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

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ABSTRACT

We study how the effectiveness of macroprudential capital buffers conditional to the systemic-risk assessment of banks responds to the degree of heterogeneity of the financial system. A multi-agent model is employed to build an artificial economy with households, firms, and banks where occasional liquidity crises emerge. The systemic importance of banks is captured by a score-based mechanism reflecting banks' characteristics in terms of size or interconnectedness. We compare three degrees of heterogeneity in the configuration of financial networks related to different banking concentrations in the loan market. The main findings suggest that: (i) reducing the heterogeneity of the banking network stabilizes the economy by itself; (ii) the identification criteria of systemic-important institutions are affected by the heterogeneity of networks; it is preferable applying systemic capital surcharges to the largest banks under high heterogeneity and targeting those most interconnected under low heterogeneity; (iii) the effectiveness of systemic capital buffers is preserved under high heterogeneity when a common asset holding contagion channel is added. However, simple measures based on risk-weighted assets capital ratios appear to be more effective in low heterogeneous systems. Thus, we argue that prudential regulation should account for the characteristics of the banking networks and tune macroprudential tools accordingly.

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1. Introduction

The stability of the banking system can be pursued with prudential instruments (capital ratios, liquidity buffers, etc.) and structural instruments (recovery and resolution plans which are oriented to contain the growth in size and by production lines of banks). Unlike models of regulation prevailing in the 1970s and 1980s (Stigler 1983), which favoured solutions oriented towards collusive oligopoly (Stigler 1964) to make the banking system stable, the current models try to intervene with a mix of micro-and macro-prudential instruments to level the playing field, creating incentives to competitive environments. In particular, regulators have pursued prudential instruments (capital ratios, liquidity buffers, etc.) and structural instruments (recovery and resolution plans oriented to contain the growth in size and by production lines of banks) to enhance the stability of the financial system. Despite these measures, the financial crisis has shown that contagion can be fuelled by entities particularly interconnected with others. This characteristic combined with the size and nature of the original risk factors led to a number of regulatory proposals aiming at reducing the probability of systemically associated failure events. The most relevant and commented on in the literature are capital buffers, some of which have been applied crosswise and homogeneously to all banks (conservation and countercyclical buffers), while others are differentiated by the type of banks (G-SIFIs buffers). However, the effectiveness of these macroprudential tools in achieving the

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purpose of minimizing systemic risk and resolving the trade-off between safety and efficiency is under question (Gabbi and Sironi 2015).

The literature has shown that the stability of the financial system is greatly affected by the interplay between bank heterogeneity and interconnectedness (Iori, Jafarey, and Padilla 2006; Gai and Kapadia 2010; Caccioli, Catanach, and Farmer 2012) and by the natural tendency of systems to evolve towards a more or less heterogeneous composition. These dynamics are likely to affect the effectiveness of regulatory measures. Banks can be heterogeneous along several dimensions such as size (Iori, Jafarey, and Padilla 2006), connectivity (Amini, Cont, and Minca 2016), degrees and asset holdings (Caccioli, Catanach, and Farmer 2012), default probabilities (Lenzu and Tedeschi 2012), shocks, size and connectivity (Loepfe, Cabrales, and Sánchez 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, Jafarey, and Padilla (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 is more uneven, leads to systemic risk to increase with interbank connectivity. The findings of Caccioli, Catanach, and Farmer (2012) reinforce this insight. Building on the seminal model of Gai and Kapadia (2010), the authors study the probability of contagion in a financial network model which accounts for banks' heterogeneity in degree and balance sheet size. The main result 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 with the default of the most interconnected banks. This entails that imposing additional capital buffers on big banks is more effective than targeting the most interconnected ones. Similar policy implications are also discussed in Loepfe, Cabrales, and Sánchez (2013). Our work also relates to the debate about the effects of competition and concentration on banking crises. There are two opposite views: *competition-fragility* states that competition destabilizes the system because greater competition increases risk-taking of banks following the erosion in profit margins (Keeley 1990; Carletti and Hartmann 2003; Beck, Demirgüç-Kunt, and Levine 2006). Conversely, the *competition-stability* view asserts that financial instability is greater when competition decreases. Stiglitz and Weiss (1988) provide a theoretical argument for the nexus between banking competition and stability, namely, banks with market power charge higher interest rates which increase the riskiness of loan portfolios due to moral hazard and adverse selection problems. Moreover, the works of Boyd and De Nicolo (2005), Boyd, De Nicolò, and Jalal (2006), Schaeck, Cihak, and Wolfe (2009) and Uhde and Heimeshoff (2009) find that competitive banking systems are more stable than oligopolistic ones. However, theoretical and empirical evidence between bank concentration, banking competition, and stability is mixed.

The contribution of this paper is to assess the effectiveness of macroprudential measures in the context of 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. Specifically, we aim to identify the suitability of different criteria for the application of systemic capital buffer, based on indicators of banks' size, connectedness, or vulnerability, under different market composition assumptions.

To simulate the impact of different capitalization measures in different banking market contexts, we conduct counterfactual policy experiments via an agent-based model (ABM) of the economy, which expands the model of Gurgone, Iori, and Jafarey (2018). In our study, we compare standard regulatory measures based on risk-weighted assets with systemic capital buffers applied to enhance the resilience of banks in the event of a systemic crisis. The buffers are calculated using three different risk assessment methods: (i) EBA method which assigns a score to each institution, calculated on the basis of their size, importance, and interconnection, to capture their degree of exposure to contagion risk; (ii) a score generated by an algorithm, called DebtRank (Battiston et al. 2012) which is a metric based on an institution centrality in the financial network consisting of both banks-firms and interbank exposures. In this case, the capital buffers of individual banks (which are nodes in the network) are determined by the ranking produced by the DebtRank based on the systemic impact they generate in case of default; (iii) a score also derived from the ranking produced by the DebtRank algorithm, but instead of measuring the impact of a defaulting bank, in this case, we compute the vulnerability of a bank measured by its relative capital loss following the default of other banks, one by one.

The shocks that can lead to bank failure are numerous and our paper simulates shocks transmitted by firms when their profitability 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 ABM 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, Bochmann, and Thurner (2017), who compare the effectiveness of Basel III capital surcharges with a tax on systemic risk in a macroeconomic ABM. Instead, we keep Basel's bucketing approach and compare alternative systemic risk assessment methods when the banking system is more or less heterogeneous.

The main findings of our analysis 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. Overall, a more homogeneous banking system is more stable, regardless of the macroprudential policy implemented. This is because, when banks are homogeneous in terms of lending to the firm sector, the interbank market maximizes opportunities for risk diversification, whose benefits exceed the drawbacks of systemic risk spreading via contagion. Interestingly, we find that, under high heterogeneity, it is preferable to apply systemic capital surcharges to the largest banks, while it is more effective to target the most interconnected ones under low heterogeneity. However, the trade-off between efficiency and stability is sensitive to the system compositions. While the economy becomes more stable and efficient when systemic capital buffers are applied to heterogeneous banks, it becomes more stable but slightly less efficient when buffers are applied to more homogeneous banks. Finally, if a common asset is marked-to-market in banks' balance sheets, we find, in line with previous studies, that this contagion channel greatly amplifies financial distress. The effectiveness of macroprudential capital buffers in reducing systemic events is preserved under high heterogeneity and targeting large banks continues to be the most effective policy in this scenario. However, systemic capital buffers further destabilize homogenous banking systems when the common asset holding contagion channel is activated, and simpler measures based on risk-weighted assets capital ratios appear to be more effective in this case.

The rest of this paper is organized as follows: Section 2 describes the modeling 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 presented in Sections 4 and 5.

2. The model

In what follows, we introduce the network structures of the model's economy in Section 2.1, provide an overview of the macroeconomic model in Section 2.2, and a detailed description of the behavior of banks in Section 2.3.

2.1. Networks

In the model, 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 predetermined 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, those banks that have only a few lending opportunities toward firms operate mainly interbank loans. They form the peripheral part of the interbank network. The network core is formed by those banks with high out-degree in the credit market that are densely connected in the interbank network by borrowing relationships. The low heterogeneity world is a flattened version of the other one. Banks are more homogeneous in lending opportunities, net worth and the interbank network does not show a core-periphery structure anymore. Furthermore, we add a third "middle" world in between the other two to control for non-linear effects. These three worlds correspond to different degrees of market concentration, which we can think about as the result of different forms of market regulation. Under high heterogeneity, a few banks dominate the market, while competition increases moving towards low concentration. The remainder of this section presents the way in which we model heterogeneity and the generative algorithms of static networks. Links formation in dynamic networks is described by the matching mechanisms in Section 2.3.

2.1.1. Credit fitness

The key factor that generates heterogeneity in banking networks is the ability of banks to lend to the firms' sector. We assume that banks are heterogeneous in a credit fitness parameter, which affects their lending opportunities and so the number of borrowers on the credit market. We justify the parameter values in terms of banks' comparative efficiency in solving asymmetric information problems in the market environment. Further details are discussed in Section 2.3.2. The attachment probability in the firms-banks credit network is determined through a preferential attachment mechanism as in Equation (11) in Section 2.3.2, where the attachment probability depends on banks' credit fitness. Fitness parameters (Figure 1) are generated from a power law probability distribution with an exponential cut-off

$$p(x) = Cx^{-\gamma}e^{-\lambda x}$$

where C is a normalization constant, γ is the power law exponent, and λ is the exponential distribution parameter.

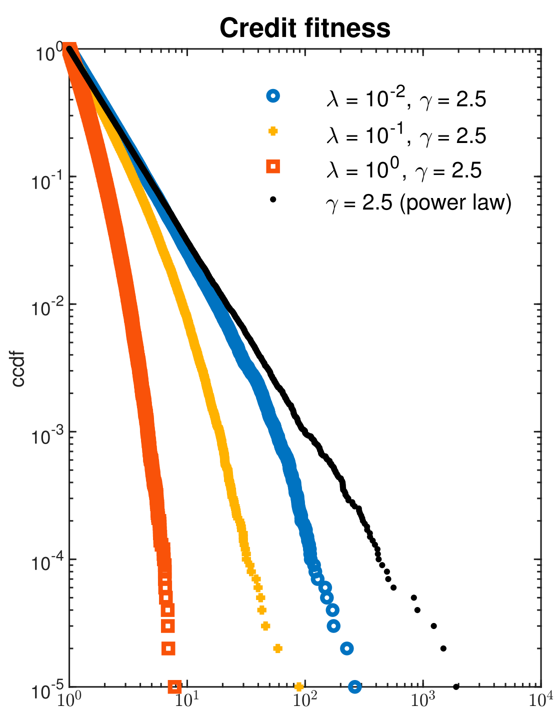


Figure 1. Loglog complementary cumulative distribution function (ccdf) of credit fitness parameters. The first three distributions in the legend reflect high ($\lambda = 10^{-2}$), mid ($\lambda = 10^{-1}$), and low ($\lambda = 10^{0}$) heterogeneity. The last one refers to a power law distribution with exponent $\gamma = 2.5$.

We prefer the exponentially truncated to the standard power law because it prevents the realization of extreme values in the right tail, which would give rise to an anomalous 'winner-takes-all' regime in the firms-banks credit network. Moreover, the exponential part can be adjusted to get more or less variance. For low values of λ, the power law component prevails, while for higher values the exponential component reduces the variance. We vary the exponential parameter λ to achieve different shapes from the same probability distribution:

(i) $\lambda = 10^{-2}$ for high heterogeneity.
(ii) $\lambda = 10^{-1}$ for mid heterogeneity.
(iii) $\lambda = 10^{0}$ for low heterogeneity.

2.1.2. Depositors' networks

To enhance the realism of the model, we allow households and firms to have more than one bank account. Random numbers drawn from a Poisson distribution with parameter $\mu = 2$ represent the number of bank accounts of each agent. We set the minimum number of links to one to ensure that everyone is connected to a bank. Next, households or firms are matched one by one to a randomly selected bank with which they are not yet connected until all disposable links are consumed. The algorithm generates an average number of links around 2.15 (greater than 2 because we increased the minimum from 0 to 1). Deposits are equally divided over links. At the end of each time, banks reward depositors at the fixed rate r^D on the average level of deposits in the accounts. The degree distribution of links is reported in Figure 2. The pseudo-code for depositors' network is reported below in Algorithm 1.

2.1.3. Shareholders' network

The bipartite shareholders' network identifies the shareholders of firms and banks. Despite our simplified framework does not provide precise treatment for equity shares, shareholders receive dividend payments from firms and banks to which they are connected and will bail them in contingent upon bankruptcy. Only households

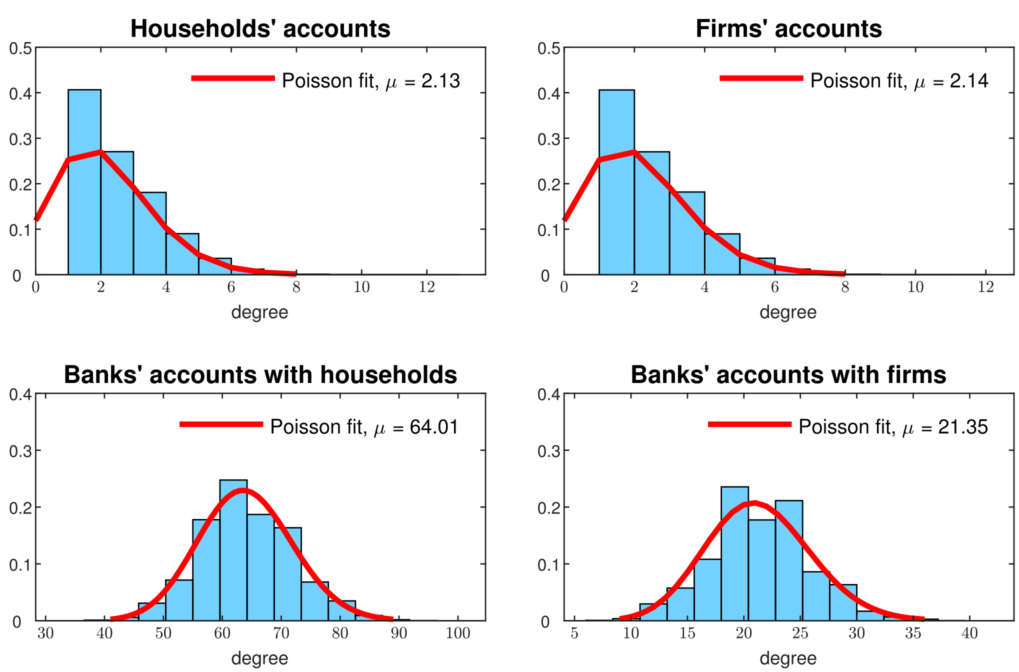


Figure 2. Degree distributions and Poisson approximations (red lines) of depositors' networks. *Top:* distribution of households' and firms' links with banks, where one account corresponds to a link. *Bottom:* distribution of banks' links with depositors.

