	-0.247	0.780	0.822	-0.279	1.000	-0.404	0.637
ib out	0.139	0.378	-0.332	-0.314	0.633	-0.404	1.000	-0.427
cred out	0.269	-0.228	0.673	0.604	-0.308	0.637	-0.427	1.000

Table 9: Cross correlations under high heterogeneity. Net worth (nwb), deposits (dep), loans to firms (loan), interbank borrowing (ibb), interbank lending (ibl), interbank in-degree (ib in), interbank out-degree (ib out), credit out-degree (cred out).

	nwb	dep	loan	ibb	ibl	ib in	ib out	cred out
nwb	1.000	0.387	0.653	0.234	0.248	0.193	0.177	0.125
dep	0.387	1.000	0.265	-0.146	0.313	-0.205	0.206	-0.015
loan	0.653	0.265	1.000	0.643	0.099	0.565	0.081	0.249
ibb	0.234	-0.146	0.643	1.000	-0.009	0.804	-0.040	0.110
ibl	0.248	0.313	0.099	-0.009	1.000	-0.038	0.709	-0.128
ib in	0.193	-0.205	0.565	0.804	-0.038	1.000	-0.062	0.133
ib out	0.177	0.206	0.081	-0.040	0.709	-0.062	1.000	-0.156
cred out	0.125	-0.015	0.249	0.110	-0.128	0.133	-0.156	1.000

Table 10: Cross correlations under low heterogeneity. Net worth (nwb), deposits (dep), loans to firms (loan), interbank borrowing (ibb), interbank lending (ibl), interbank in-degree (ib in), interbank out-degree (ib out), credit out-degree (cred out).

3.5. Effects of systemic capital buffers when no crises occur

In this section we compare SCBs when no crises occur. To operate the comparison we use boxplots[7] and ignore those simulations in which systemic events, as defined in Section 3.3, took place.

Output gap and credit We start from the analysis of macroeconomic variables. The distribution of the output gap and output volatility is illustrated in Figure 13. The output gap is defined as the deviation of aggregate supply from the maximum potential output, which under our assumptions is constant (further details in A.1). Output volatility is computed as the standard deviation of output growth rate. Boxplots in Figure 13 do not exhibit any noteworthy difference in the medians. This result could in principle support the adoption of SCBs because they do not entail output losses with respect to the benchmark. The volatility of output shows a downward shift from high to low heterogeneity, hence the system is more stable when the banking networks tend towards homogeneity.

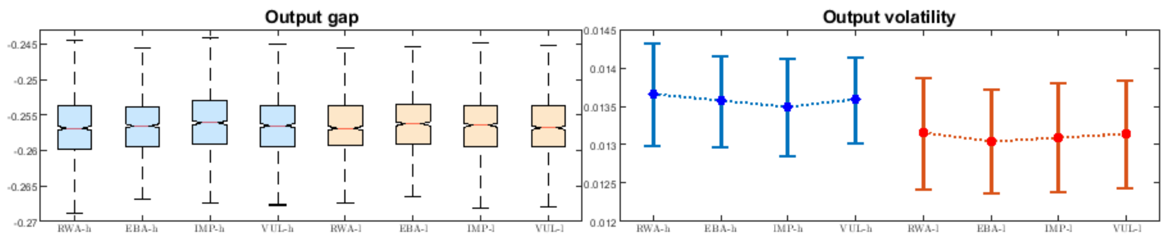


Figure 13: Output gap (left) and output volatility (right) for high (blue) and low (red) heterogeneity. The output gap is the ratio of the deviation of actual output to potential output. Output volatility is computed as the standard deviation of output growth rate. Markers report the mean, vertical bars are standard deviation.

We look at credit to firms and interbank lending in Figure 14. There is a weak increase in both types of lending with respect to the benchmark, however the clearest change is lower interbank loans under low heterogeneity. This descends directly from the assumptions in Section 2.2 and is partly described by Figure 7a: by switching to the homogeneous world all banks have a similar number of depositors and lending opportunities. Thus, the core-periphery structure of the interbank market reduces to a more homogeneous one without big credit lenders that demand large amounts of liquidity. Analogously to the output gap, the advantages produced by SCBs are small: the increases in credit to firms or banks are around 1% the benchmark. These gains are linked to the reduction in banks' defaults when macroprudential capital buffers are activated (Figure 15). At first glance, macroprudential policy stabilizes the macroeconomic environment, reducing defaults and consequently decreasing disruptions in total production.

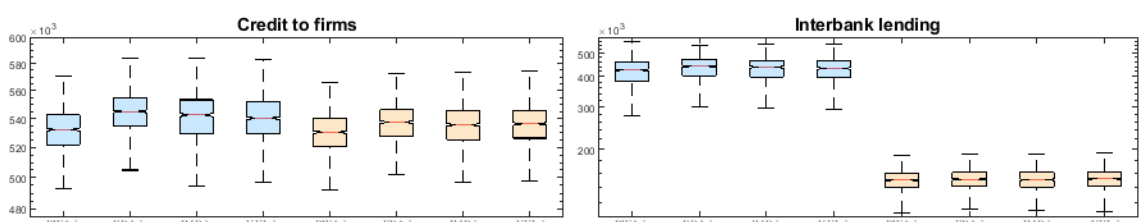


Figure 14: Credit to firms (left) and interbank lending (right) for high (blue) and low (red) heterogeneity. The y-axis is in logarithmic scale.

[7]The horizontal lines within the boxes are sample medians, while the lines below and above the median represent first and third quartiles. The black lines above and below the box are the whiskers, which extend from the nearest quartile to 1.5 times the interquantile range. Observations above the top whisker (or below the bottom whisker) are outliers, represented by dots. Notches display a confidence interval above and below the median defined as

$$median \mp 1.57 \times \frac{InterQuantileRange}{\sqrt{n}}.$$

If the notches of a pair of boxplots do not overlap, we can reject the null that the medians come from the same population with 95% confidence, namely their difference is statistically significant *(McGill et al., 1978)*.

Defaults and losses Defaults and losses are essential for assessing the effectiveness of SCBs, whose scope is to mitigate systemic-risk. We have at our disposal a set of SCBs based on different assessments of systemic-risk. In principle, capital buffers based on measures reflecting risk accurately should improve stability by reducing systemic defaults. In opposition, here we look at their effect in normal times. Looking at defaults from loans to firms in Figure 15 it turns out that all types of SCBs beat the benchmark. The difference is clearer for high heterogeneity. So, additional capital surcharges reduce defaults from systematic risk. We can think that imposing extra buffers limits individual exposure to loans. It is more effective under high heterogeneity when big lenders supply most of the credit. Despite this, we should look at the effectiveness of reducing interbank contagion and liquidation defaults. Still, considering the quartiles of the distribution in boxplots does not provide a clear picture, so we omit the related subfigure and refer the reader to Figure 9. in Section 3.2.

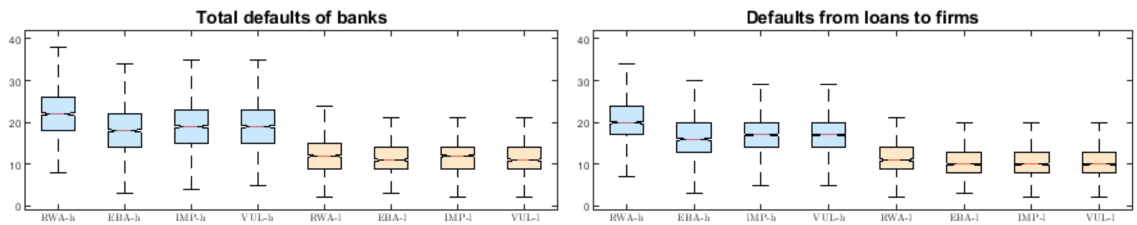


Figure 15: Total defaults of banks (left) and defaults from loans to firms (right) for high (blue) and low (red) heterogeneity.