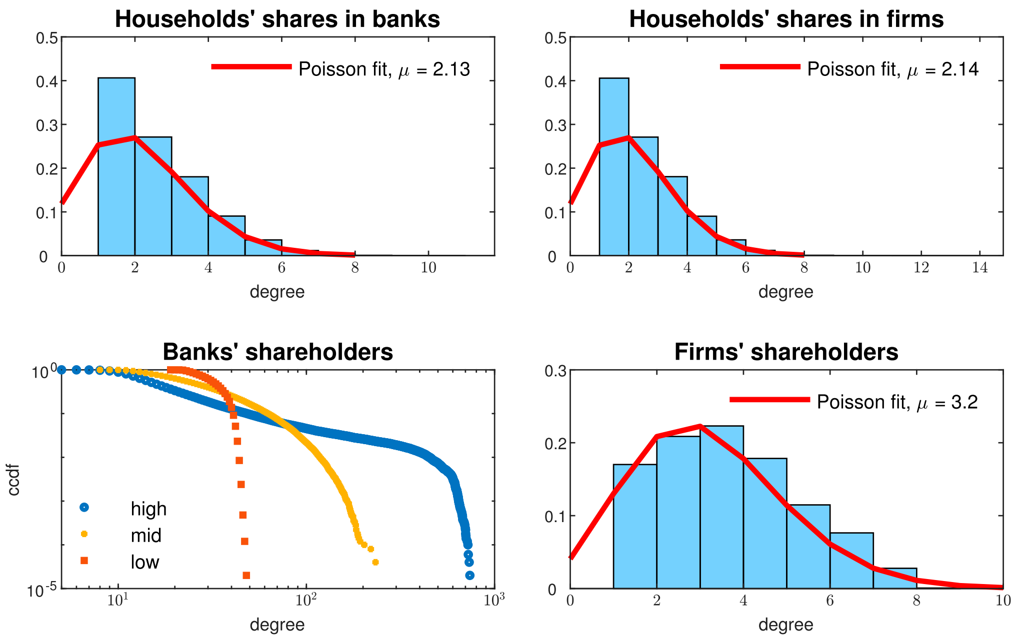


Figure 3. Degree distribution and Poisson approximations (red lines) of shareholders' networks. *Top:* distribution of households' links with banks and firms, where one share corresponds to a link. *Bottom:* distribution of banks' and firms' links with shareholders. High, mid, and low refer to the distributions of the credit fitness parameter.

Algorithm 1: Depositors' network

Households (firms) receive links extracted from a Poisson distribution ($\mu = 2$) ;
The minimum number of links is set to 1 ;
while *total number of links > 0* **do**
  form a list of households (or firms) with at least one link;
  for *each i in list randomly pick a bank b* **do**
    if *i and b not connected* **then**
      form a link;
      subtract one from *i*'s links;
    else
      go to the next *i*;

are entitled to be shareholders of banks and firms. Since about 55% of US households invest in the stock market[1], we pick this share randomly from the pool of households. To match households and firms, we copy the same mechanism as in the depositors' network. For banks, we create a network where the number of shareholders is proportional to the credit fitness parameters. This reflects the idea that banks with the best lending opportunities, measured by the credit fitness, are those that are more likely to grow in size, therefore, have the largest number of shareholders. The generative algorithm of the households-banks network starts by randomly assigning links to 55% of households, as for the depositors' network. Then an amount of links proportional to the fitness is preallocated to each bank. Finally, households and banks are randomly matched until the residual number of links of both goes to zero. Only one link for each pair of households-banks (or firms) is allowed. Pseudo-code and the degree distribution are displayed in Algorithm 2 and Figure 2.

Algorithm 2: Households-banks shareholders' network

55% of households receive links extracted from a Poisson distribution ($\mu = 2$);
The minimum number of links is set to 1 ;
Banks receive links proportional to their fitness: $links_b = \frac{x_b}{\sum_b x_b} \sum_i links_i$;
while *total number of links > 0* **do**
  for *a randomly chosen bank b* **do**
    form a list of households with at least one link not connected to b;
    pick an household i randomly from the list;
    form a link between i and b;
    subtract one from b's links;
    subtract one from i's links;

2.2. The macroeconomy

The model builds on an amended version of the ABM in Gurgone, Iori, and Jafarey (2018), though the financial sector has been further developed. The reader is referred to Table A21 in Appendix A.5 for a comparison with the original model. The economy is populated by three groups of agents: households, firms, and banks. Moreover, there are a government, a central bank, and a special agency. All entities have their own balance sheet and obey 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 central bank 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 the wage bills in advance, hire workers, produce and sell output on the goods market. The banking sector invests in bills and 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 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.

2.2.1. Timing

(1) The interbank market opens: demand and supply are determined respectively by the difference between banks' expected liquidity target and the 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 based on a frictional matching process. 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.
(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) Shareholders replace bankrupt firms with newborn start-ups and/or recapitalize banks.

(11) Unions update their required wage rate following a Phillips rule.
(12) The government collects tax revenues and issues bills, which are bought by banks and the central bank.

2.2.2. Households

There are N^H households that work, consume, and save. All supply inelastically one unit of labor remunerated at the wage rate set by the union 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 (Section 2.1). Households' wealth is the value of deposits kept in bank accounts. 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.

2.2.3. Firms

The sector is made up of N^F firms that produce a homogeneous perishable good using labor only as input and a linear production function. Firms' net worth is composed of the difference between deposits and loans from banks, as described in Table 1. 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:

(1) Adaptively set a target output level based on past sales from which firms calculate a labor target. If sold output in the previous period is lower than production, the target is revised downwards, otherwise it is increased.
(2) If internal funds are not enough to hire the workforce necessary to produce the target output at the current wage rate, firms seek financing by borrowing in the credit market. The matching mechanism with banks is described in Section 2.3.3.
(3) Hire workers until the wage bill has been met or no further employable workers can be found, then produce.
(4) Set a price for output and attempt to sell it. Firms have some monopolistic power arising from consumers' search costs so that prices are higher than marginal costs. Unlike Gurgone, Iori, and Jafarey (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 4). Unit costs include labor and credit cost.
(5) After production and pricing took place, the goods market opens and consumers spend their consumption budget.
(6) 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.
(7) Bankruptcy occurs if the net worth turns negative at the end of the period. In that case, a firm is re-capitalized by its shareholders after $timer^F$ periods by a randomly chosen amount $\in [0.1, 1]$.

Table 1. Balance sheets of banks and firms.

Banks		Firms	
Assets	Liabilities	Assets	Liabilities
L	$Dep^h + Dep^f$	Dep^f	L
I^l	I^b		
R			
B			
	nw^B		nw^F

Note: Loans to firms (L), interbank lending (I^l), reserves (R), treasury bills (B), households' and firms' deposits (Dep^h, Dep^f), interbank borrowing (I^b).

2.2.4. 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 households' bank accounts. The firm sector borrows funds from banks, pays workers, and sells goods to households. Firms deposit revenues from sales in banks. After taxes are collected the government repays the one-period maturity bills, thus closing the monetary circuit.

The government keeps stationary the stock of public debt by operating a balanced budget policy under which the transfers to households G are adjusted to keep the stock of bills constant

$$\Delta B_t = 0 = r^B B_t + G_t - T_t - \Pi_t^{CB}$$
$$\Rightarrow G_t = \max(T_t + \Pi_t^{CB} - r^B B_t,\ 0) \quad (1)$$

where r^b is the interest rate, B is the outstanding stock of government bills, T are tax revenues, and Π^{CB} are the profits of the central bank repatriated to the government. This formulation is different from the original one, where the stock of bills could vary and G was fixed. Here the overall amount of money is fixed. The change is motivated by the comparison of the model under different policies. It requires that aggregate wealth given by the sum of the net worth of all agents is kept constant and equal to the total amount of bills in the system.[2] Furthermore, 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 2.3.4, we assumed that the central bank does not provide emergency liquidity to banks.

2.3. Banks

Banks play simultaneously in the credit and interbank markets by lending to firms and trading liquidity. Lending to the real sector is financed out of deposits and interbank funds. If liquidity is not immediately available from these sources banks sell assets in a special market at the price determined in Equation (18). Moreover, at the beginning of every time step (or equivalently at the end of the previous ones) and before participating in the credit and interbank markets, banks protect themselves against potential defaults on loans by allocating a fraction f^{bills} of their deposits in safe treasury bills. For the sake of simplicity, we assume that bills reach maturity in one period and that f^{bills} is fixed and equal across all banks. The composition of banks' and firms' balance sheets is reported in Table 1.[3]

The net worth of bank b at time t is

$$nw_{b,t}^B = R_{b,t} + L_{b,t} + I_{b,t}^l + B_{b,t} - Dep_{b,t} - I_{b,t}^b \quad (2)$$

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). Since the risk weight on cash and bills is zero, $RWA_{b,t} \equiv \omega_1 L_{b,t} + \omega_2 I_{b,t}^l$.

$$nw_{b,t}^B \geq \frac{1}{\lambda} RWA_{b,t} \quad (3)$$

Gross profits Π^B are given by the difference between interest inflows and outflows, where r^L is the rate paid to deposits on the central bank's account, r^f is the rate on loans to firms whose residual maturity is indicated by the subscript k, r^{ib} is the interest rate on interbank lending, $r^B > r^L$ is the interest rate paid on bills, 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.

$$\Pi^B_{b,t} = R_{b,t-1}r^L + \sum_{j=1}^{J} L_{bj,t-k_j} r^f_{bj,t-k_j} + \sum_{q=1}^{Q} I^l_{bq,t-1} r^{ib}_{bq,t-1} + B_{b,t-1}r^B - D_{b,t-1}r^D - \sum_{z=1}^{Z} I^b_{bz,t-1} r^{ib}_{bz,t-1} \tag{4}$$

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.

$$\Delta nw^B_{b,t} = (1-\theta^B)(1-\delta^B)\Pi^B_{b,t} - \sum_{j=1}^{J} loss^F_{t,bj} - \sum_{q=1}^{Q} loss^B_{t,bq} - c(nw^B_{b,t-1})^2 \tag{5}$$

2.3.1. *Recovery rates*

In case of bankruptcy of bank i, the nominal value of illiquid assets is not immediately convertible in cash and must first be liquidated. The liquidation value of assets is $\mathcal{A}_i^{liq}$, where $\mathcal{A}_i^{liq} \leq \mathcal{A}_i$. Moreover, we assume that creditors are not equal under 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 others have been compensated. The recovery rate on interbank assets is therefore

$$\varphi_i = \max\left(0, \frac{\mathcal{A}_i^{liq} - Dep_i}{\mathcal{L}_i - Dep_i}\right) \tag{6}$$

where *loss given default* is $1-\varphi$.

2.3.2. *Credit market*

It is well-known from the literature on asymmetric information that banks play a prominent role in channeling funds from savers to borrowers because of their expertise in collecting information (Bhattacharya and Thakor 1993; Stiglitz and Weiss 1988). The informative advantage leads to solving problems of adverse selection and moral hazard in financial markets, which in our model translates into the assumption that all banks are equally able to assess an unbiased measure of borrowers' default probabilities, as in Equation (8). Nevertheless, we also assume that the maximum number of lending relationships reflected by the credit fitness parameter depends somehow on banks' intrinsic characteristics, such as screening abilities, cost of monitoring, contract enforcement power, or propensity to engage in long-term lending relationships. These characteristics affect banks' efficiency in solving asymmetric information problems, meaning that the most efficient banks have an advantage in processing loans. The efficiency of a bank compared to the least efficient one reflects the distribution of the credit fitness parameters. In concentrated markets, corresponding to the high heterogeneity world, banks' efficiency is dispersed so that there are many inefficient and a few efficient banks, which dominate the market. When the market is competitive and less concentrated, that is in the low heterogeneity world, the banking sector as a whole becomes more efficient. The idea is consistent with the recent findings in the work of (Chemmanur et al. 2020) that documented an increase in the screening efficiency of banks after that greater competition was brought in the sector by the reforms made with the entry of China into the WTO. Despite our simplistic approach, providing a detailed derivation of credit fitness in terms of banks' ability in solving asymmetric information problems is outside the scope of the paper.

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 Equation (7). 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 Equation (3).

$$L^s_{b,t+1} = \frac{\lambda}{\omega_1} nw^B_{b,t} - \frac{\omega_1}{\omega_2} I^l_{b,t} - L_{b,t} \tag{7}$$

The default probability ρ^f assigned to a firm j depends on its desired leverage rate, i.e. total demanded credit to net worth ratio ℓ, where ℓ^*, ν^f, and u^f are calibration parameters.[4]

$$\rho^f_{b,t} = u^f \exp\left[\nu^f\left(\frac{\ell_j}{\ell^*} - 1\right)\right] \tag{8}$$

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

$$r^f_{bj,t} = \frac{1 + cf_{b,t}}{1 - \rho^f_{bj,t}} - 1 \tag{9}$$

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.

$$cf_{b,t} = w^D_{b,t} r^D + w^I_{b,t} r^b_{t-k,b}, \quad s = \{Dep, I^b\} \tag{10}$$

2.3.3. 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 are built from banks' credit fitness (see Section 2.1), that is $\nu_b = \frac{x_b}{\sum_b x_b}$. The probability that a firm j switches to the candidate partner b and cuts the links with its previous lender z is regulated by (11).

$$p^{switch}_{jb} = \frac{1}{1 + \exp\left[-\kappa(\nu_b - \nu_z)\right]} \tag{11}$$

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 a previous lender, j is matched with b.

2.3.4. 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 a target cannot be reached, illiquid assets (loans to firms) are sold. Differently from Gurgone, Iori, and Jafarey (2018), where illiquid banks always borrow under the discount window of the central bank, here we assume that banks prefer to retrieve liquidity in the market: turning to the window would signal their riskiness in that cannot access other sources of funding as documented in Armantier et al. (2015). Therefore, borrowing from the central bank is interpreted by peers as a sign of weak financial conditions that could put at risk future lending. We assume that banks' reluctance due to the stigma of peers is such that it always prevents the central bank from the provision of emergency liquidity. The assumption is essential for the emergence of occasional liquidity crises and avoids the introduction of more elaborate mechanisms.

The liquidation process is detailed in Section 2.4 where the asset price is determined by Equation (18). 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 4.

The interbank demand and supply originate from (12). Bank b needs to borrow additional liquidity if the inequality (12) is not satisfied otherwise it offers the positive difference in the interbank market.

$$R_{b,t} - rrDep_{b,t} \geq liq^{tag}_{b,t} \tag{12}$$

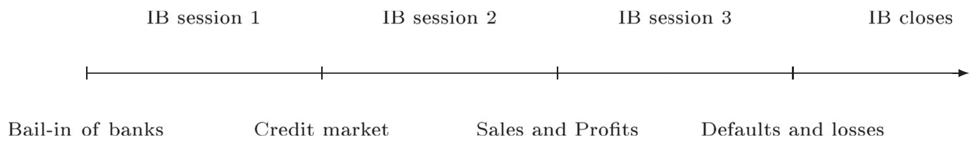


Figure 4. Timeline of the interbank market (IB).

The left-hand side is the liquidity held at the central bank net of compulsory reserves. The liquidity buffer $liq^{tag} = \beta(out^E - in^E)$ depends on the difference between expected cash outflows and inflows during one period. The expected 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 exponentially weighted average of past values. The expected inflows are the sum of interest payments on loans to firms, the principal of loans that are paid back at the end of t weighted by borrowers' default probabilities, the revenues from reserves at the central bank, and bills.

As for loan supply, the supply of interbank funds in Equation (13) is constrained by the minimum regulatory capital requirements.

$$I^s_{b,t} = \min\left(R_{b,t} - rrDep_{b,t} - liq^{tag}_{b,t},\ \frac{\lambda}{\omega_2} nw^B_{b,t} - \frac{\omega_1}{\omega_2}\sum_{j\in J} L_{bj,t-k} - \sum_{z\in Z} I^l_{bz,t-k}\right) \tag{13}$$

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

$$r^{res}_{bz,t} = \frac{1 + r^L}{1 - \rho^B_{bz,t}} - 1 \tag{14}$$

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^B, where lev^*, v^B, and u^B are calibration parameters.

$$\rho^B_{z,t} = u^B \exp\left[v^B\left(\frac{lev_z}{lev^*} - 1\right)\right] \tag{15}$$

2.3.5. 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 Equation (14). 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.

$$r^{bid}_{z,t} = \frac{r^H + r^L}{2}(1 + \varepsilon_{z,t}), \quad r^{bid}_{z,t} \in [r^L, r^H] \tag{16}$$

The mark-up is increased if there is unfilled demand and decreased otherwise.

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

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

2.3.6. 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, Gatti, and Grazzini (2015) so that the maximum amount of outstanding loans to firm j is

$$L_{bj,t}^{max} \equiv L_{bj,t} \leq \frac{\zeta\, nw_{b,t}^{B}}{\rho_{j,t}^{f}}$$

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.

$$VaR_t^{\alpha}(L + I^l) \leq nw_t^B \Rightarrow \frac{L + I^l}{nw_t^B} \leq \frac{1}{VaR_t^{\alpha}} \tag{17}$$

Therefore, banks will manage the total credit supply to comply with Equation (17) so that the leverage ratio does not exceed $\frac{1}{VaR^{\alpha}}$.

2.3.7. Recapitalization

When the net worth of a bank is negative it declares bankruptcy. Its assets are liquidated and distributed to creditors so that the net worth equals zero. The only elements left on the balance sheet are deposits and a corresponding amount of R. The bank is not replaced by another one but receives fresh capital from its shareholders after staying out of business for a minimum of $timer^B$ periods or until it can be recapitalized. The new capital is paid by banks' shareholders proportionally to their number. The assumption is consistent with the construction of shareholders' network presented in Section 2.1, i.e. banks with a larger number of connections with firms have more shareholders than the others. 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) was 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, $\phi\sqrt{N_b^{sh}}$ 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 5. In all simulations, the cyclical dynamics of the model produces a recurring pattern of firms' defaults and losses. 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. The shocks originating in the firms' sector determine deterioration in banks' balance sheets due to losses on loans. From there, two amplification channels may be activated: direct balance sheet contagion and indirect interbank illiquidity.

Following direct contagion (Figure 6), shocks from firms propagate to banks. Banks whose equity turns negative sell their assets (bills and loans to firms) to have the cash needed for repaying creditors. The sale price may further inflate creditors' losses (see Equation (18) in the last paragraph). The distress is propagated through the interbank market if bankrupted agents have interbank liabilities and from banks to firms.[5]

The indirect illiquidity hoarding channel (Figure 7) is activated infrequently but can produce crises with high losses and longer bankruptcy chains. It comes into play when the deterioration of banks' balance sheets leads to rationing in the interbank market since the availability of interbank funds is subject to the risk-management strategy of banks (Equation (17)), which is adjusted to respond to a fall in returns. A liquidity shortage causes

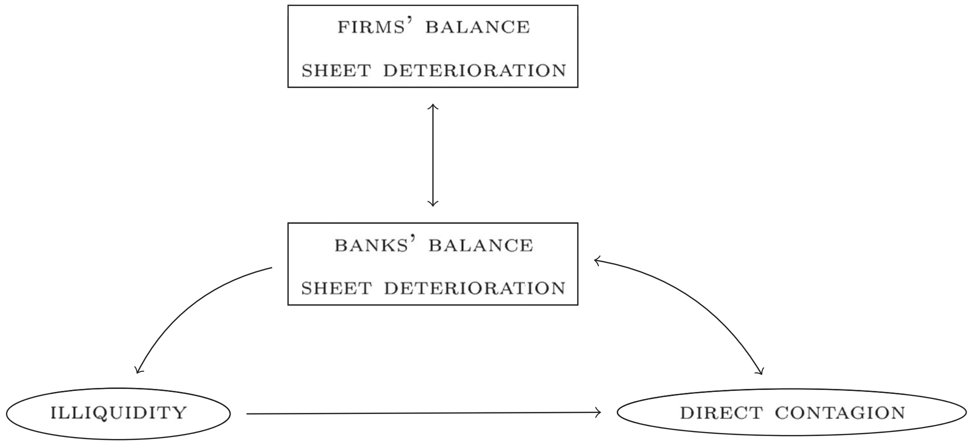


Figure 5. Distress is transmitted from firms to banks through credit market, from banks to banks in interbank market and from banks to firms through banks' deposits.

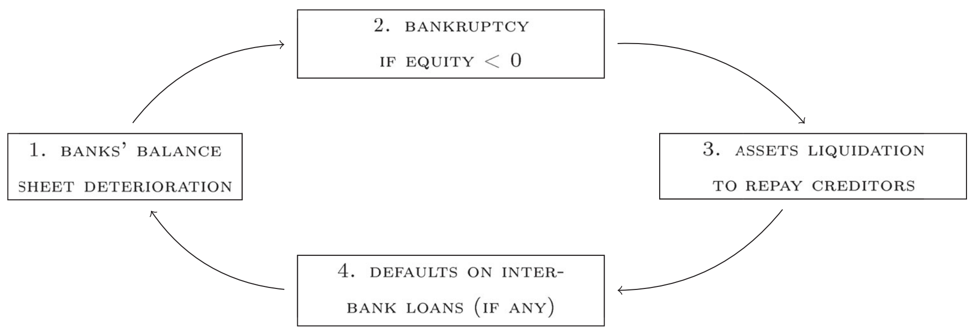


Figure 6. Direct contagion channel.

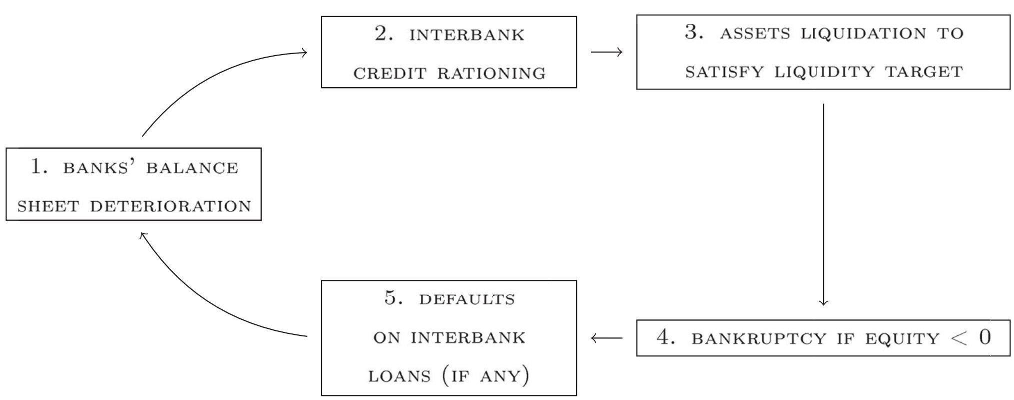


Figure 7. Liquidity hoarding channel.

consequently the liquidation of part of the assets to meet banks' liquidity targets. By selling in falling markets, bankruptcies may arise, if one or more banks sell substantial amounts. In such a case, distress is further propagated through direct contagion. Figure 8 shows a representative run of the model where a liquidity shortage on the interbank market creates an economic downturn.

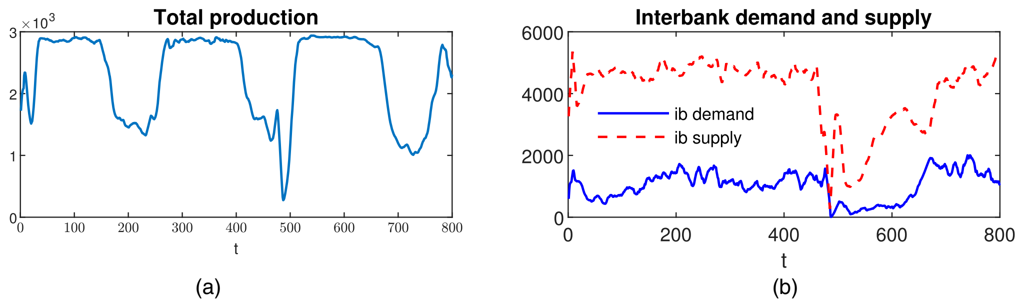


Figure 8. A liquidity crisis occurs around $t = 485$. A default cascade following assets liquidation causes a slump in aggregate supply.

2.4.1. Liquidation of assets

Banks liquidate assets (bills or loans to firms) in two cases: when they run out of liquidity, as explained above, and to repay creditors after failure. The role of the liquidator is operated by a special agency that buys the assets of bank b at price p

$$p^i_\tau = p^i_{\tau-1}\left(1 - \frac{\Delta q^i_{b,\tau}}{q^i_t}\frac{1}{\epsilon^i}\right), \quad i = \{bills, loans\} \tag{18}$$

where $\Delta q_{b,\tau}$ is the asset amount that bank b needs to liquidate,[6] ϵ^i is the asset price elasticity, q_t is the total amount of assets in period t. Banks that need liquidity enter the market in a random order, so that the first one sells at the most favorable price 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 $p_0 = 1$. Banks sell first the stock of bills, as those are more liquid than loans ($|\epsilon^{bills}| > |\epsilon^{loans}|$). 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. The liquidation produces a price impact on the balance sheet of the seller solely. A model extension in which assets are mark-to-market and the price change affects other banks via a common asset holding channel is discussed in Section 3.5.

2.5. Systemic capital buffers

The banking sector is regulated through capital requirements. All financial institutions must comply with minimum capital requirements that correspond to a fixed ratio of RWA. We introduce another supplementary requirement that adds up to minimum capital requirements. This is an additional capital surcharge called '*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.[7] 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 as 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.[8] 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.

2.5.1. Score-based capital buffers

How we assign SCBs relies on scores. Banks are subject to the 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 score.

Scores are classified into five categorical buckets or classes, as shown in Table 2. Each bucket corresponds to an interval determined on the distribution of scores resulting from simulations in which banks are only subject to risk-weighted adjusted capital requirements. In other words, we first simulate the model to obtain the distribution of scores (see Figure 9) 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 2. Buckets are linked to the capital buffers in the last column of Table 2 that add on minimum capital requirements. The method for selecting the score quantiles assigned to capital buffers is discussed in Appendix A.4.1. Under our calibration ($a = 0.8$), $q_0 = 50$, $q_1 = 64.9$, $q_3 = 76.8$, $q_4 = 86.3$, $q_5 = 93.9$. When SCBs are activated, Equation (3) is substituted by

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

where η is the buffer value based on a 6 periods moving average of the score.

Table 2. Determination of capital buffers.

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

Note: Scores are classified in intervals based on selected quantiles (q).

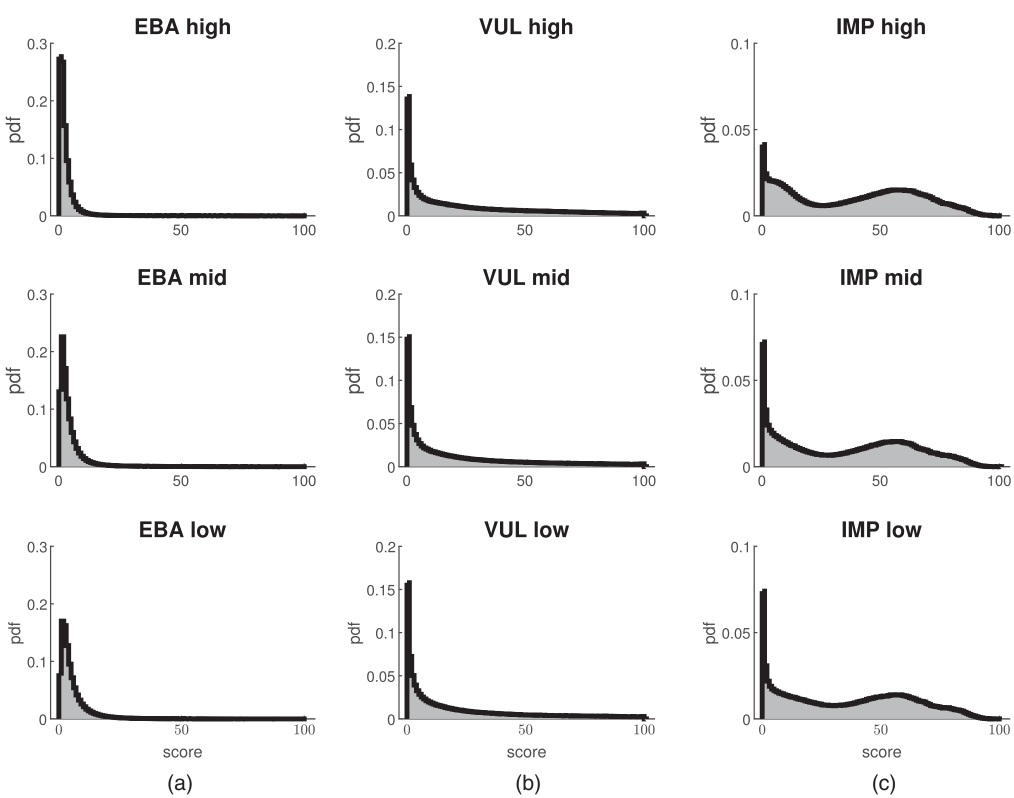


Figure 9. Distribution of systemic risk scores normalized between 0 and 100 under high *(top)*, mid *(middle)*, and low *(bottom)* heterogeneity computed by: EBA (a), DebtRank vulnerability (b), DebtRank impact (c).

2.5.2. 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 an 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 3 reports the indicators, weights, and 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 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 the bucketing mechanism presented in Table 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.

$$h_{b,T} \equiv \frac{nw^B_{b,T} - nw^B_{b,0}}{nw^B_{b,0}} \tag{19}$$

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 500 Monte-Carlo simulations of the model in Matlab for each type of systemic capital buffer under high and low heterogeneity. The length of one simulation is $T = 850$ from which we eliminate the transient time of 300 periods. The seed of the pseudo-random number generator takes different random values in every Monte-Carlo iteration so that networks are rebuilt each time.

Table 3. EBA scoring system for the identification of O-SIIs.

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

3.1. Heterogeneity

Figure 10 shows the effects of changing the heterogeneity in network structures. The complementary cumulative distribution functions (ccdfs) of banks' degrees exhibit longer right tails in the heterogeneous world. The result follows from changing the distribution of the credit fitness parameter. The net worth of banks and firms moves in opposite directions by varying the heterogeneity. The change corresponds to the variation in interest rates: when heterogeneity is high, borrowing from banks is more expensive because of the cost of interbank liquidity.

The interest rate regimes can be associated with the degrees of market concentration reflected by network structures (see Section 2.3.2). The result is consistent with the literature. For instance, in Corvoisier and Gropp (2002) higher market concentration leads to increased interest margins for loans, although in our model this is achieved through the cost of interbank funds rather than bank collusion. The similarity between banks' portfolios measured by the *Generalized Jaccard index*[9] reveals that dissimilarity is more marked when heterogeneity is high.