Lastly, we consider losses. We have two sets of figures, one with the value of losses (Figure 16) and another with losses to equity of banks (Figure 17). The second set is a control for the former to make sure that losses are comparable in every scenario. The two sets present similar results except that the equity of banks is lower under homogeneity, as can be verified in Figure 6. This especially affects losses from loans to firms, whose ratio to equity turns out to be greater in the homogeneous case. Therefore, banks are more exposed to firms under low network heterogeneity. In exchange, they are less exposed to other types of losses. This suggests that systemic-risk connected to liquidity crises is weaker under low heterogeneity even if SCBs are not activated. Finally, we see that losses from loans to firms are higher than the benchmark when SCBs are put in place (Figure 16). The model construction is responsible for this behavior: lowered defaults from loans stabilize banks' equity and thus improve firms' access to credit, but at the same time raise the exposure of banks to the firms' sector and losses (see footnote 6).

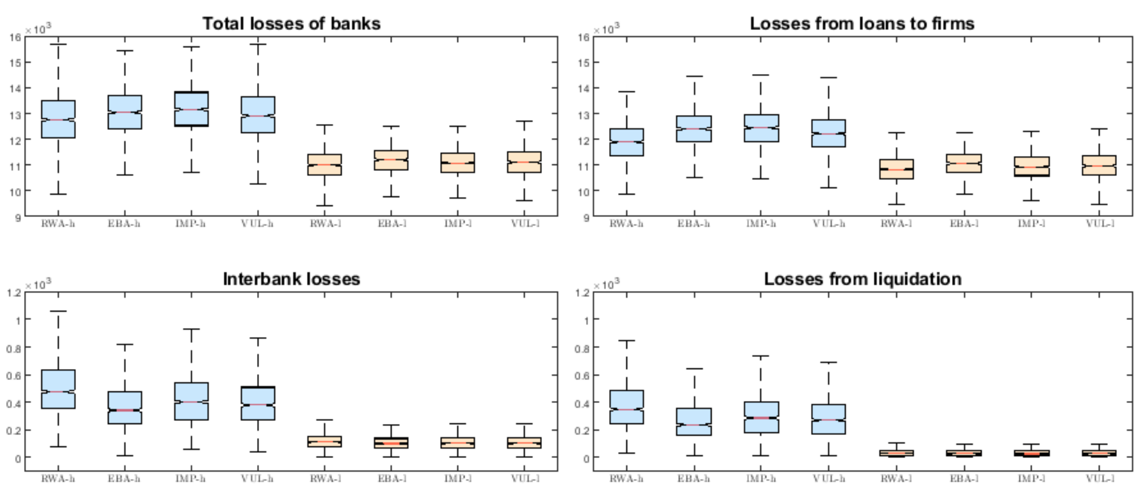


Figure 16: Total losses of banks (top-right), losses from loans to firms (top-left), interbank lending, (bottom-right), and asset liquidation (bottom-left) for high (blue) and low (red) heterogeneity.

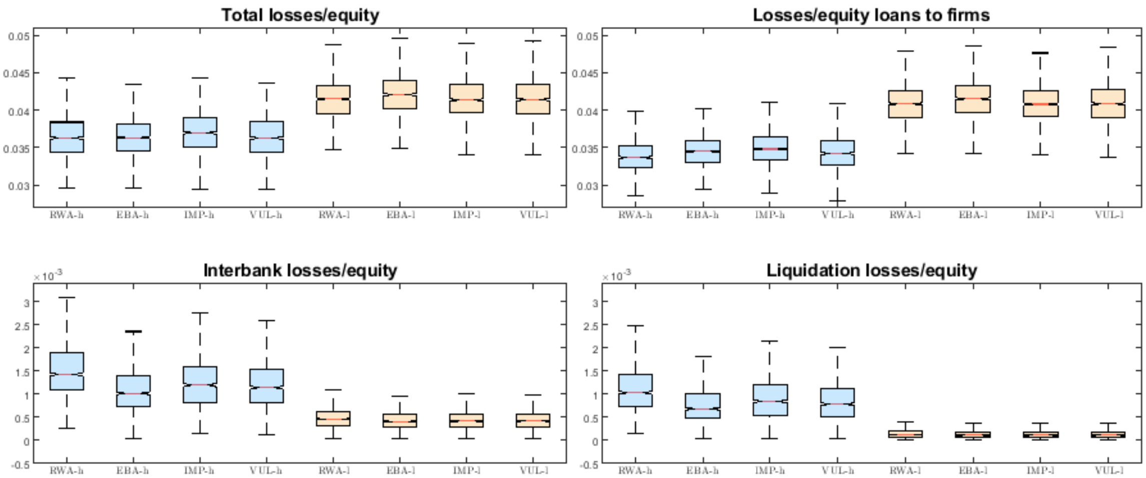


Figure 17: Total losses to equity of banks (top-right), losses to equity from loans to firms (top-left), interbank losses (bottom-right), and asset liquidation (bottom-left) for high (blue) and low (red) heterogeneity.

3.6. Violations of capital buffers

Some SBCs may work worse than others since enforcing is more difficult for banks. So, we study the violations of capital buffers to exclude that effectiveness depends on feasibility. This could unveil the criticalities of the score-based mechanism and clarify if macroprudential requirements are manageable for banks. We start from the distribution of capital buffers in each bracket by looking at the histograms in Figure 18. The relative frequency in every group is decreasing with successive brackets. This can be inferred also from the distribution of systemic-risk scores in Figure 5, which helps to explain why the vertical distance between groups is smaller in the "low" case. Moreover, the EBA tends to be distributed more evenly on the domain than other types, albeit all show positive skewness. Hence, in the majority of cases, no capital buffers are imposed. In other cases, frequencies are inversely proportional to the buffer values. Figure 19 reports "violations ratio", *i.e.* the ratio of total number of violations to the times a specific buffer is required. A violation occurs when the equity to RWA ratio of a bank is lower than the buffer required by the macroprudential authority. The violations ratio under high heterogeneity is between 0 and 5% circa, while under low heterogeneity it is roughly 10 times lower. In addition, it increases with the values on the horizontal axis, so that banks fail more often to raise capital for higher buffers. However, moving from 2.5% to 3% we observe a frequency reduction for EBA and IMP, while it keeps increasing for VUL. An explanation for this dissimilarity refers to the VUL method of systemic-risk assessment. It gives higher scores to more vulnerable banks, which may not comply with regulatory requirements simply because the value of their assets is low (they are neither credit nor interbank lenders). Recall that in our model banks comply with capital requirements by retaining dividends or decreasing their RWA. Consequently, if their assets are scant, it is more difficult to achieve the target capital ratio. On the other hand, the scores assigned by EBA and IMP account for impact, that is positively correlated to asset size. Finally, we analyze the violations ratios to quantify the deviations from the required capital buffers. From Figure 19 it turns out that most violations occur for SCBs above 2%, but the distance between the actual equity:RWA ratio and the required buffer is unknown. The heatmaps in Figure 24 show that violations distribute foremost at short distances from the required buffer, decreasing as the distance increases. Approximately, circa one-half of the violations are distant between 0 and 3% from the required capital buffers.

The violation analysis suggests that banks successfully adapt their behavior to comply with regulation most of the time (at least 95% success rate with high heterogeneity and 99% with homogeneity). Violations occur at the upper values of buffers, but the extent of violations is limited to short distances in the majority of cases. Total violations and ratios are lower in the homogeneous world. Overall, these findings point out that the effectiveness of capital buffers cannot be related to their feasibility.

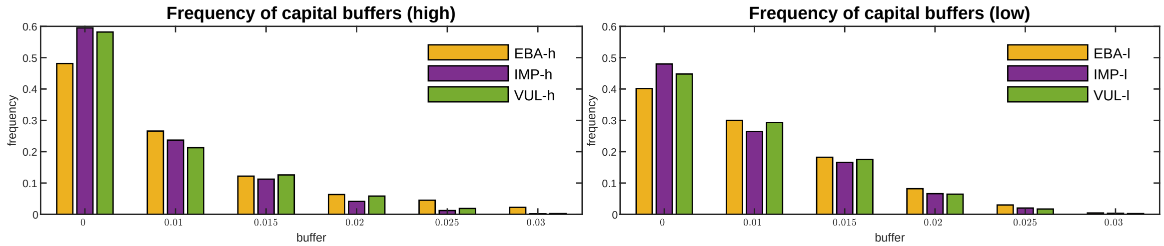


Figure 18: Frequency of systemic capital buffers per bracket under high (left) and low (right) heterogeneity. The systemic risk buffers range between 0.01 and 0.03. At 0 only minimum capital requirements apply.

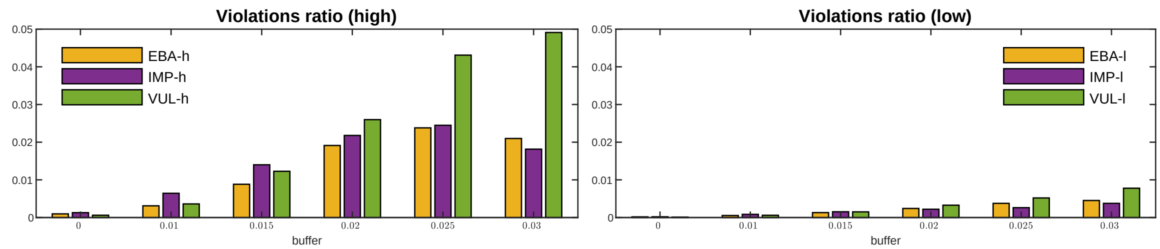


Figure 19: Violations ratio of systemic capital buffers per bracket under high (left) and low (right) heterogeneity. The systemic risk buffers range between 0.01 and 0.03. At 0 only minimum capital requirements apply.

Finally, to have an idea about the additional capital requested by SCBs, we look at the ratio between additional capital surcharges of the top 20% banks to total additional capital. For each SCB, we take the top 20% of banks sorted by descending score. The additional capital is proportional to the net worth of banks, on the compliance with prudential requirements, and the distribution of buffers under each rule. So, it should be read together with Figures 18 and 19. Figure 20 displays the results, from which it turns out that EBA-h and IMP-l are the SCBs that require the highest capital to the top-scoring banks.

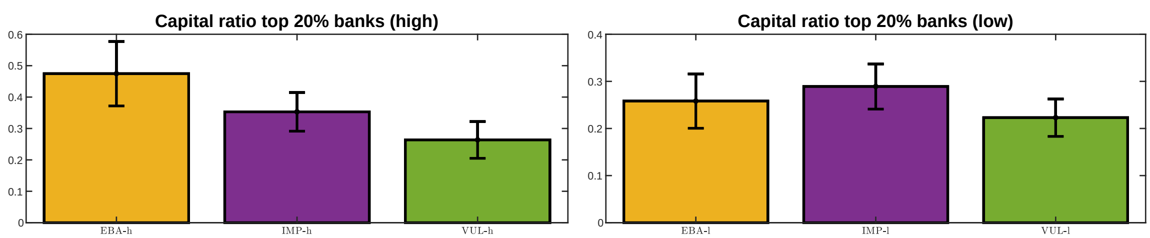


Figure 20: Additional capital surcharges of top 20% banks to total additional capital surcharges. High (left) and low (right) heterogeneity. Banks are classified conditional on maximum scores per simulation under each type of capital buffer.

4. Discussion

The research question stated in the introduction aims to assess the effectiveness of several types of macro-prudential capital buffers when the banking system is more or less heterogeneous. In this respect, we discuss the findings presented in Section 3.

We start from the degree of heterogeneity in the interbank market. Consistent with *Iori et al. (2006)*, we observe that a homogeneous banking system, and specifically interbank network, leads to more stability compared to the heterogeneous case. The interbank market allows maximizing risk diversification with banks homogeneous in deposits. At the same time, the homogeneity of banks in terms of assets (loans to firms and interbank claims), lowers knock-out effects and therefore reduces the probability of contagion or extreme events. As a matter of fact, the interbank network is denser under homogeneity. This improves the availability of liquidity and reduces the variance in demand and supply, lowering the frequency of liquidity crises. In contrast to a part of the literature *(Beale et al., 2011; Wagner, 2008, among others)*, we do not observe an increase in the probability of systemic crises from more risk diversification of banks. Instead, the benefits of risk-sharing seem to exceed the drawbacks of risk spreading. It is worth stressing that our model only captures direct contagion since it lacks a common asset holding channel. Moreover, we cannot control interbank connectivity, which is endogenously determined by the matching in credit and interbank markets. Therefore we cannot observe how defaults and losses would react by changing it when the network tends to homogeneity, as in *Gai and Kapadia (2010)*.

Concerning capital buffers, they are effective if applied to the systemic-important banks. Financial stability is improved if the most important banks are first identified by systemic-risk assessment and then targeted by capital buffers. It is helpful to recall two crucial concepts from the literature: banks' size and inter-connectedness. The first identifies banks that are *too-big-to fail*, the second those *too-interconnected-to-fail*. Depending on the characteristics of the banking network, capital buffers built on these factors can be more or less effective. A clarifying study is carried out in *Caccioli et al. (2012)*, who compare contagion for banking networks with random and power-law distributed sizes and degrees. In contrast, the construction of SCBs in this paper relies on a less stark distinction between size and interconnectedness. In one case, EBA only builds on balance-sheet indicators, which capture asset size and, to a lower extent, balance-sheet mediated interconnectedness. On the other, IMP and VUL are not built on pure network centrality measures (e.g. Katz, betweenness, eigenvector, *etc.*) but are obtained from a mixture of balance-sheet data and network interlinkages. Besides, despite our assumptions in Section 2.2, the networks resulting from Monte Carlo simulations are neither scale-free nor fully random but lean towards one extreme or another. Both types of networks show heterogeneity to different extents and the distribution of assets and degrees goes hand-in-hand (see A.3).