Figures 11 and 12 visualize the transactions networks that occurred in the interbank market and between firms and banks throughout representative simulations from low to high heterogeneity. The size of nodes is adjusted for the weighted in- and out-degrees of banks or firms, which represents interbank borrowing (Figure 11(a–c)), lending to firms (Figure 12(a–c)), and borrowing from banks (Figure 12(d–f)). The difference between high and low heterogeneity is visually clear for banks, whereas the variation in firms' borrowing is negligible (Figure 12(d–f)). In the less heterogeneous interbank network (Figure 11(c)), all banks are similar in terms of borrowing, in contrast with the more heterogeneous case (Figure 11(a)). Network statistics in Table 4 confirm the visual analysis: in Figure 11(a), few hubs borrow most interbank liquidity. Moreover, moving from the Figure 11(a–c), the networks are denser, average weighted degree and disassortative mixing decline, and the share of liquidity borrowed by the largest borrower reduces. In Figure 12, firms' borrowing does not show a wide variation but the dispersion (CV in Table 5) in banks' lending changes remarkably from high to low, as it

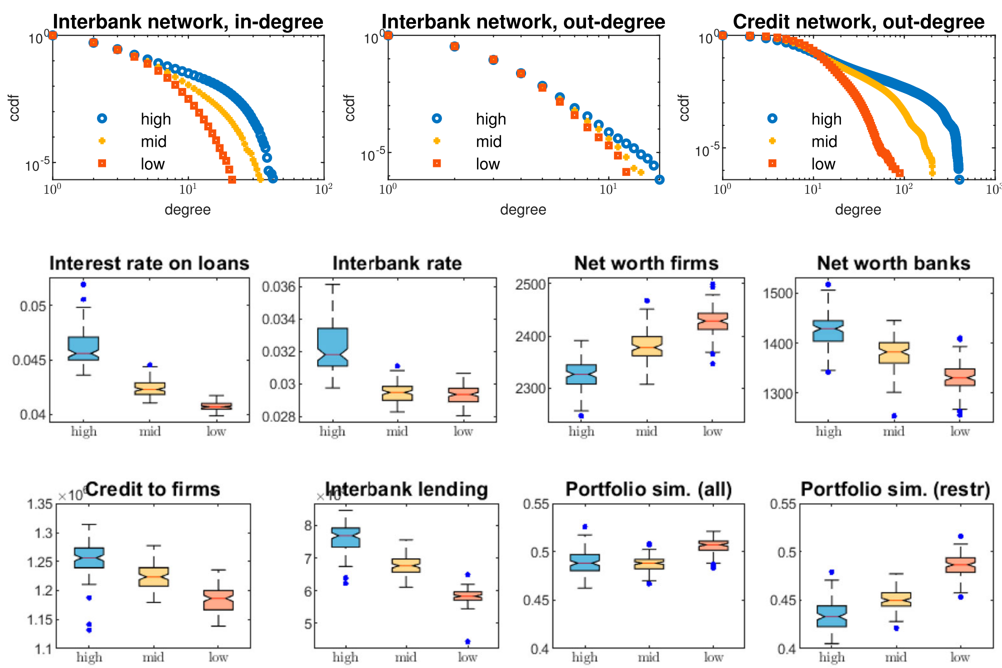
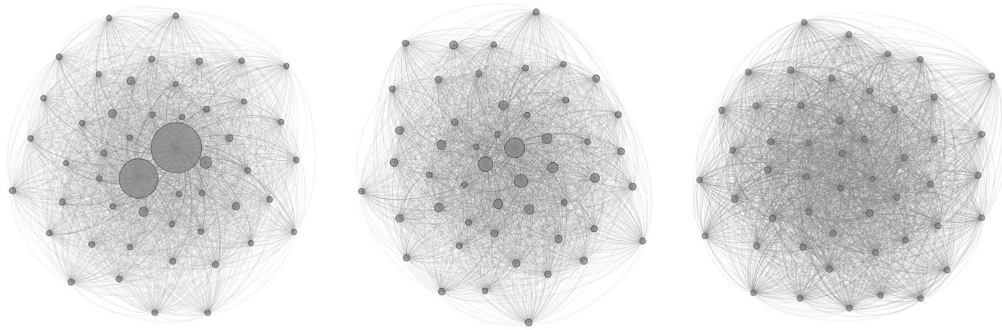
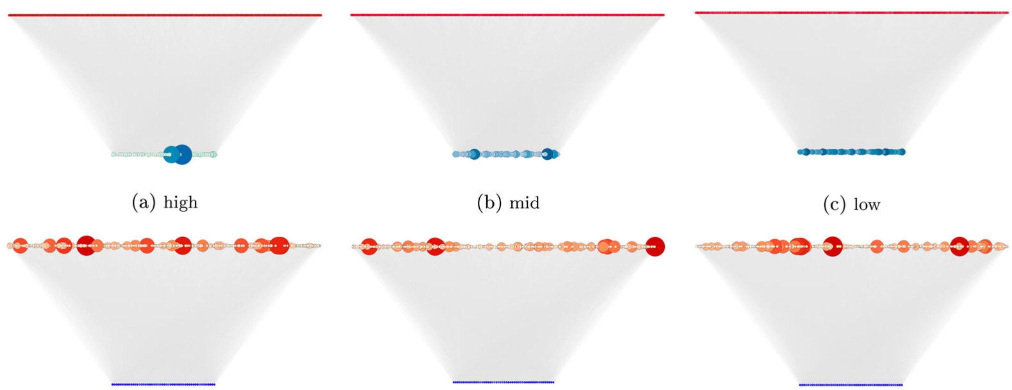


Figure 10. Ccdfs in log-log scale and boxplots for selected variables under high (blue circles), mid (yellow diamonds), and low (red squares) heterogeneity. The 'restr' version of portfolio similarity refers to the similarity between the top and bottom 10% of banks sorted by their credit fitness parameters (color online).



(a) high (b) mid (c) low

Figure 11. Interbank network under high (a), mid (b), and low (c) heterogeneity. 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. Networks are plotted in Gephi using the Force Atlas algorithm.



(a) high (b) mid (c) low

(d) high (e) mid (f) low

Figure 12. Bimodal firms-banks network of the credit market under high (a,d), mid (b,e), and low (c,f) heterogeneity. Banks are blue and firms red circles. *Top:* Lending to firms. Banks' sizes and shades show the weighted out-degree (number of outgoing links weighted by the amount lent). *Bottom:* Borrowing from banks. Firms' sizes and shades show the weighted in-degree (number of incoming links weighted by the amount borrowed). Networks are plotted in Gephi using the Geo Layout.

Table 4. Descriptive network statistics for Figure 11(a–c).

Statistics	High (a)	Mid (b)	Low (c)
Average weighted degree	14031.42	11933.90	8877.12
Density	0.88	0.92	0.99
Average assortativity	−0.44	−0.36	−0.30
Share of liquidity borrowed by the largest bank	0.28	0.13	0.03

is visible in Figure 12(a) where lending to firms is operated by a few big banks. The total intermediated credit decreases slightly from high to low.

In summary, the assumptions about network structures in Section 2.1 produce the desired outcomes when applied to the full model: they lead to different degree distributions, dissimilar portfolios, and net worth of banks. Moreover, under high heterogeneity a small group of banks engages especially in lending to firms, while a larger one supplies interbank funds to the first (Table 5).

Table 5. Descriptive statistics for Figure 12(a–f).

Statistics	High (a, d)	Mid (b, e)	Low (c, f)
CV (firms' borrowing)	1.88	1.88	1.83
CV (banks' lending)	13.16	4.28	2.23
credit ratio	1.00	0.98	0.93
density	0.05	0.06	0.06

Note: *CV* is the coefficient of variation, *credit ratio* is the ratio of credit to firms to credit under high heterogeneity.

3.2. Analysis of systemic scores

In this section, we study the characteristics and the mechanisms driving SBCs by considering the scores derived from systemic risk metrics on which they are based. The following abbreviations apply henceforth: *RWA* is the benchmark case where banks are only required to have a capital greater or equal to a fraction of their risk-weighted assets. *EBA* refers to capital buffers for O-SII, *IMP* refers to buffers based on DebtRank impact, and *V UL* to those based on DebtRank vulnerability.

First, we study the auto- and cross-correlations of systemic scores. Autocorrelations in Table 6 show the time persistency of scores computed by different systemic risk measures and tell us about the variability of the risk buckets to which banks are assigned. For EBA and IMP, autocorrelation is higher and more persistent under high heterogeneity, while moving to mid and low it becomes weaker and decays faster. VUL shows the lowest values, which indicates that scores computed by looking at vulnerability are less persistent as banks move between risk buckets more often than in the other cases. Most importantly, the faster decline of autocorrelation when heterogeneity is low suggests that the characteristics of banks change more rapidly, making it harder to operate an effective macroprudential policy. The cross-correlations in Table 7 control for the joint variations of scores. The correlations between EBA-IMP and EBA-VUL are low, while the coefficients for IMP-VUL are above 0.7. The last is not surprising since both are based on the same algorithm: if banks with high impact are well interconnected, they are exposed to many other banks so that their vulnerability may be high. However, it is not necessarily true that the banks with the largest impact are always vulnerable (or vice versa) because the statistic is computed on the entire range of scores.

Table 8 reports marginal effects from logit regressions. The objective is to understand what variables are the most relevant for banks to being included in the riskiest buckets. We consider bank-level cross-sectional data for each SCB under high, mid, and low heterogeneity. The response binary variable y is 1 if a bank is assigned to the riskiest buckets, namely has a buffer greater or equal than 2.5%. The regressors include banks' share of total assets, share of interbank supply, share of interbank lending and borrowing, normalized betweenness centrality for the directed interbank network, and risk-weighted assets to equity. All except the latter are between 0 and 100 so that the estimated parameters could be interpreted as the increase in the probability to be in the risky buckets

Table 6. Autocorrelation coefficients on banks' scores.

Lag	EBA-h	EBA-m	EBA-l	IMP-h	IMP-m	IMP-l	VUL-h	VUL-m	VUL-l
+1	0.932	0.733	0.529	0.764	0.726	0.564	0.590	0.717	0.564
+10	0.809	0.605	0.391	0.494	0.580	0.387	0.179	0.560	0.370
+25	0.723	0.426	0.242	0.416	0.401	0.235	0.118	0.390	0.228
+50	0.650	0.189	0.072	0.348	0.175	0.067	0.075	0.181	0.073

Table 7. Cross-correlation coefficients on banks' scores.

	EBA-IMP	EBA-VUL	IMP-VUL
High	0.083	0.163	0.755
Mid	0.079	0.181	0.752
Low	0.037	0.198	0.724

Table 8. Logit regression, average marginal effects.

	Dependent variable								
	SCB								
	EBA-h (1)	IMP-h (2)	VUL-h (3)	EBA-m (4)	IMP-m (5)	VUL-m (6)	EBA-l (7)	IMP-l (8)	VUL-l (9)
tot.assets	0.113***	−0.021***	0.018***	0.090***	−0.049***	−0.006	0.079***	−0.088***	−0.035***
	(0.003)	(0.005)	(0.006)	(0.002)	(0.006)	(0.006)	(0.002)	(0.006)	(0.006)
ib.supply	−0.012***	−0.022***	0.019***	−0.013***	0.005	0.031***	−0.013***	0.010**	0.070***
	(0.001)	(0.004)	(0.004)	(0.001)	(0.004)	(0.004)	(0.001)	(0.004)	(0.005)
ib.lending	0.013***	−0.009***	0.041***	0.008***	−0.006***	0.042***	0.009***	0.005**	0.025***
	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
ib.borrowing	0.036***	−0.018***	−0.029***	0.023***	−0.015***	−0.040***	0.021***	−0.026***	−0.036***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
betweenness	−0.007***	0.189***	0.020***	−0.004***	0.199***	0.045***	−0.007***	0.150***	0.030***
	(0.003)	(0.008)	(0.006)	(0.001)	(0.008)	(0.004)	(0.001)	(0.006)	(0.005)
RWA.CET1	0.022***	0.218***	0.377***	0.009***	0.198***	0.381***	0.016***	0.257***	0.386***
	(0.002)	(0.008)	(0.009)	(0.001)	(0.007)	(0.009)	(0.001)	(0.007)	(0.009)
Observations	41,594	34,008	33,134	46,758	31,873	33,851	46,689	35,492	33,851
McFadden's R2	0.67	0.16	0.23	0.66	0.19	0.26	0.57	0.13	0.24
Log Likelihood	−6,852.287	−17,590.830	−16,789.780	−7,020.158	−16,306.920	−16,320.230	−8,138.655	−20,441.680	−16,320.230
Akaike Inf. Crit.	13,718.580	35,195.650	33,593.550	14,054.320	32,627.850	32,654.460	16,291.310	40,897.360	32,654.460

Note $y = 1$ for capital buffers greater or equal to 2.5%. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

following a unit increase in the regressors. Since SCBs are determined based on six lags moving average of scores, the values of regressors are computed through moving averages too. So, we explain the response variable by explanatory variables referred to the periods in which average scores are calculated. The loan, net worth, and deposit shares are highly correlated and are omitted from the regression as they cause a VIF above 10. Summary statistics, cross-correlations, and VIF are reported in Appendix A.2. The functional form of the logit regression is specified in (20).

$$P(y = 1|X) = F\left(\beta_0 + \sum_{k=1}^{K} \beta_k x_k\right) \tag{20}$$

where the binary response variable y is equal to one if a bank is assigned a buffer greater or equal than 2.5%, $X = (x_1, \dots, x_k)'$ is the vector of regressors, β_0 is the intercept, β_k is the k^{th} slope coefficient, x_k is the k^{th} regressor, and F is the cdf of the logistic function.

The EBA score reflects its design based on the balance-sheet indicators. Balance-sheet shares have some effect on the probability to have a high buffer. Not surprisingly, given the 33.3% weight assigned to the indicator, (see Section 2.5), a unit increase in `tot.assets` entails a large increase in marginal effects (+11.3% under high heterogeneity). More puzzling is the decrease of the same coefficient moving to mid and low heterogeneity, which indicates that a one-point increase in the total asset share has a reduced impact on the probability to receive a high capital buffer. This behavior is discussed further below.

The most relevant characteristics of banks classified in the top buckets by IMP are betweenness centrality and RWA/equity ratio. So, being a central node on the interbank network and being leveraged are good predictors for being a systemic bank according to IMP. As one would expect, the RWA-to-equity ratio has a strong marginal effect for VUL. The results are consistent with the cross-correlations in Table 7 because both IMP and VUL show a strong influence of `RWA.CET1` on the dependent variable. Finally, it is worth noticing that the value of the coefficients `betweenness` for IMP and `RWA.CET1` for VUL stays more or less constant for all degrees of heterogeneity.

The decrease in the estimated coefficients on `tot.assets` moving from high to low may signal a reduction in the effectiveness of EBA as a macroprudential tool. To investigate further, we visualize the distribution of scores under high, mid, and low heterogeneity in Figure 13. The figure displays red vertical lines corresponding to the values above which banks are classified in the riskiest buckets (under our calibration, the values corresponding to 2.5% and 3% are computed, respectively, on the 86th and 94th score percentiles.) While the red line stays close to its initial level (EBA high), the positive skewness of the distribution shrinks. The right tail moves backward because banks' balance sheets become more similar. The change in the distribution of selected regressors is illustrated in Figure A1 in the Appendix. It turns out that there is a drastic reduction of loan share from high to low, where the maximum reduces about from 80 to 20. The shares of other balance sheet variables move in the same direction, though with a lower magnitude. Therefore, with the homogenization of balance sheets following the variation in the credit fitness parameter, the scoring mechanism of EBA cannot capture the most systemic banks anymore. The change in EBA score distribution is partly translated into a reduced occurrence of capital buffers. The effect can be noticed in Figure 14 with the increase of the 0% frequency moving from high to low heterogeneity.

3.3. Effects of SCBs on production efficiency

We look at the deviation of output from full capacity to measure the effect on the real economy of imposing additional capital buffers on the banking system.

Before commenting on results, it is helpful to remark on some of the model assumptions. First, the maximum production capacity of the economy is fixed as firms produce with labor input only and labor productivity is constant. Second, to ease the comparison between alternative policies, the overall amount of money is the same for all simulations, irrespective of heterogeneity or specific SCBs. Last, despite the total amount of resources is given, their distribution between firms, households, and banks can vary.