In our model, the distribution of liquidity is the most relevant change for macroprudential policy when moving from high to low heterogeneity. In addition, changing the degree of heterogeneity changes the characteristics of the most important banks, and consequently how they should be identified. When heterogeneity is high, loans to firms and interbank borrowing are strongly correlated because deposits are not enough for large lenders to finance loans to firms. Thus, a policy that specifically targets large lenders protects creditors from interbank defaults and, overall, reduces liquidity crises and contagion. We find that such a policy is represented best by EBA. The result seems consistent with those in *Caccioli et al.* since the greatest contribution to EBA's score comes from banks' size in terms of total assets (see Table 4). One can think of EBA as the buffer that most reflects asset size. When the system is less heterogeneous, the distribution of banks' deposits is more uniform. It alters the behavior of banks and so the cross-correlation within banks' balance-sheets. Now the most systemic banks cannot be identified only based on asset size because the relationship between lending to firms and borrowing from banks is weaker. The availability of deposits to finance lending reduces the need to access to interbank funds. In this context, IMP turns out to be the most effective policy. It can identify the most important nodes because it captures both interconnectedness and liabilities by explicitly taking into account the network of interlocked balance-sheets. Conversely, when heterogeneity is high, IMP cannot recognize large credit lenders as the most systemic banks. IMP ignores the size of the shocks that could arise from the exposure of banks to the firms' sector. Still, high exposure may trigger huge losses that reverberate on connected nodes, although the hit banks are not the most interconnected nor the one with the highest interbank liabilities. Looking from another angle, under high heterogeneity it is more likely that those banks identified by EBA as the most systemic go into default and trigger contagion. For what concerns VUL, it is never the best policy in any scenario. Its score reflects the vulnerability of banks conditional to the defaults of other banks in the network. So it does not account for the largest or most interconnected banks but protects the most vulnerable ones. However, regulating all banks by their vulnerability also prevents the default of the most systemic banks. This makes VUL the second-best policy under high heterogeneity.

Finally, the static network structure described in Section 2.2 successfully produces a dichotomy between heterogeneity and homogeneity in key variables, among which banks' net worth, portfolio similarity, and degree distribution. This is important because it shows how a heterogeneous core-periphery type interbank network naturally arises when banks are different in deposits and lending opportunities. In other words, exogenous factors like geographical differentiation can contribute to shaping interbank topology and creating communities as observed in *(Iori et al., 2007)* for the Italian interbank market.

5. Conclusion

In this study we compare a set of macroprudential capital buffers in banking systems characterized by low and high heterogeneity through a stylized macro-financial agent-based model in which liquidity crises may arise.
The research shows that:

- *(i)* Lowering heterogeneity in banks' size and network degree leads to more stability regardless of macroprudential policy. Capital buffers have a limited effect on financial stability compared to standard capital requirements when heterogeneity is low.
- *(ii)* Changing the heterogeneity of the banking network modifies the criteria for the identification of systemic-important banks. Under low heterogeneity, banks rely less on interbank funds because the distribution of deposits is more uniform. As a result, there is no a first-best policy valid for both types of banking networks.
- *(iii)* Imposing capital buffers to the largest banks in terms of asset size, specifically loans to firms, is the best policy under high heterogeneity. When shifting from high to low heterogeneity, such a policy is ineffective as the correlation between lending to firms and interbank borrowing becomes weaker. Thus, the best policy turns into targeting banks based jointly on their liabilities and interconnectedness.

While our model builds on a simplified framework, it contributes to understanding the effects of macroprudential capital buffers when interbank contagion amplifies financial distress. The findings suggest that the macroprudential framework should account for the evolution of the financial system because regulatory tools might become ineffective shifting from high to low heterogeneous banking systems. Therefore, it is critical for financial authorities to monitor the degree of heterogeneity and put in place a contingent financial regulation.

Some limitations apply. First and foremost, the model does not include a contagion channel from common asset holding. Assets are not marked-to-market and in any case, banks do not invest in common assets. So, when assets are liquidated, the balance sheets of other banks are not affected by a price change. This reduces the effect of correlated exposures and joint failures which should be especially relevant under homogeneity. Second, the model is intended as a proof of concept rather than a realistic one. In particular, the simple structure of the balance sheets could limit the accuracy of systemic-risk assessments and thus weaken the reach of systemic capital buffers.

To go past the limitations of results, the model could be extended to account for the common assets holding contagion channel. Adding it would allow us to further explore the system under homogeneity. For instance, we could explore the interaction of macroprudential tools and correlated portfolios or the systemic effects of groups of banks whose individual relevance is negligible. Furthermore, the paper studies capital buffers given two settings of network heterogeneity. Two substantial questions arising from this work are to check if macroprudential capital buffers work to reduce the degree of heterogeneity in the banking system and investigate under what conditions capital buffers might become harmful for financial stability.

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A. Appendix

A.1. The macroeconomic model

The model underlying the simulations traces closely *Gurgone et al. (2018)*. However, since the focus of the paper is on macroprudential policy and the financial sector we detach the description of the macroeconomic framework from Section 2 and outline the principal characteristics below. We provide a brief description of the macro model and stress the differences where the original one was amended (Table 11).

Timing The sequence of events in the model is described below.

1. The interbank market opens: demand and supply are determined respectively by the difference between a bank's expected liquidity target and its actual liquidity.
2. Banks compute their maximum credit supply subject to regulatory constraints. Firms decide their planned hiring and production levels and use these to compute their credit demand.
3. The credit market opens: each bank computes the interest rate charged to each possible borrower. Firms enter the market and seek out potential lenders.
4. The labor market operates and production takes place. Firms compute their labor demand in line with their planned output levels. They hire workers on the basis of a frictional matching process and all employed workers are paid the same wage, which is set each period by a union.
5. Households spend their consumption budget, starting from sellers that charge lower prices.
6. Firms and banks that obtain positive profits pay taxes and distribute dividends. They update the dividend share.
7. Banks liquidate assets if they fall short of their liquidity buffer.
8. A loop cycle accounts for potential cascades of bankruptcies in the firms and banks sectors.
9. The credit and the interbank markets close. Firms and banks settle their obligations.
10. The government collects tax revenues and issues bills, which are bought by the Central Bank. Unions update their required wage rate following a Phillips rule.
11. Shareholders replace bankrupt firms with newborn start-ups and/or recapitalize banks.

Households There are N^H households that work, consume, and save. All households supply equal amounts of labor and own shares in banks and firms. Departing from the original model, shareholders are not equally distributed but are assigned to banks and firms according to a fixed shareholders' network (see Section 2.2). Households' wealth is the value of deposits kept in a bank account, while shares are not explicitly valued because there is no secondary market. Households receive their income from wages net of taxes, interest on deposits, dividends, and fiscal transfers. The variation in deposits between two periods is given by the sum of total income minus consumption. Households plan to consume a fraction c_1 of their current labor income and a fraction c_2 of their wealth. If the consumption budget cannot be achieved due to rationing on the goods market, the stock of deposits is increased by involuntary saving. Each household supplies one unit of labor inelastically, which is remunerated at the wage rate set by the union. It is adjusted sluggishly, based on an adaptive mechanism, in order to prevent the wage time series from jumping up or down sharply. The adjustment takes into account a simple moving average of past realized values of inflation and unemployment.

Firms The business sector is made up of N^F firms that produce a homogeneous perishable good using labor only as input. Firms' net worth is composed of the difference between deposits and loans from banks, as described in Table 2. We assume that firms anticipate the wage bill to hire workers so that carrying out production plans is subject to a cash-in-advance constraint. Bank credit funds the difference between financial needs and net worth.

The sequence of firms' actions in each period is summarized as follows:

- Set a target output level from which they calculate a labor target. The target output is computed adaptively based on past sales. If sold output in the previous period is lower than production, the target is revised downwards, otherwise, it is increased.
- Seek financing by borrowing if needed (subject to access to the credit market in that period) to meet the expected wage bill. If internal funds are not enough to hire the workforce necessary to produce the target output at the current wage rate, firms enter the credit market. The matching mechanism with banks is described in 2.3.1.
- Hire workers until the wage bill has been met or no further employable workers can be found, then produce by means of a linear production function.
- Set a price for their output and attempt to sell it. We assume that firms have some monopolistic power arising from consumers' search cost so that prices are higher than marginal costs. Unlike *Gurgone et al. (2018)*, we assume that firms increase (decrease) the mark-up on the unitary cost of output if aggregate demand exceeds (fall behind) aggregate supply (see also footnote [1]). Unit costs include labor and credit cost.
- After production and pricing took place, the goods market opens and consumers spend their consumption budget.
- Firms' gross profits equal sales revenues minus wage costs and interest charges. If profit is greater than zero the firm pays taxes and dividends, otherwise it absorbs the losses. Net profits equal gross profits minus taxes.
- If $nw^F_{j,t} < 0$ the firm is insolvent at the end of the period and bankruptcy occurs. In that case it is re-capitalized by its shareholders after $timer^F$ periods by a capital randomly chosen between 0.1 and 1.