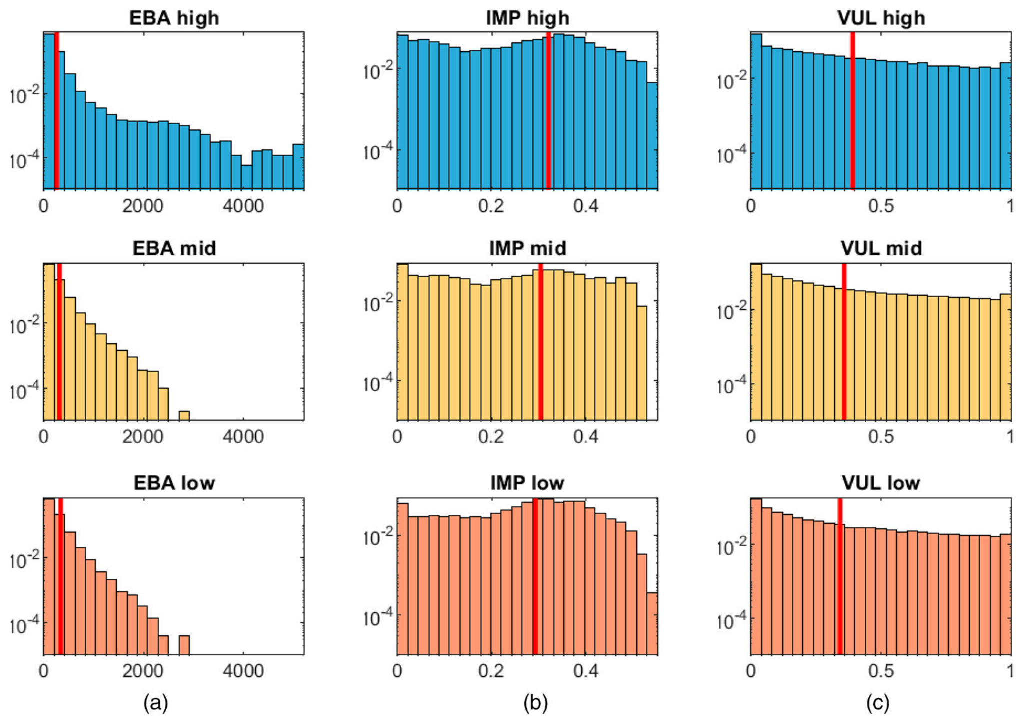


Figure 13. Histograms of scores for high (blue), mid (yellow), and low (red) heterogeneity. The scale of the *y*-axis is logarithmic. The red vertical lines are the thresholds that separate the buckets associated to 2.0% from the 2.5% buffer.

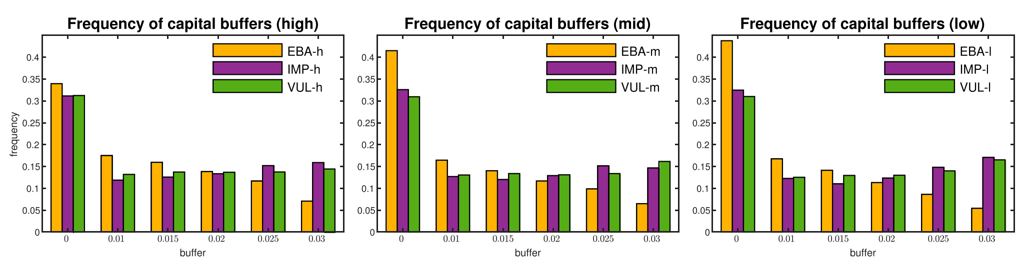


Figure 14. Frequency of SBCs per buffer value for high to low heterogeneity.

Figure 15 displays output gap and volatility. Overall, there is an improvement moving toward a more homogeneous system even though the magnitudes of effect on the real economy are small. As shown in Figure 10, the movement in interest rates determines an adjustment in the aggregate net worth of firms and banks and credit. The system becomes more stable (fewer defaults means more production) and a lower interest environment enhances the efficiency of the firms' sector. However, SCBs improve production efficiency only under high heterogeneity, while for other levels there is a small decline. The result is linked to the level of heterogeneity rather than to a specific SCB: for a given level of heterogeneity, SCBs produce a decrease in the interbank rate by limiting the demand of most systemic banks, reduce banks' cost of funds and raise their net worth. As money is given in a fixed amount, the net worth of firms decreases and credit demand goes up compared to RWA. Therefore, the leverage of firms is always increasing under SCBs. Under low and mid, the output gap is greater for SCBs because the firms' sector is less stable due to the growth of interest rate. In other words, firms' defaults impair total production. While under high heterogeneity the drop in the interbank rate yields to a decrease in r^f from Equation (9), for low and mid heterogeneity r^f increases because the higher leverage is not offset by a sufficient drop in the cost of funds. So, a higher default probability of firms prevails and pushes r^f up compared to RWA.

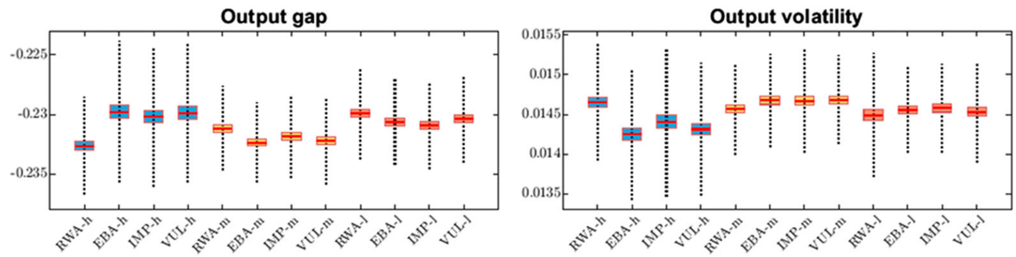


Figure 15. Output gap (left) and output volatility (right) for high (blue), mid (yellow), and low (red) heterogeneity. Red lines represent the mean, boxes are the 95% confidence interval of the mean, and dotted vertical lines are 1 standard deviation. The output gap is the ratio of the deviation of actual output to potential output, which under our assumptions is constant (further details in Section A.5). Output volatility is computed as the standard deviation of output growth rate.

In short, SCBs improve the macroeconomic performance of the economy for heterogeneous banking systems. They cause a small loss in efficiency for more homogeneous systems, though the last follows from model assumptions and calibration.

3.4. *Effect of SCBs on financial stability*

3.4.1. *Aggregate defaults and losses*

Here we assess the effect of SCBs on total defaults and losses of banks by visualizing their distributions. First, we show how the financial system regularly behaves by looking at what happens around the medians in boxplots in Figure 16 where outliers in the tails are hidden. Next, we show the entire distributions of defaults and losses to equity in Figures 17 and 18, which permits a better grasp of what happens in the tails as the most extreme events are sometimes associated with systemic crises (see Section 3.4.2).

Overall, Figure 16 displays a decreasing pattern moving from high to low heterogeneity, Moreover, SCBs are effective in reducing defaults and losses to equity. However, defaults from loans to firms and liquidation defaults do not decline by decreasing the heterogeneity, and losses from firms to equity are not reduced by SCBs. Concerning defaults from loans to firms, they are going up because of the increasing exposures of banks to loans (credit to equity ratio), while at the same time losses to equity decline as diminishing loan to equity ratios of firms yield a lower loss given default (credit and equities of banks and firms are displayed in Figure 10). Despite decreasing with heterogeneity, losses to equity on firms' loans are not reduced by SCBs because firms' leverage increases with SCBs as explained in Section 3.3. The last element in Figure 16 displays a bar chart reporting the average number of liquidation defaults per Monte Carlo.[10] Even if the occurrence of liquidation defaults is infrequent, they are increasing from high to low heterogeneity. This brings us to Figures 17 and 18, which disclose the distributions of total defaults and average losses to equity. The upward pattern above is reflected in the ccdfs for defaults and losses, which show longer tails for decreasing levels of heterogeneity. So, why do the tails of liquidation losses and defaults are increasing moving to low heterogeneity? Briefly, because the interbank market channels fewer funds. The interbank demand-supply mismatch is made worse by decreasing the credit fitness parameter. The system becomes more robust to interbank and liquidation losses due to lowered demand of interbank funds and reduced exposure to interbank lending following the change in the distribution of credit fitness. Banks borrow less on average, interbank borrowing and lending to equity ratios decrease, and the distributions of liquidation and interbank losses shift leftward (see green and red lines in Figures 17 and 18). Although the medians are lower, there are more defaults and losses to equity in the tails. Decreasing the heterogeneity of the banking system makes the availability of interbank funds scarcer. Hence, when banks cannot borrow all the liquidity they need, it is more likely that they go bankrupt. A similar logic operates for interbank defaults and losses, as those that liquidate assets first borrowed part of their funding needs on the interbank market. Moreover, the rightward extension of the tail of defaults and losses from loans to firms may be related to the second-round effects of banks defaulting on firms' deposits driven by liquidations.

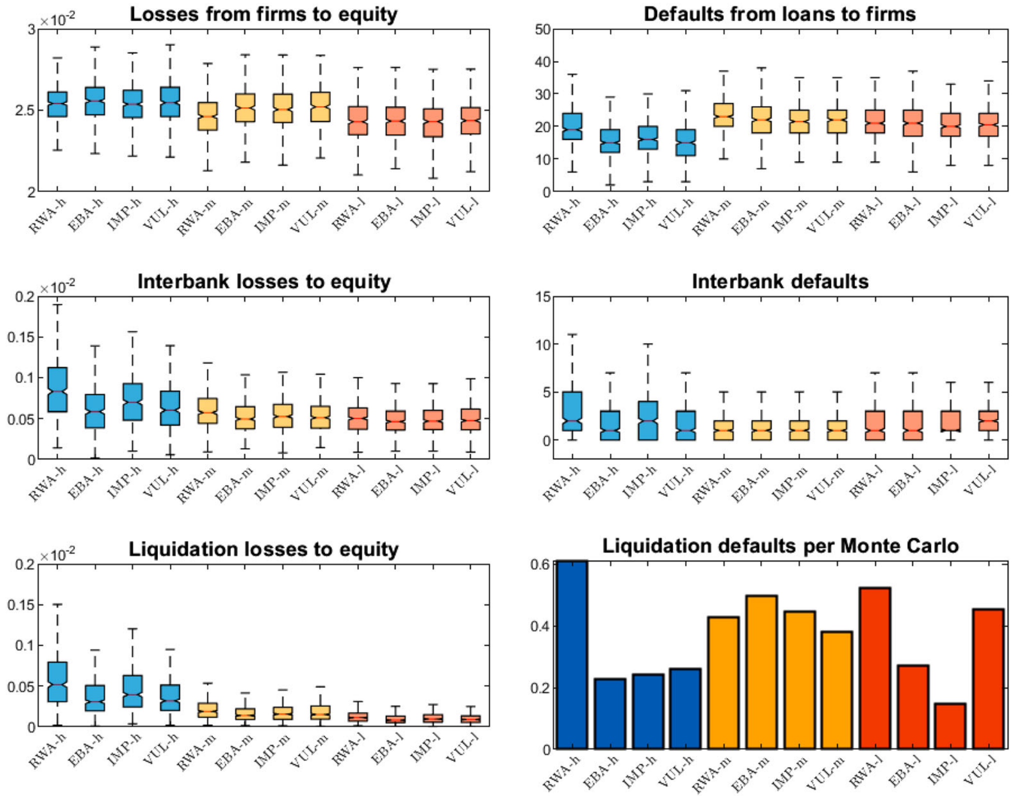


Figure 16. Mean losses to equity and total defaults under high, mid, and low heterogeneity. Outliers are not displayed.

SCBs improve financial stability. In general, they move the distributions below that for RWA.[11] The advantage of imposing additional capital surcharges is clear under high heterogeneity and less evident for mid and low. The best results are achieved by EBA (high and mid) and IMP (low).

In short, the study of aggregate defaults and losses to equity shows that SCBs improve systemic stability under high heterogeneity but offer limited gains when the system tends to homogeneity. Moreover, the incidence of liquidation-related events becomes stronger for low heterogeneity, which suggests to policymakers to be more careful about liquidity regulation in such an environment.

3.4.2. Systemic crises

To understand the effects of SCBs on financial stability, we compare their effectiveness in stabilizing the system by looking at systemic crises.

Crises can arise, although they are infrequent events that are not visible at every run of the model. Then we look at their frequency in the set of Monte-Carlo simulations and visualize the results in Figure 20. We define "*systemic events*" as those episodes in which a financial crisis feed-backs to the real economy (real-financial transmission channels are described in Section 2.4). The definition encapsulates the characteristics of a path-breaking event in this specific model. Precisely, the following three conditions identify a systemic event: (i) at least 10% of banks go bankrupt in a single unit of time due to interbank contagion, liquidation of assets, or both; (ii) within ten periods from (i), at least 25% of banks are defaulted or inactive waiting for recapitalization; (iii) within 10 periods from (i), there is a drop in total production of at least 15% compared to its long-run cyclical component.

The deviation in total production is computed by separating low and high frequencies by means of the HP filter with a smoothing parameter of 14,400 (Figure 19(a)). Moreover, we account for (ii) and (iii) in the 10

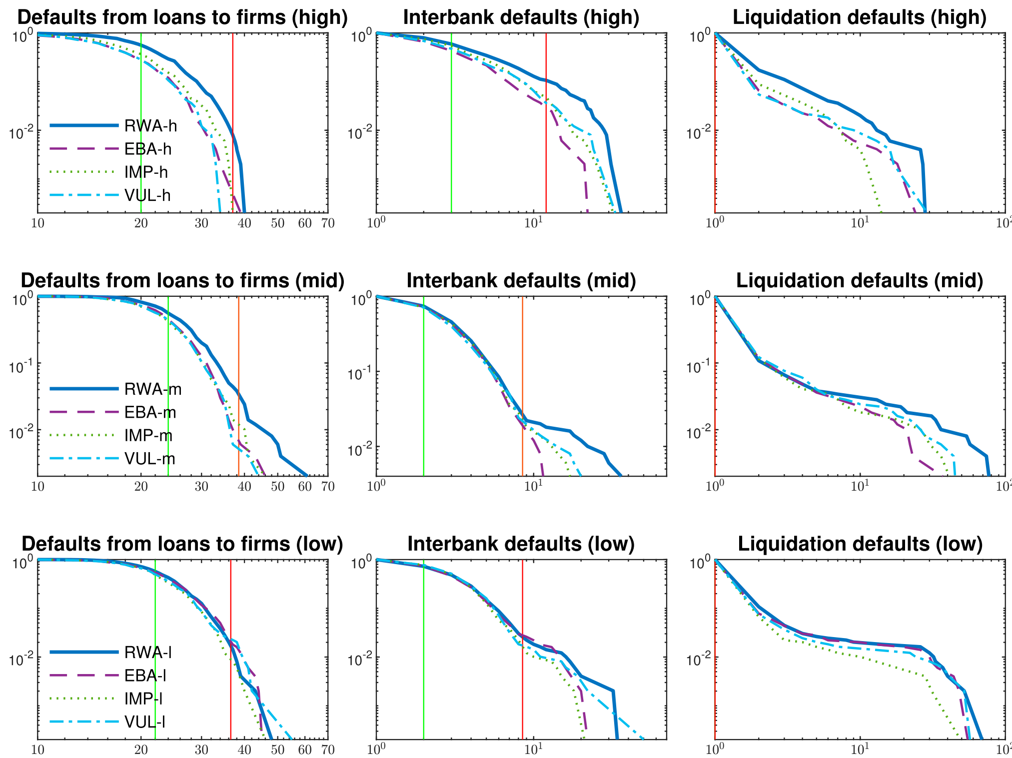


Figure 17. Ccdfs of banks' defaults under high, mid, and low heterogeneity. The red vertical lines are traced at $X > q_3 + 1.5(q_3 - q_1)$ and mark the points in the right tail of the benchmark distribution (RWA). The vertical green lines are the medians of the benchmark distribution (RWA). Ccdfs are computed on the sum of defaults per Monte Carlo simulation.

periods following (i) to capture the distress that propagates indirectly to the balance sheets of agents following the model dynamics. The length choice is motivated by the autocorrelation of the high-frequency component, which decays after about 10 lags (Figure 19(b)). For an alternative definition of a systemic event see Figure A2 in Appendix A.3.1.

As to systemic events in Figure 20: The subfigure on the left (Figure 20(a)) accounts for the frequency of systemic events. The first fact that stands out is the stark reduction in the frequencies moving from high to low heterogeneity. SCBs always decrease the frequency when heterogeneity is high compared to the benchmark. All SCBs are effective in reducing the frequency of crises for all degrees of heterogeneity but the ranking of SCBs changes in the least heterogeneous case, in which IMP becomes the best policy. The ranking of SBCs is preserved in subfigure (Figure 20(b)) reporting total defaults and losses by summing over all systemic events. Red bars are taller than the yellow ones because of the greater incidence of liquidation defaults and losses to equity, as reported in Figure 21.

The analysis reveals that systemic events are rare but they occur more often when the financial network is highly heterogeneous. SCBs especially enhance financial stability in the more heterogeneous case. EBA is the best policy under the first network configuration, while IMP works better under the other. However, EBA loses its effectiveness when the system is more homogeneous. Such a behavior could be interpreted with the help of the results in Section 3.2: SIFI are correctly identified based on banks' sizes until the system becomes more homogeneous. When the balance sheets of banks are more similar, "size invariant" criteria like those based on network centrality work better. Moreover, IMP captures the effects of second rounds of contagion (Figure 22(b)), which in our model are triggered more often by liquidation than other types of defaults. A final consideration concerns the total capital required by each type of SBCs to the banking system. It could be expected that SBCs demanding the highest amount of capital work better. However, it is not necessarily true. From Figure 22(a) it

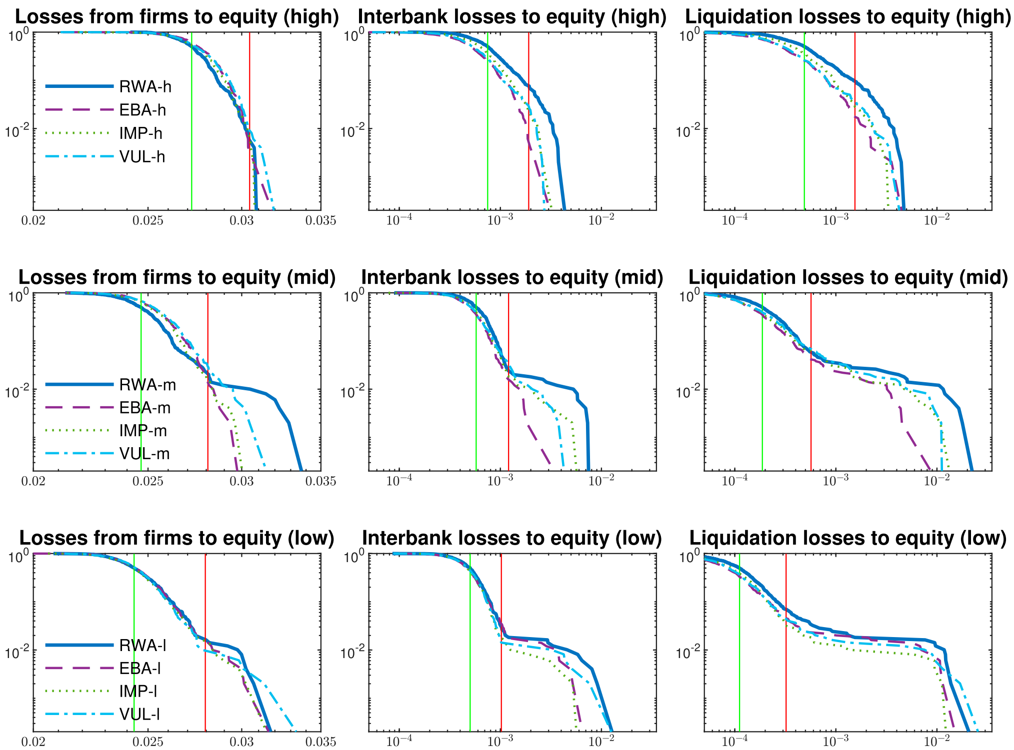


Figure 18. Ccdfs of banks' losses under high, mid, and low heterogeneity. The red vertical lines are traced at $X > q_3 + 1.5(q_3 - q_1)$ and mark the points in the right tail of the benchmark distribution (RWA). The vertical green lines are the medians of the benchmark distribution (RWA). Ccdfs are computed on the sum of defaults per Monte Carlo simulation.

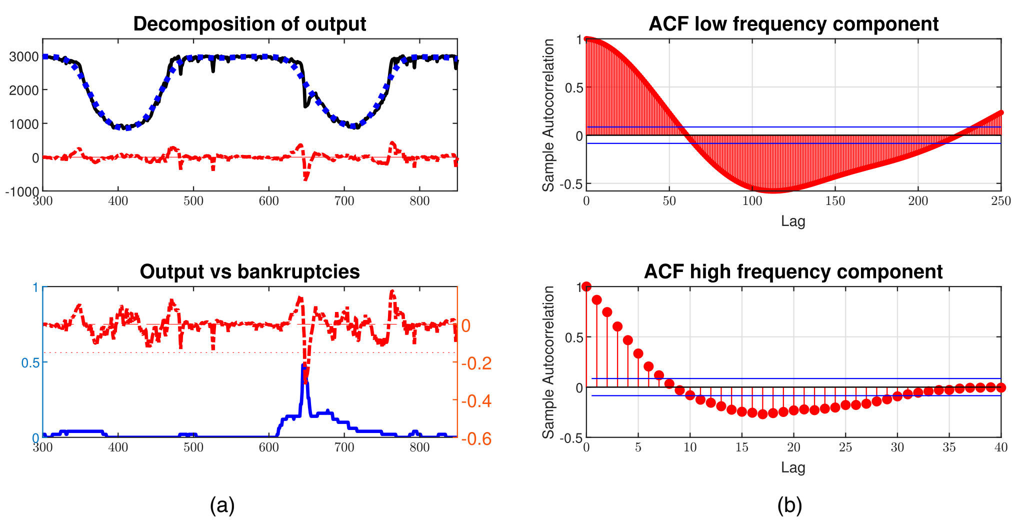


Figure 19. (a) *Top:* total output (black), low (blue dotted) and high frequency (red dash-dotted) components. *Bottom:* high frequency component of output (red dash-dotted), share of failed and inactive banks (blue). (b) *Top:* autocorrelation function (ACF) for the low frequency component of output. *Bottom:* autocorrelation function for the high frequency component of output.

turns out that EBA and VUL require more capital than IMP but they are not the first best policies under all degrees of heterogeneity. Rather than total required capital, the allocation of buffers across banks matters the most, as an effective policy should assign the top buffers to systemic-important banks. In such circumstances,

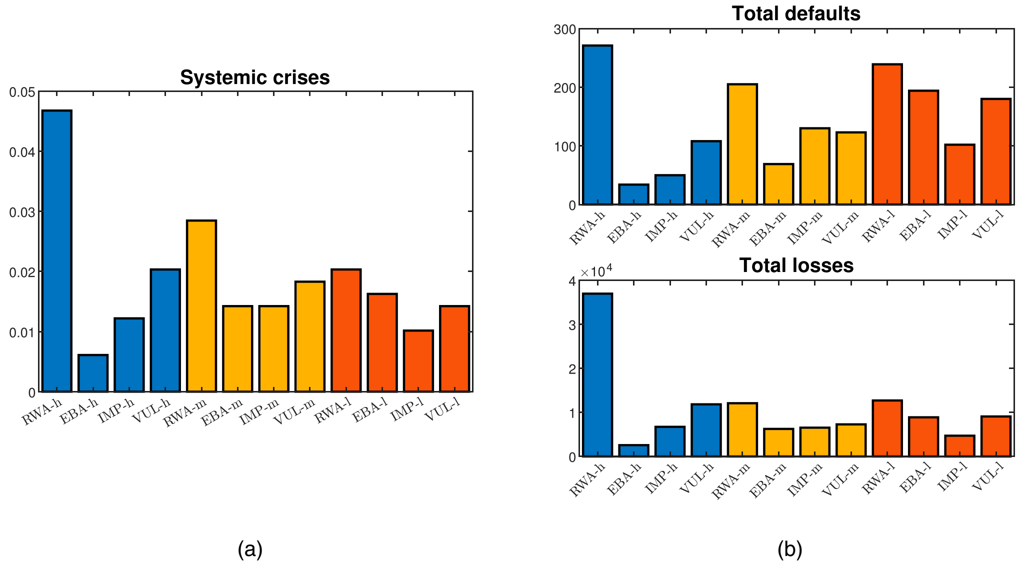


Figure 20. Frequency of systemic events (a). Total number of defaults and losses in systemic crises (b). High (blue), mid (yellow), and low (red) heterogeneity.

even a capital parsimonious policy like IMP is effective in reducing systemic events and is in fact the most effective in the case of low heterogeneity.

3.5. Common asset holding channel

This section introduces a preliminary analysis of another source of banks' heterogeneity, that is similarity in terms of common asset holdings. Beyond being a source of heterogeneity, diverse distributions of the common asset affect the stability of the financial system due to price contagion. This is the third channel of contagion, beyond the two considered in the previous section (see Section 2.4), that is extensively present in the literature. In what follows, we refer to it as Common Asset Holding Channel (CAHC). Here we set up a preparatory study to understand how similarity in terms of common assets may affect the effectiveness of the macroprudential policy. A more detailed analysis is postponed to future work.

If banks invested in a common asset, an initial shock that reduces its price may deteriorate the balance sheets of owners and induce a depreciation spiral driven by fire sales (Figure 23). To avoid adding further complexity to our framework, we keep unchanged the model except that banks' common assets are now marked-to-market. Therefore, the distress of one bank can create a shock that propagates to the others through overlapping portfolios. The initial causes of distress remain the same, that is counterparty losses and funding liquidity. We run the analysis assuming that common assets are treasury bills. As remarked in Section 2.3, banks invest a part of their deposits in bills. Following either a bankruptcy event or interbank illiquidity, banks liquidate their assets (bills and loans to firms). To study common asset holding contagion, we assume that bills are marked-to-market, therefore the price impact of sales erodes the equity of other banks. In turn, the decline in equity may trigger new bankruptcies, causes a downward change in the price of bills, and a negative fire-sale externality that extends to the entire banking sector. A sensitivity analysis on the values of price elasticity ϵ^{bills} is in Appendix A.4.2. The net worth identity is modified to include the price of bills p^{bills}, whose evolution is described in Equation (18)

$$nw^B_{b,t} = R_{b,t} + L_{b,t} + I^l_{b,t} + p^{bills}_t B_{b,t} - Dep_{b,t} - I^b_{b,t}. \tag{21}$$

Figure 24 reports the frequency of systemic crises, total losses to equity, and defaults compared to the case without fire-sales externalities. In all cases, the CAHC works as an amplification mechanism. As for the previous case, the system is stabilized moving from high to low heterogeneity but SCBs reduce the frequency of crises,

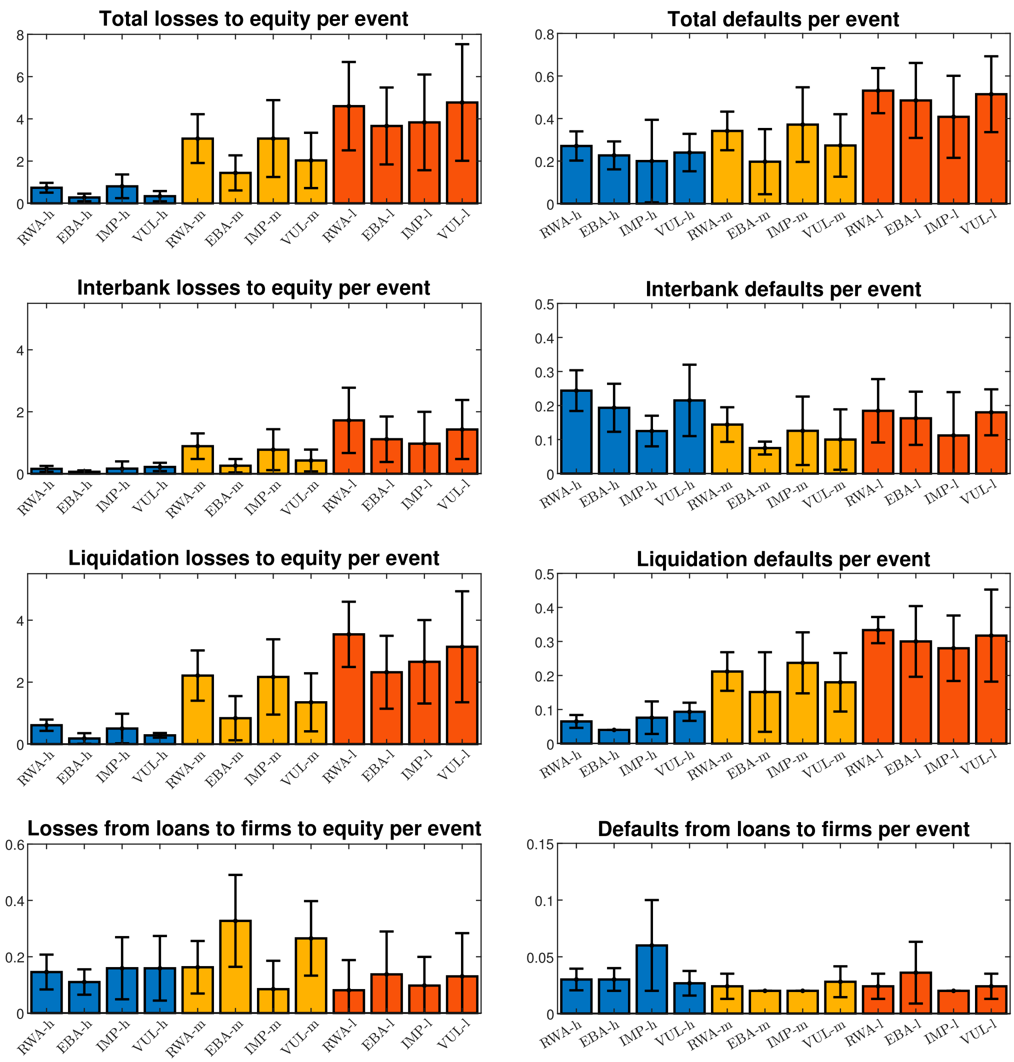


Figure 21. Losses to equity (left) and share of banks' defaults (right) per systemic event. High (blue), mid (yellow), and low (red) heterogeneity. Error bars are 95% confidence intervals.

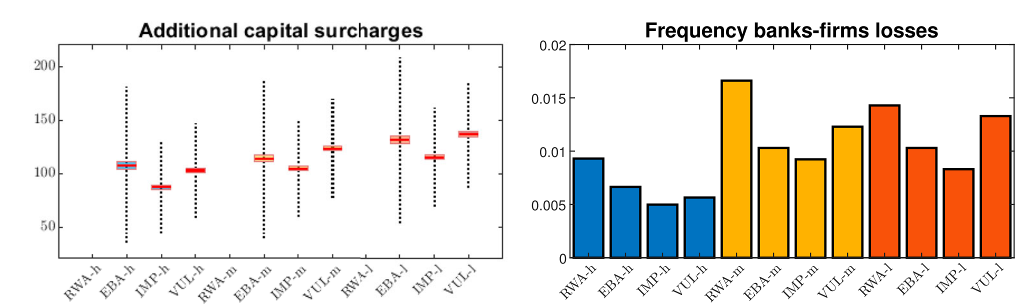


Figure 22. Additional capital surcharges, mean per Monte Carlo simulation. High (blue), mid (yellow), and low (red) heterogeneity. Red lines represent the mean, boxes are the 95% confidence interval of the mean, and dotted vertical lines are 1 standard deviation (a). Frequency of firms losses on deposits following banks' defaults as a proxy for second and further round effects: banks' defaults on firms' deposits may trigger the default of firms' on banks loans *et cetera*. High (blue), mid (yellow), and low (red) heterogeneity (b).