Government and Central Bank The working of the economy is made possible by transfers from the Government to the household sector. High powered money is created by the Central Bank buying the bills issued by the Government. The funds raised from this sale are transferred to the household sector's bank accounts. The firm sector borrows funds from banks, pays workers to produce, and then sells the goods to households. Firms then deposit revenues from sales in banks. After taxes are collected the Government repays the one-period maturity bills, thus closing the monetary circuit.

The objective of the Government is to keep stationary the stock of public debt. Therefore, it operates a balanced budget policy by adjusting the transfers to households G to keep the stock of bills constant.

$$\begin{aligned} \Delta B_t = 0 &= r^B B_t + G_t - T_t - \Pi_t^{CB} \\ \Rightarrow G_t &= \max(T_t + \Pi_t^{CB} - r^B B_t,\ 0) \end{aligned} \tag{22}$$

where B is the outstanding stock of government bills at time t, T are tax revenues and Π^{CB} are the profits of the CB repatriated to the government.

This formulation is different from the original one, where the stock of bills could vary and G was fixed. The change is motivated by the comparison of the model under different policies. It requires that aggregate wealth given by the sum of net-worth of all agents is kept constant and equal to the total amount of bills in the system. It is useful to recall that the model is stock-flow consistent, which means that by the aggregate balance sheet identity the negative net worth of the government is balanced by the positive net worth of the private sectors so that aggregate net worth is zero.

$$\sum_{i \in N^H} nw_{i,t}^H + \sum_{j \in N^F} nw_{j,t}^F + \sum_{h \in N^B} nw_{h,t}^B + nw_t^G = 0$$

Furthermore, the present behavior of the Government avoids that the public debt grows indefinitely due to a spiral driven by interest on outstanding debt.

In addition to purchasing bills, the Central Bank pays an interest rate on reserves deposited by banks and earns the interest on bills plus the profits from the Special Agency. The corridor through which all lending to firms and banks takes place is determined by the Central Bank and is bounded by the rate paid on bank reserves and the rate at which banks can borrow from the standing facility. As remarked in Section 2.3.2, we assumed that Central Bank does not provide emergency liquidity to banks.

Differences	GIG	GIJ
Interbank and credit networks	dynamic, heterogeneous (Sect. 2.2)	static, homogeneous (Sect. 2.1.2)
Depositors and shareholders' networks	static, heterogeneous (Sect. 2.2)	static, homogeneous (Sect. 2.1.2)
Mark-up rule	based on excess demand ($A^d - A^s$)	based on the change in market-share (Δy), Eq. (15)
	$\mu_t = \begin{cases} \mu_{t-1}(1+0.1) & if\ A_{t-1}^d > A_{t-1}^s \\ \mu_{t-1}(1-0.1) & otherwise \end{cases}$	$\mu_t = \mu_{t-1}(1 + \Delta y_{t-1})$
Unitary cost of output	includes the cost of borrowing	does not include the cost of borrowing, Eq. (17)
Money (bills)	G adjusts to keep the stock of bills constant, Eq. (22)	G is fixed, the stock of bills varies, eq (5)
Lender of last resort	no	yes, Eq. (7)

Table 11: Main differences in the macroeconomic model of this paper (GIG) and that in Gurgone et al. (2018) (GIJ).

A.2. DebtRank

DebtRank is a systemic-risk measure and an algorithm introduced in *Battiston et al. (2012)*. It is conceived as a network measure inspired by feedback centrality with financial institutions representing nodes. Distress propagates recursively from one (or more) node to the other, potentially giving rise to more than one round of contagion. Despite DebtRank is a measure of impact in a strict sense, the algorithm can also provide measures of vulnerability. We employ differential DebtRank *(Bardoscia et al., 2015)*, which is a generalization of the original DebtRank *(Battiston et al., 2012)* that improves the latter by allowing agents to transmit distress more than once. Moreover, our formulation has similarities with *Battiston et al. (2016)*, where it is assumed a sequential process of distress propagation.

DebtRank takes as input the assets/equity of firms and banks and the network of cross-exposures. It simulates the effects of an initial shock on the equities of agents, whose distress is transmitted linearly from debtors to creditors until there are no new losses. It gives back the values of the relative equity loss at the end of the simulation. The output of the algorithm permits to compute the scores of banks in terms of impact and vulnerability.

The ***relative equity loss*** for banks (h) and firms (f) is defined as the change in their net worth (respectively nw^B, and nw^F) from $\tau = 0$ to τ with respect to their initial net worth.

$$h_i(\tau) = \min\left[\frac{nw_i^B(0) - nw_i^B(\tau)}{nw_i^B(0)}\right]$$

$$f_j(\tau) = \min\left[\frac{nw_j^F(0) - nw_j^F(\tau)}{nw_j^F(0)}\right]$$

The ***impact*** of each bank on the rest of the system is denoted by g. It is the overall loss in equity produced by the default of bank i, which includes equity of both firms and banks. The score for bank z is obtained by averaging g over 500 iterations of the algorithm.

$$g_z = \frac{\sum_{i \neq z} h_{i,T}\ nw_{i,0}^B + \sum_j f_{j,T}\ nw_{j,0}^F}{\sum_i nw_{i,0}^B + \sum_j nw_{j,0}^F} \tag{23}$$

The ***vulnerability*** of banks is obtained from the same algorithm for impact, but rather than recording g we account for the relative equity loss of banks, indicated by h after we force the default of other banks one by one. At the end of the 500 iterations we have an array of dimension $500 \times (N^B - 1)$ for each bank, whose entries are its relative equity loss. The average value of h_i is the vulnerability score for bank i.

$$h_{i,T} \equiv \frac{nw_{i,T}^B - nw_{i,0}^B}{nw_{i,0}^B} \tag{24}$$

The algorithm is implemented as follows. We impose the default of banks $z \in \{1, \ldots, N^B\}$ one at a time by setting $h_z(0) = 0$. The dynamics of the relative equity loss of other banks $i \in \{1, \ldots, N^B\}$, $i \neq z$ and firms $j \in \{1, \ldots, N^F\}$ is described by the sequence:[8]

1. Banks' losses on interbank loans:

$$h_i(\tau+1) = \min\left[1,\ h_i(\tau) + \sum_{k \in K} \Lambda_{ik}^{bb}(1 - \varphi_k^{ib})(p_k(\tau) - p_k(\tau-1))\right]. \tag{25}$$

2. Firms' losses on deposits:

$$f_j(\tau+1) = \min\left[1, f_j(\tau) + \Lambda_{jk}^{fb}(1 - \varphi_k^{dep})(p_k(\tau) - p_k(\tau-1))\right]. \tag{26}$$

3. Banks' losses on firms' loans:

$$h_i(\tau+1) = \min\left[1,\ h_i(\tau) + \sum_{j \in J} \Lambda_{ij}^{fb}(1 - \varphi_j^{loan})(p_j(\tau) - p_j(\tau-1))\right]. \tag{27}$$