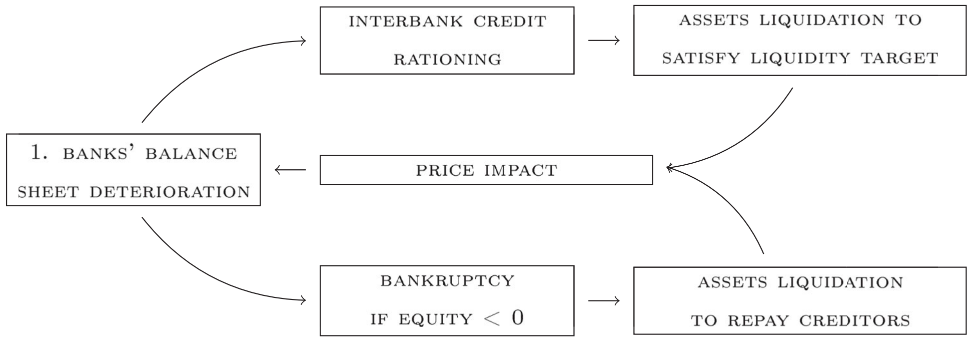


Figure 23. Common asset holding channel.

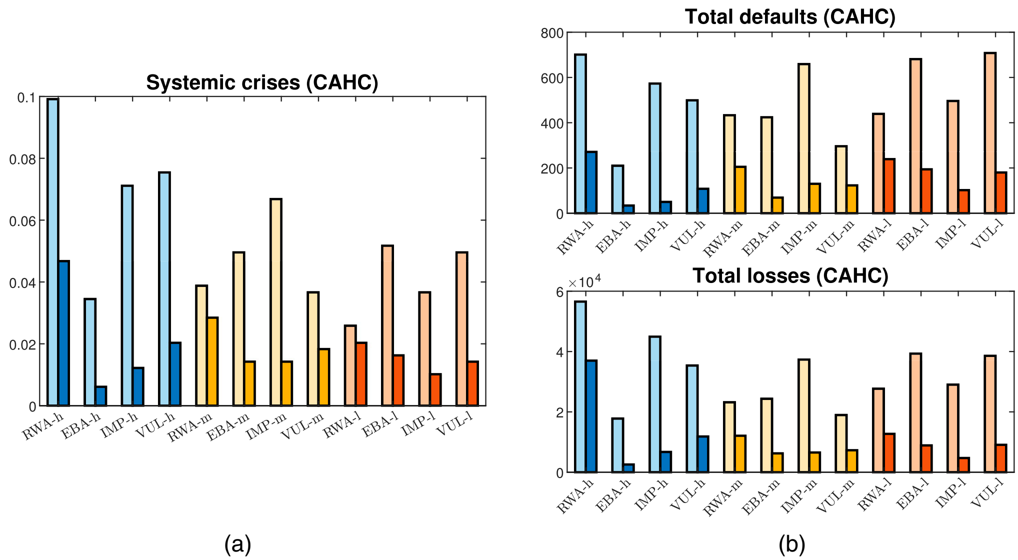


Figure 24. Frequency of systemic events (a). Total number of defaults and losses in systemic crises (b). High (blue), mid (yellow), and low (red) heterogeneity. Shaded colors refer to the case with the CAHC.

compared to the RWA case, only under high heterogeneity. The decomposition of defaults and losses to equity for crisis is reported in Figure 25. Not surprisingly liquidations have the largest impact. Despite a higher frequency, defaults and losses to equity per event are always reduced with respect to the case with the sole minimum capital requirements, showing that there is a trade-off between frequency and severity of crises when additional capital surcharges run. At first sight, it looks puzzling that the frequency of crises for mid and low heterogeneity grows by activating SCBs. Nonetheless, it has an explanation in terms of the model design. As described in Section 3.3, for a given level of heterogeneity, SCBs augment the net worth of banks and lending to firms compared to the RWA case. More credit implies more deposits, so banks buy more bills following our assumptions. Under high heterogeneity, the increase in banks' net worth moves the bills-to-equity ratio below the mean ratio prevailing under *RWA-h*. But for mid and low heterogeneity, the increase in equity does not offset the increase in bills. The ratios move above those in *RWA-m* and *RWA-l*. Therefore, the contagion dynamics is amplified by holding of common assets. The positive relationship between bills/equity and liquidation defaults and losses/equity of banks is displayed in Figure 26.

Even accounting for the endogenous dynamics produced by the model design by which bills-to-equity is increased with SCBs, it emerges that the effectiveness of SCBs for systemic stability is maximum when heterogeneity is high. The same is true for production efficiency in Figure 27, which displays similar results to the case without the CAHC (Figure 15).

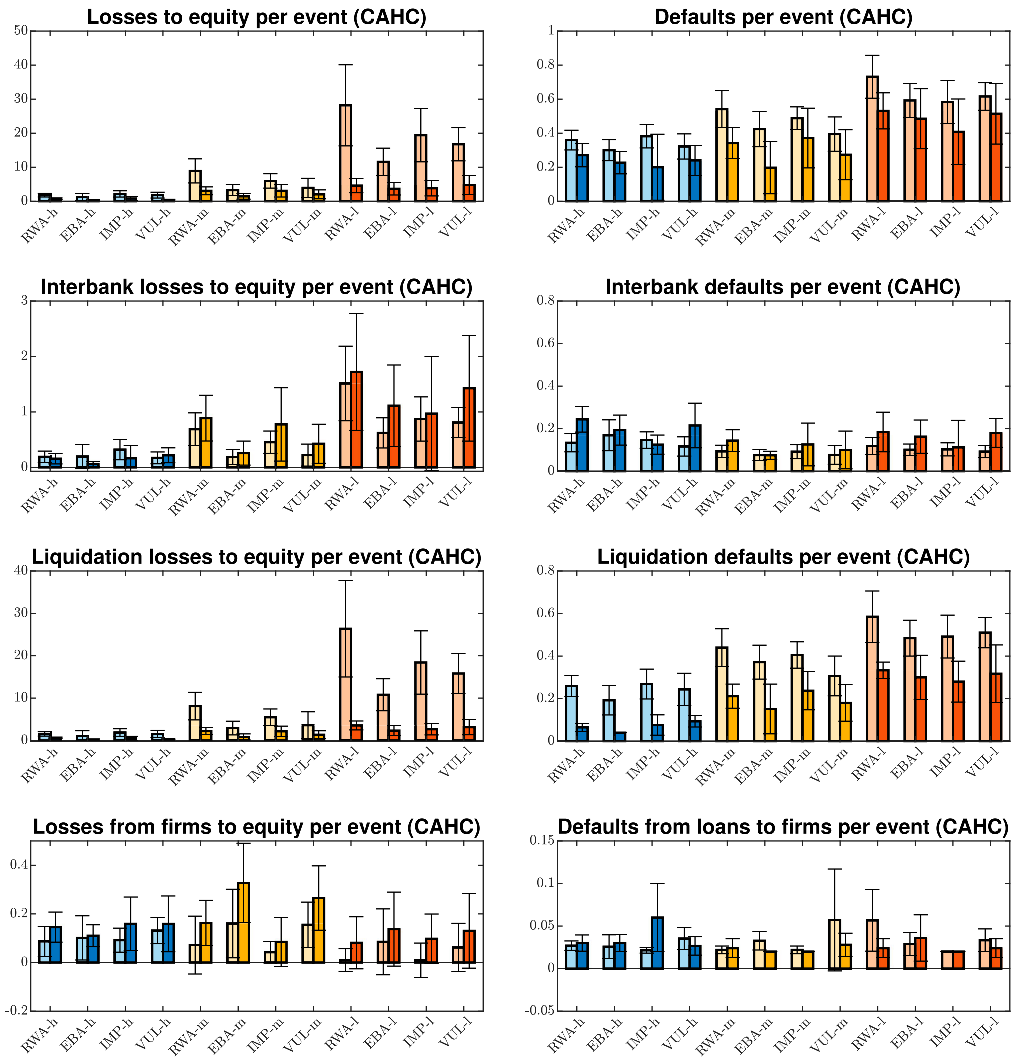


Figure 25. Losses to equity (left) and share of banks' defaults (right) per systemic event. High (blue), mid (yellow), and low (red) heterogeneity. Shaded colors refer to the case with the CAHC. Error bars are 95% confidence intervals.

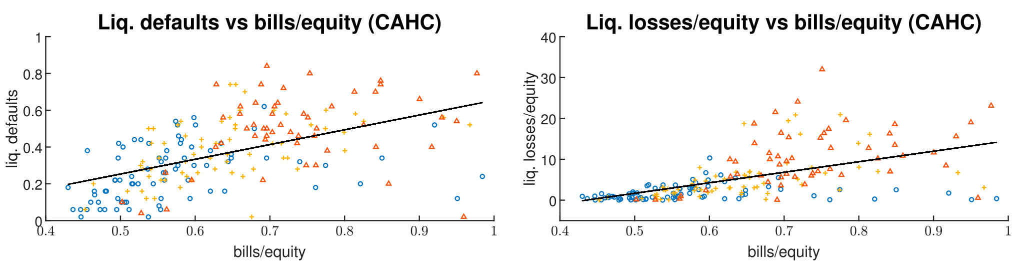


Figure 26. Liquidation defaults (share of banks) and liquidation losses to equity versus bills-to-equity (average per simulation) for systemic crises. All types of capital requirements are pooled together. High (blue circles), mid (yellow plus), and low (red triangles) heterogeneity.

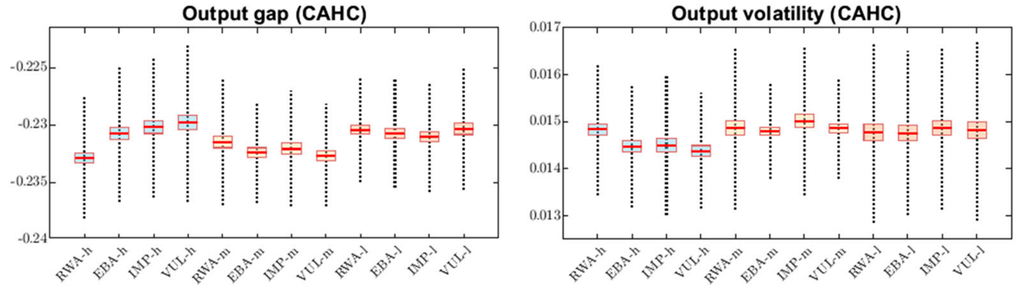


Figure 27. Output gap (left) and output volatility (right) with the CAHC for high (light blue), mid (light yellow), and low (light red) heterogeneity. Red lines represent the mean, boxes are the 95% confidence interval of the mean, and dotted vertical lines are 1 standard deviation.

4. Discussion

We discuss the findings presented in Section 3 starting from the degree of heterogeneity in the interbank market. Consistent with Iori, Jafarey, and Padilla (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 for maximizing risk diversification. At the same time, the asset homogeneity (loans to firms and interbank claims) lowers knock-out effects and therefore reduces the probability of contagion or extreme events. In contrast to a part of the literature (*among others* Beale et al. 2011; Wagner 2008), 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. Even so, a less conservative calibration of ϵ^{bills} when the common asset holding channel is activated may generate results more in line with these studies. Also, 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).

Our results are related to the concepts of *too-big-to fail* and *too-interconnected-to-fail*, which are associated with banks' size and interconnectedness respectively. Depending on the characteristics of the banking network, capital buffers targeted to one or the other can be more or less effective. A clarifying study is carried out in Caccioli, Catanach, and Farmer (2012), who compare contagion for banking networks with random and power-law distributed assets 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, *etc.*) but are obtained from a mixture of balance-sheet data and network interlinkages. Besides, despite our assumptions in Section 2.1, the networks resulting from simulations are neither scale-free nor fully random but lean towards one extreme or another. All types show heterogeneity to different extents and the distribution of assets and degrees goes hand-in-hand. In our model, 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. Such a policy is represented best by EBA. The result seems consistent with those in Caccioli, Catanach, and Farmer (2012) since the greatest contribution to EBA's score comes from banks' size in terms of total assets (see Table 3). In contrast, when the system is less heterogeneous, most systemic banks cannot be identified only based on asset size. In this context, IMP turns out to be the most effective policy. It can identify the most important nodes because it captures impact by explicitly taking into account the network of interlocked balance sheets. Moreover, the score from IMP is less variable than EBA to changes in network heterogeneity and reflects second and further rounds of contagion that occur in the banking network. Since second and further rounds effects occur more frequently when the system is more homogeneous, in that case IMP provides a better measure of a systemic impact than alternatives.

Concerning capital buffers, financial stability is improved if the most important banks are correctly identified by a proper systemic risk assessment and targeted by capital buffers. It is important to remark that growing total capital surcharges is not by itself stabilizing the system, rather it is achieved by the correct identification and regulation of the most systemic banks. If those are the largest banks in terms of assets, then buffers based on size improve stability but demand high capital surcharges. On the other hand, if systemic banks are better identified by another measure, like IMP, less extra capital is needed to stabilize the system. An accurate analysis of the most efficient levels of capital per systemic risk assessment (*like* Alter, Craig, and Raupach 2018), which requires combining different sizes of risk buckets and capital buffers, requires further research. In terms of design and implementation of additional capital requirements, it emerges that buffers based on balance sheet indicators (like EBA) should be avoided at low levels of heterogeneity because it becomes harder to identify systemic banks following greater balance sheets similarity. Moreover, EBA requires more capital compared to IMP and VUL, meaning that it entails greater costs of capital and lowers the availability of interbank funds.

Our findings are in line with the so-called *competition-stability* and *concentration-fragility* views (Boyd and De Nicolo 2005; Boyd, De Nicolò, and Jalal 2006; Uhde and Heimeshoff 2009; Schaeck, Cihak, and Wolfe 2009), which claim that bank competition leads to more stability and concentration is destabilizing. Under low heterogeneity, our assumptions lead all banks to have similar market shares in terms of lending, lower interest rates, and thinner profit margins resulting in a competitive and scarcely concentrated market. Conversely, when heterogeneity is high, competition decreases, and the market is concentrated. In the last case, we observe greater instability. Although in our model competition is inversely related to concentration, there is no such a clear relationship in real banking systems. European banking systems that can be thought heterogeneous and homogeneous in terms of concentration are, among the other, Estonia and Finland (high concentration), and Germany and Luxemburg (low concentration).[12]

Some policy implications emerge from this study: the benefit from SBCs is maximum when the system is heterogeneous, which corresponds to a concentrated banking system, even with a common asset holding channel. In this environment, additional capital surcharges targeting ”too-big-to-fail” institutions are indisputably beneficial and should therefore be included in the policy toolkit. Even homogeneous systems are stabilized by SCBs when marked-to-market accounting is not activated. However, the effectiveness of capital buffers diminishes because greater stability can be achieved just by reducing heterogeneity. So, a policymaker should carefully balance the marginal advantages from SBCs to the connected cost of banks' capital. Moreover, moving from high to low heterogeneity, the frequency of systemic crises diminishes but they are characterized by a higher incidence of defaults and losses from the liquidation of assets. Accordingly, regulation should put in place policies that prevent liquidity risks in the first place, which could be complemented by strengthening the loss-absorbing capacity of banks through additional capital surcharges. Such policies could take advantage of centrality-based measures, like DebtRank-impact, which are best equipped to account for second and further rounds of contagion.

5. Conclusion

In this study, we compare a set of macroprudential capital buffers in banking systems characterized by low, mid, 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 banking networks 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) There is no first-best policy valid for all types of banking networks. Imposing additional capital buffers to the largest banks in terms of asset size, that is targeting too-big-to-fail banks, is the best policy under high heterogeneity. When shifting from high to low heterogeneity, a systemic risk assessment based on impact and network centrality, that is targeting too-interconnected-to-fail banks, becomes more effective.