Where p_k is the ***default probability*** of debtor k and φ^i, $i = \{loan, ib, dep\}$ is the recovery rate on loans, interbank loans and deposits. Recovery rates are randomly distributed between 0.5 and 1. Default probabilities are linear in (25) and (27), so that $p_k(\tau) = h_k(\tau)$, while we assume that firms' losses on deposits in (26) respond to the Furfine algorithm. In other words, the distress propagates only in case of default of the debtor so that

$$p_k(\tau-1) = \begin{cases} 1 & if\ h_k(\tau-1) = 1 \\ 0 & otherwise. \end{cases}$$

Λ is the ***exposures matrix*** that includes credit/debt relationships in the firms-banks and interbank networks. It describes potential losses over equity related to every asset at the beginning of the algorithm. All entries are obtained as the ratio of the

[8] Every step is executed until convergence, that is $\sum_i h_i(\tau) - h_i(\tau-1) = 0$.

liabilities of debtors and the net worth of the corresponding creditors. It is written as a block matrix, where Λ^{bb} refers to the interbank market, Λ^{bf} refers to deposits, Λ^{fb} refers to firm loans, and Λ^{ff} is a matrix of zeros.

$$\Lambda = \begin{bmatrix} \Lambda^{bb} & \Lambda^{bf} \\ \Lambda^{fb} & \Lambda^{ff} \end{bmatrix}$$

The matrix Λ is displayed below for $N^B = 2$ banks and $N^F = 3$ firms. In our specification there are no interlinkages in the firms sector, hence $\Lambda^{ff} = 0$.

$$\Lambda = \begin{bmatrix} 0 & \frac{Ib_{12}}{nw_2^B} & \frac{D_{13}}{nw_1^F} & \frac{D_{12}}{nw_2^F} & \frac{D_{15}}{nw_3^F} \\ \frac{Ib_{21}}{nw_1^B} & 0 & \frac{D_{23}}{nw_1^F} & \frac{D_{24}}{nw_2^F} & \frac{D_{25}}{nw_3^F} \\ \frac{L_{31}^f}{nw_1^B} & \frac{L_{32}^f}{nw_2^B} & 0 & 0 & 0 \\ \frac{L_{41}^f}{nw_1^B} & \frac{L_{42}^f}{nw_2^B} & 0 & 0 & 0 \\ \frac{L_{51}^f}{nw_1^B} & \frac{L_{52}^f}{nw_2^B} & 0 & 0 & 0 \end{bmatrix}$$

A.3. Cross-correlation and network statistics

(a) High heterogeneity

	hb	fb	pseu cred	dep	credit	deg cred	ib lend	ib out	ib borr	ib in	size
hb	1.00	0.49	-0.40	0.47	-0.45	-0.44	0.59	0.59	-0.45	-0.50	-0.06
	(1.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
fb	0.49	1.00	-0.34	0.91	-0.30	-0.34	0.85	0.64	-0.36	-0.44	0.30
	(0.00)	(1.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
pseu cred	-0.40	-0.34	1.00	-0.32	0.86	0.95	-0.50	-0.78	0.93	0.92	0.49
	(0.00)	(0.00)	(1.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
dep	0.47	0.91	-0.32	1.00	-0.26	-0.32	0.90	0.65	-0.34	-0.42	0.40
	(0.00)	(0.00)	(0.00)	(1.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
credit	-0.45	-0.30	0.86	-0.26	1.00	0.95	-0.51	-0.78	0.97	0.95	0.63
	(0.00)	(0.00)	(0.00)	(0.00)	(1.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
deg cred	-0.44	-0.34	0.95	-0.32	0.95	1.00	-0.54	-0.81	0.98	0.96	0.54
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(1.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ib lend	0.59	0.85	-0.50	0.90	-0.51	-0.54	1.00	0.87	-0.55	-0.64	0.21
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(1.00)	(0.00)	(0.00)	(0.00)	(0.00)
ib out	0.59	0.64	-0.78	0.65	-0.78	-0.81	0.87	1.00	-0.83	-0.89	-0.19
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(1.00)	(0.00)	(0.00)	(0.00)
ib borr	-0.45	-0.36	0.93	-0.34	0.97	0.98	-0.55	-0.83	1.00	0.98	0.57
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(1.00)	(0.00)	(0.00)
ib in	-0.50	-0.44	0.92	-0.42	0.95	0.96	-0.64	-0.89	0.98	1.00	0.49
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(1.00)	(0.00)
size	-0.06	0.30	0.49	0.40	0.63	0.54	0.21	-0.19	0.57	0.49	1.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(1.00)

(b) Low heterogeneity

	hb	fb	pseu cred	dep	credit	deg cred	ib lend	ib out	ib borr	ib in	size
hb	1.00	0.01	-0.03	0.02	-0.01	-0.01	0.03	0.03	-0.02	-0.03	0.01
	(1.00)	(0.58)	(0.09)	(0.34)	(0.68)	(0.56)	(0.13)	(0.16)	(0.33)	(0.14)	(0.63)
fb	0.01	1.00	-0.03	0.57	0.33	0.13	0.50	0.43	-0.15	-0.31	0.37
	(0.58)	(1.00)	(0.10)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
pseu cred	-0.03	-0.03	1.00	-0.04	0.22	0.44	-0.16	-0.21	0.23	0.24	0.04
	(0.09)	(0.10)	(1.00)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.05)
dep	0.02	0.57	-0.04	1.00	0.53	0.16	0.83	0.67	-0.28	-0.45	0.60
	(0.34)	(0.00)	(0.03)	(1.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
credit	-0.01	0.33	0.22	0.53	1.00	0.74	0.26	0.00	0.52	0.37	0.78
	(0.68)	(0.00)	(0.00)	(0.00)	(1.00)	(0.00)	(0.00)	(0.87)	(0.00)	(0.00)	(0.00)
deg cred	-0.01	0.13	0.44	0.16	0.74	1.00	-0.09	-0.29	0.57	0.54	0.39
	(0.56)	(0.00)	(0.00)	(0.00)	(0.00)	(1.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ib lend	0.03	0.50	-0.16	0.83	0.26	-0.09	1.00	0.90	-0.48	-0.63	0.44
	(0.13)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(1.00)	(0.00)	(0.00)	(0.00)	(0.00)
ib out	0.03	0.43	-0.21	0.67	0.00	-0.29	0.90	1.00	-0.68	-0.80	0.23
	(0.16)	(0.00)	(0.00)	(0.00)	(0.87)	(0.00)	(0.00)	(1.00)	(0.00)	(0.00)	(0.00)
ib borr	-0.02	-0.15	0.23	-0.28	0.52	0.57	-0.48	-0.68	1.00	0.95	0.25
	(0.33)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(1.00)	(0.00)	(0.00)
ib in	-0.03	-0.31	0.24	-0.45	0.37	0.54	-0.63	-0.80	0.95	1.00	0.08
	(0.14)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(1.00)	(0.00)
size	0.01	0.37	0.04	0.60	0.78	0.39	0.44	0.23	0.25	0.08	1.00
	(0.63)	(0.00)	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(1.00)

Table 12: Cross-correlation of selected variables for banks (p-values in parenthesis). Total degree in the depositors' network (hb: households, fb: firms), total degree in the pseudo-credit network (pseu cred), deposits (dep), credit to firms (credit), total degree in the credit network (deg cred), interbank lending (ib lend), out-degree in the interbank network (ib out), interbank borrowing (ib borr), in-degree in the interbank network (ib in) size of banks (size) measured by net worth. Correlations are computed on the cumulated values over 100 Monte Carlo simulations.

	fb dep	hb dep	pseudo-credit	share	**credit**	**ib**
Avg degree	10.00	30.00	40.46	124.01	12.64	2.30
Median degree	7.00	24.00	4.00	62.00	5.00	2.00
Max degree	148.00	72.00	250.00	518.00	186.00	21.00

Table 13: Descriptive statistics of networks, high heterogeneity. Firms-banks deposits network (fb dep), households-banks deposits network (hb dep), pseudo-credit network (pseudo-credit), banks' shareholders network (share), dynamic credit network (credit), total in-degree in the interbank network (ib).

	fb dep	hb dep	pseudo-credit	share	**credit**	**ib**
Avg degree	10.00	30.00	46.17	138.36	8.35	1.72
Median degree	10.00	30.00	46.00	139.00	8.00	1.00
Max degree	47.00	21.00	63.00	198.00	39.00	14.00

Table 14: Descriptive statistics of networks, low heterogeneity. Firms-banks deposits network (fb dep), households-banks deposits network (hb dep), pseudo-credit network (pseudo-credit), banks' shareholders network (share), dynamic credit network (credit), total in-degree in the interbank network (ib).

A.4. Main parameters and initialization

Table 15: Main parameters and initialization of variables.

Parameter	Description	Value
T	Length of the simulation	800
N^F	Number of firms	250
N^H	Number of households	750
N^B	Number of banks	25
α	Labour productivity	2
W_0	Initial wage rate	2
θ	Tax rate	0.15
δ	Dividend share	0.05
c_1	Marginal propensity to consume out of income	0.8
c_2	Marginal propensity to consume out of savings	0.2
r^L	Interest rate on reserves	0.005
r^D	Interest rate on deposits	0.005
r^B	Interest rate on bills	0.005
r^H	Interest rate on advances	0.1
rr	Reserve coefficient	0.1
v_f	Calibration parameter, Eq. (9)	2
u^f	Calibration parameter, Eq. (9)	$1-\frac{1+r^D}{1+r^H}$
ℓ^*	Calibration parameter, Eq. (9)	4
v_b	Calibration parameter, Eq. (17)	2
u^{ib}	Calibration parameter, Eq. (17)	$1-\frac{1+r^L}{1+r^H}$
lev^*	Calibration parameter, Eq. (17)	$\lambda/2$
λ	Minimum capital requirements	0.07
σ_1	Sensitivity of the wage rate to unemployment	0.1
σ_2	Sensitivity of the wage rate to hysteresis	0.05
u^*	Full-employment rate of unemployment	0.1
Fh	Share of firms observed on the goods market	0.25
μ	Initial mark-up rate	0.01
$\bar{d}$	Maximum duration of loans	3
$\underline{d}$	Minimum duration of loans	1
$timer^B$	Time between bankrupt and recapitalization of banks	10
$timer^F$	Time between bankrupt and recapitalization of firms	2
B^{tag}	Bills	2000
ω_1	Risk weight on loans to firms	1
ω_2	Risk weight on interbank loans	0.3
γ	Mark-up adjustment on interbank bids	0.15
n^τ	number of borrowing attempts in the interbank market	5
ϕ	Coefficient on banks' recapitalization	1
$fitness^d$	Fitness value, Eq. (1)	$U(0,1)$
$link^{max}$	Threshold number of links	$40 \cdot N^B$
a^d	Calibration parameter, Eq. (1)	$0.005 * N^F$
a^s	Calibration parameter, Eq. (2)	$0.002 \cdot \sum outdegree^c$
Dep_0^H	Initial deposits per household	0
Dep_0^F	Initial deposits per firm	Y/lev_0
Y	Initial planned output per firm	$\alpha N^H/N^F$
lev_0	Initial leverage per firm	$LogNorm(0.6881, 0.1)$
nw_0^F	Initial net worth per firm	Dep_0^F
Dep_0	Initial deposits per bank	$(\sum Dep_{0j}^F + \sum Dep_{0i}^H)/N^B$
nw_0^B	Initial net worth per bank	$500\frac{N_b^{sh}}{\sum_{i=1}^{N^B} N_i^{sh}}$
R_0	Initial liquidity of banks	$Dep_0^B + nw_0^B$
G_0	Eq. (22) is modified in the first 10 periods of the simulation until B^{tag} is reached	$\max(B^{tag} + T_t + \Pi_t^{CB} - r^B B_t,\ 0)$

A.5. Choice of score quantiles

In Section 2.5 we described the score-based system on which SCBs construct. Capital buffers are assigned to banks depending on the risk bucket in which they are classified. The buckets match selected quantiles of the score distribution under either high or low heterogeneity. The first quantile (q_0) corresponds to the median. We assume that banks whose score is below the median are not subject to additional capital surcharges. The other buckets are computed so that the distance between two consecutive quantiles is regulated by a parameter $a \in (0, 1]$.
Quantiles q are chosen following

$$q_n = q_{n-1} + a^{n-1} d$$

where $n = \{0, \ldots, N\}$ is an index, d is a distance set to ensure that the $q_S = 1$, *i.e.* $d = \frac{med}{\sum_{k=0}^{N-1} a^k}$, with $med = 0.5$ the median. If $a = 1$, all quantiles are equidistant, while when $0 < a < 1$ successive quantiles have a decreasing distance. For instance, if $N = 5$ and $a = 1/2$: $d \approx 0.25$, $q_0 = 0.5$, $q_1 \approx 0.75$, $q_2 \approx 0.88$, $q_3 \approx 0.95$, $q_4 \approx 0.98$.

Ideally, we want to choose the quantiles succession with decreasing distances so that only the most systemic banks have the highest buffers. This is done by setting the parameter a. If a produces excessively uniform intervals, capital buffers might be too mild for highly systemic banks and too strict for others. On the other hand, if a yields too narrow intervals, capital buffers would be too loose for many banks, making SBC meaningless. Therefore we conduct a sensitivity analysis to find the optimal value of a. Results are reported in Figures 21, 22 and 23.

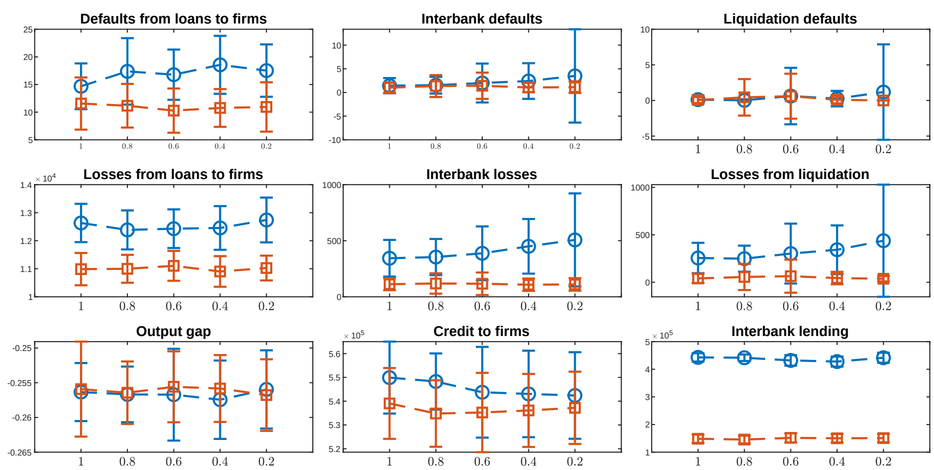

Figure 21: Sensitivity analysis on the values of a for systemic-capital buffers based on EBA under high (blue circles) and low (red squares) heterogeneity. Error bars represent standard deviation of the mean.

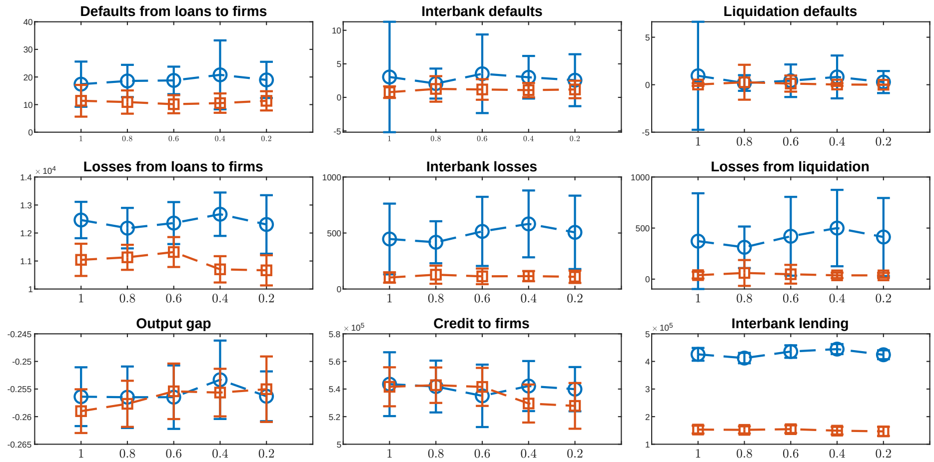

Figure 22: Sensitivity analysis on the values of a for systemic-capital buffers based on IMP under high (blue circles) and low (red squares) heterogeneity. Error bars represent standard deviation of the mean.

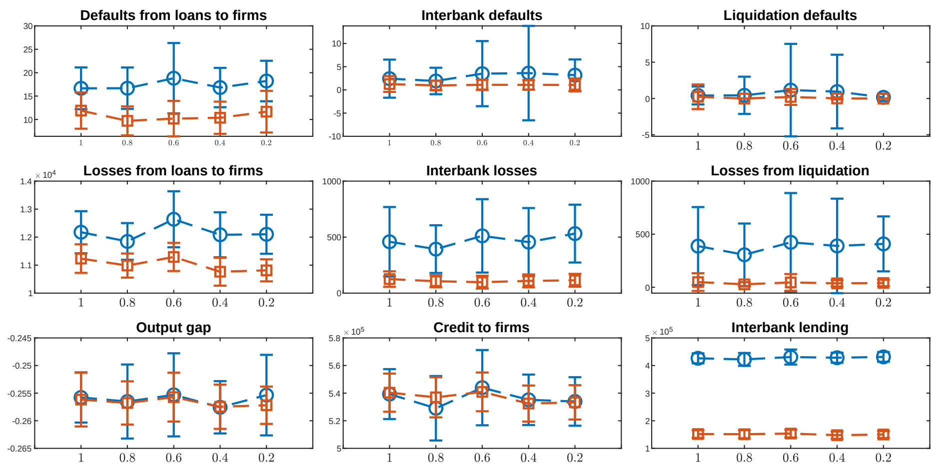

Figure 23: Sensitivity analysis on the values of a for systemic-capital buffers based on VUL under high (blue circles) and low (red squares) heterogeneity. Error bars represent standard deviation of the mean.

A.6. Heatmaps: distances from required buffers

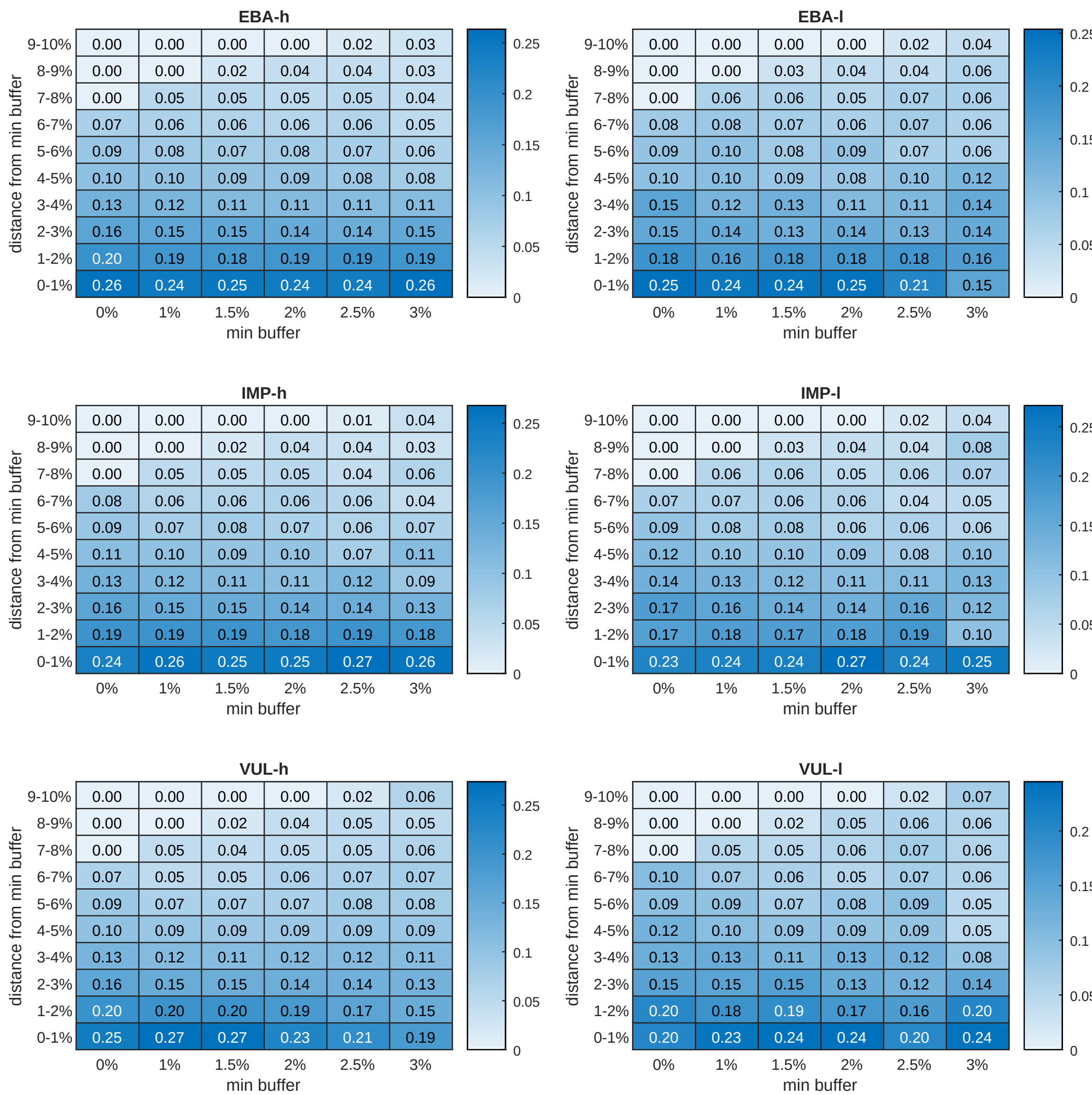

Figure 24: The heatmaps display the share of violations of systemic capital buffers within each bracket. The colormap and digits inside the cells report the number of violations to total violations within a bracket, so that the sum of rows is equal to 1. Columns report the extra buffer on top of the minimum capital requirements. A value of 0% corresponds to a minimum capital requirement $\frac{CET1}{RWA} = 7\%$, a systemic capital buffer of 1% corresponds to $7 + 1 = 8\%$ total capital buffer, etc.. Rows are sorted by the deviation from required buffers in case of violation. For instance, in the top-right corner, the systemic buffer is 3% so that the total buffer is given by the minimum 7% plus 3%. The row value indicates that a bank fails to comply from 9 to 10% because its actual capital/RWA ratio is between 0% and 1%.

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