(iii) Systemic capital buffers are stabilizing and improving the production efficiency in heterogeneous systems even if a common asset holding channel is enabled.

While our model builds on a simplified framework, it contributes to understanding the effects of macroprudential capital buffers when interbank contagion, liquidations, and common asset holding amplify financial distress. The findings suggest that the macroprudential framework should account for the evolution of the financial system because regulatory tools might become ineffective if the banking system shifts from high to low heterogeneity.

Some limitations to this study apply. First, in reality, there is an intricate set of prudential, fiscal, and monetary policies connected to preventing financial instability or to economic recovery. By focusing on capital requirements, we do not account for the complete framework and policy interactions. There can be spillover effects we do not capture, as the interaction of countercyclical and systemic capital buffers. Therefore, a note of caution is required in interpreting our results. 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. Finally, even if the linear bucketing approach, that we implement in this paper, is one of the most commonly used methods by European national regulatory authorities, different choices are possible. A recent survey carried out by the EBA (EBA 2020) has shown that the lack of generally accepted principles has led to heterogeneous calibration across countries in terms of the numbers and width of the buckets. Our study is an early attempt to develop a model-based approach to calibrate O-SII buffer rates. However, further study is needed to optimize the choice of the buckets and to identify robust principles that could underpin a cross-country harmonized approach.

Notes

1. Gallup Poll Social Series Work, https://news.gallup.com/poll/266807/percentage-americans-owns-stock.aspx.
2. 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 the aggregate net worth is zero.

$$\sum_{i\in N^H} nw^H_{i,t} + \sum_{j\in N^F} nw^F_{j,t} + \sum_{h\in N^B} nw^B_{h,t} + nw^G_t = 0.$$

3. Although the inclusion of further elements in banks' balance sheets, such as derivatives to hedge against risk, would increase the realism of the model, we choose to include the least number of elements to limit the overall complexity of the agent-based model.
4. 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 are 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.
5. Despite a deposit guarantee scheme for firms and households is not implemented, by bankruptcy law (see "Recovery rates" in Section 2.3) depositors are the most guaranteed creditors.
6. To sell loans, banks first determine their liquidity need, then compute the fair value of their portfolio loan by loan. Next they determine Δq taking into account Equation (18). 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:

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

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. A similar but simpler process is put in place to sell bills. Since the maturity of bills is one period and default probability is zero, fair corresponds to the book value of bills.
7. We refer to the capital buffer for other (domestic) systemically important institutions (O-SII) absent any cross-jurisdictional activity of banks in our framework.
8. *'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.
9. The similarity between the portfolios of the pair (b, k) is $Jacc_{b,k} = \frac{\sum_{s=1}^{S} \min(\Psi_{b,s}, Psi_{k,s})}{\sum_{s=1}^{S} \max(\Psi_{b,s}, Psi_{k,s})}$, where $S = 4$ is the total number of assets and $\Psi_{b,s}$ is the share of asset s in b's portfolio, such that $\sum_{s=1}^{S} \Psi_{b,s} = 1$. $Jacc \in [0, 1]$, where the maximum similarity is achieved at 1 and the minimum at 0.

10. Since all median values are zero, the boxplot would not be informative.
11. An exception holds for losses on firms' loans to equity, especially under high and mid-levels of heterogeneity. The result, which is not necessarily true in reality, is a consequence of model design and due to increase leverage of firms, as explained above commenting Figure 16.
12. Data on bank concentration are available from Bankscope, Bureau van Dijk (BvD).

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No potential conflict of interest was reported by the author(s).

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Appendix

A.1. 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 to equity ratios 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 bank z on the rest of the system is denoted by g_z. It is the overall loss in equity produced by the default of z, which includes equity of both firms and banks. The score is obtained by averaging g over 500 iterations of the algorithm.

$$g_z = \frac{\sum_{i \neq z} h_{i,T}\, nw^B_{i,0} + \sum_j f_{j,T}\, nw^F_{j,0}}{\sum_i nw^B_{i,0} + \sum_j nw^F_{j,0}} \tag{A1}$$

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 forcing 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.

$$h_{i,T} \equiv \frac{nw^B_{i,T} - nw^B_{i,0}}{nw^B_{i,0}} \tag{A2}$$

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:[13]

(1) Banks' losses on interbank loans:

$$h_i(\tau + 1) = \min\left[1,\ h_i(\tau) + \sum_{k \in K} \Lambda^{bb}_{ik}(1 - \varphi^{ib}_k)(p_k(\tau) - p_k(\tau - 1))\right]. \tag{A3}$$

(2) Firms' losses on deposits:

$$f_j(\tau + 1) = \min\left[1, f_j(\tau) + \Lambda^{bf}_{jk}(1 - \varphi^{dep}_k)(p_k(\tau) - p_k(\tau - 1))\right]. \tag{A4}$$

(3) Banks' losses on firms' loans:

$$h_i(\tau + 1) = \min\left[1,\ h_i(\tau) + \sum_{j \in J} \Lambda^{fb}_{ij}(1 - \varphi^{loan}_j)(p_j(\tau) - p_j(\tau - 1))\right]. \tag{A5}$$

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 (A3) and (A5), so that $p_k(\tau) = h_k(\tau)$, while we assume that firms' losses on deposits in (A4) respond to the Furfine algorithm. In other words, the distress propagates only in case of default of the debtor so that

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

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 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 $\Lambda^{ff} = 0$.

$$\Lambda = \begin{bmatrix} 0 & \frac{Ib_{12}}{nw^B_2} & \frac{D_{13}}{nw^F_1} & \frac{D_{12}}{nw^F_2} & \frac{D_{15}}{nw^F_3} \\ \frac{Ib_{21}}{nw^B_1} & 0 & \frac{D_{23}}{nw^F_1} & \frac{D_{24}}{nw^F_2} & \frac{D_{25}}{nw^F_3} \\ \frac{L^f_{31}}{nw^B_1} & \frac{L^f_{32}}{nw^B_2} & 0 & 0 & 0 \\ \frac{L^f_{41}}{nw^B_1} & \frac{L^f_{42}}{nw^B_2} & 0 & 0 & 0 \\ \frac{L^f_{51}}{nw^B_1} & \frac{L^f_{52}}{nw^B_2} & 0 & 0 & 0 \end{bmatrix}$$

A.2 Regression auxiliary statistics

Table A1. Variance Inflation Factor (VIF).

	Dependent variable								
	SCB								
	EBA-h (1)	IMP-h (2)	VUL-h (3)	EBA-m (4)	IMP-m (5)	VUL-m (6)	EBA-l (7)	IMP-l (8)	VUL-l (9)
tot.assets	3.4943	5.9904	7.4816	3.3731	3.7974	4.4888	3.6137	4.0310	3.4106
ib.supply	4.2166	2.4543	2.6891	4.2433	2.4494	3.0318	4.4152	3.1132	2.9657
ib.lending	2.0007	1.8077	2.0406	1.9479	1.5513	1.9424	1.5952	1.7062	1.4416
ib.borrowing	2.2218	5.5293	7.3571	1.8730	3.1147	3.7944	1.5973	2.4380	2.3463
betweenness	1.1223	1.1071	1.1243	1.0943	1.0860	1.0895	1.1395	1.0755	1.0777
RWA.CET1	1.4433	2.4400	2.5557	1.2769	2.0395	2.5826	1.3288	2.4111	2.5366

Table A2. Correlation Matrix (EBA-h).

	y	tot.assets	net.worth	deposits	ib.supply	loans	ib.lending	ib.borrowing	betweenness	RWA.CET1
y	1	0.582	0.557	0.370	0.297	0.439	0.204	0.412	0.129	0.360
tot.assets	0.582	1	0.796	0.579	0.509	0.739	0.323	0.660	0.177	0.336
net.worth	0.557	0.796	1	0.270	0.217	0.767	0.115	0.676	0.205	0.242
deposits	0.370	0.579	0.270	1	0.910	−0.038	0.692	−0.129	−0.113	−0.039
ib.supply	0.297	0.509	0.217	0.910	1	−0.095	0.687	−0.150	−0.123	−0.112
loans	0.439	0.739	0.767	−0.038	−0.095	1	−0.185	0.951	0.225	0.449
ib.lending	0.204	0.323	0.115	0.692	0.687	−0.185	1	−0.219	−0.122	−0.150
ib.borrowing	0.412	0.660	0.676	−0.129	−0.150	0.951	−0.219	1	0.227	0.470
betweenness	0.129	0.177	0.205	−0.113	−0.123	0.225	−0.122	0.227	1	0.243
RWA.CET1	0.360	0.336	0.242	−0.039	−0.112	0.449	−0.150	0.470	0.243	1

Table A3. Correlation Matrix (EBA-m).

	y	tot.assets	net.worth	deposits	ib.supply	loans	ib.lending	ib.borrowing	betweenness	RWA.CET1
y	1	0.621	0.552	0.386	0.288	0.647	0.166	0.497	0.116	0.314
tot.assets	0.621	1	0.686	0.844	0.742	0.570	0.496	0.308	0.058	0.210
net.worth	0.552	0.686	1	0.430	0.390	0.624	0.294	0.380	0.126	0.042
deposits	0.386	0.844	0.430	1	0.902	0.111	0.639	−0.159	−0.089	0.011
ib.supply	0.288	0.742	0.390	0.902	1	−0.026	0.652	−0.194	−0.106	−0.100
loans	0.647	0.570	0.624	0.111	−0.026	1	−0.147	0.856	0.195	0.452
ib.lending	0.166	0.496	0.294	0.639	0.652	−0.147	1	−0.259	−0.077	−0.146
ib.borrowing	0.497	0.308	0.380	−0.159	−0.194	0.856	−0.259	1	0.195	0.416
betweenness	0.116	0.058	0.126	−0.089	−0.106	0.195	−0.077	0.195	1	0.270
RWA.CET1	0.314	0.210	0.042	0.011	−0.100	0.452	−0.146	0.416	0.270	1

Table A4. Correlation Matrix (EBA-l).

	y	tot.assets	net.worth	deposits	ib.supply	loans	ib.lending	ib.borrowing	betweenness	RWA.CET1
y	1	0.531	0.444	0.379	0.279	0.641	0.159	0.470	0.081	0.301
tot.assets	0.531	1	0.604	0.938	0.822	0.508	0.468	0.118	0.031	0.180
net.worth	0.444	0.604	1	0.458	0.427	0.535	0.294	0.166	0.110	−0.007
deposits	0.379	0.938	0.458	1	0.901	0.249	0.517	−0.133	−0.056	0.050
ib.supply	0.279	0.822	0.427	0.901	1	0.053	0.537	−0.195	−0.079	−0.082
loans	0.641	0.508	0.535	0.249	0.053	1	−0.080	0.713	0.152	0.495
ib.lending	0.159	0.468	0.294	0.517	0.537	−0.080	1	−0.214	−0.033	−0.105
ib.borrowing	0.470	0.118	0.166	−0.133	−0.195	0.713	−0.214	1	0.144	0.425
betweenness	0.081	0.031	0.110	−0.056	−0.079	0.152	−0.033	0.144	1	0.321
RWA.CET1	0.301	0.180	−0.007	0.050	−0.082	0.495	−0.105	0.425	0.321	1

Table A5. Correlation Matrix (IMP-h).

	y	tot.assets	net.worth	deposits	ib.supply	loans	ib.lending	ib.borrowing	betweenness	RWA.CET1
y	1	−0.236	−0.220	−0.594	−0.576	−0.062	−0.480	−0.022	0.409	0.241
tot.assets	−0.236	1	0.971	−0.344	−0.450	0.967	−0.642	0.946	0.204	0.710
net.worth	−0.220	0.971	1	−0.314	−0.418	0.939	−0.604	0.908	0.176	0.622
deposits	−0.594	−0.344	−0.314	1	0.968	−0.554	0.845	−0.609	−0.689	−0.691
ib.supply	−0.576	−0.450	−0.418	0.968	1	−0.647	0.898	−0.692	−0.662	−0.798
loans	−0.062	0.967	0.939	−0.554	−0.647	1	−0.784	0.996	0.316	0.804
ib.lending	−0.480	−0.642	−0.604	0.845	0.898	−0.784	1	−0.810	−0.638	−0.871
ib.borrowing	−0.022	0.946	0.908	−0.609	−0.692	0.996	−0.810	1	0.340	0.826
betweenness	0.409	0.204	0.176	−0.689	−0.662	0.316	−0.638	0.340	1	0.464
RWA.CET1	0.241	0.710	0.622	−0.691	−0.798	0.804	−0.871	0.826	0.464	1

Table A6. Correlation Matrix (IMP-m).

	y	tot.assets	net.worth	deposits	ib.supply	loans	ib.lending	ib.borrowing	betweenness	RWA.CET1
y	1	−0.496	−0.413	−0.631	−0.548	−0.131	−0.451	−0.058	0.540	0.338
tot.assets	−0.496	1	0.887	0.174	−0.073	0.838	−0.360	0.737	−0.265	0.399
net.worth	−0.413	0.887	1	0.154	−0.039	0.740	−0.287	0.629	−0.258	0.209
deposits	−0.631	0.174	0.154	1	0.946	−0.376	0.733	−0.509	−0.601	−0.666
ib.supply	−0.548	−0.073	−0.039	0.946	1	−0.591	0.842	−0.688	−0.548	−0.833
loans	−0.131	0.838	0.740	−0.376	−0.591	1	−0.751	0.981	0.042	0.750
ib.lending	−0.451	−0.360	−0.287	0.733	0.842	−0.751	1	−0.796	−0.481	−0.889
ib.borrowing	−0.058	0.737	0.629	−0.509	−0.688	0.981	−0.796	1	0.091	0.784
betweenness	0.540	−0.265	−0.258	−0.601	−0.548	0.042	−0.481	0.091	1	0.396
RWA.CET1	0.338	0.399	0.209	−0.666	−0.833	0.750	−0.889	0.784	0.396	1

Table A7. Correlation Matrix (IMP-l).

	y	tot.assets	net.worth	deposits	ib.supply	loans	ib.lending	ib.borrowing	betweenness	RWA.CET1
y	1	−0.695	−0.560	−0.647	−0.596	−0.153	−0.491	0.005	0.419	0.294
tot.assets	−0.695	1	0.850	0.715	0.531	0.508	0.216	0.214	−0.511	0.007
net.worth	−0.560	0.850	1	0.627	0.515	0.377	0.258	0.095	−0.470	−0.219
deposits	−0.647	0.715	0.627	1	0.956	−0.231	0.773	−0.512	−0.624	−0.602
ib.supply	−0.596	0.531	0.515	0.956	1	−0.447	0.869	−0.670	−0.605	−0.779
loans	−0.153	0.508	0.377	−0.231	−0.447	1	−0.677	0.935	0.042	0.783
ib.lending	−0.491	0.216	0.258	0.773	0.869	−0.677	1	−0.807	−0.520	−0.881
ib.borrowing	0.005	0.214	0.095	−0.512	−0.670	0.935	−0.807	1	0.171	0.849
betweenness	0.419	−0.511	−0.470	−0.624	−0.605	0.042	−0.520	0.171	1	0.377
RWA.CET1	0.294	0.007	−0.219	−0.602	−0.779	0.783	−0.881	0.849	0.377	1

Table A8. Correlation Matrix (VUL-h).

	y	tot.assets	net.worth	deposits	ib.supply	loans	ib.lending	ib.borrowing	betweenness	RWA.CET1
y	1	−0.235	−0.255	−0.147	−0.235	−0.158	−0.173	−0.132	−0.023	0.189
tot.assets	−0.235	1	0.972	−0.506	−0.541	0.973	−0.717	0.953	0.276	0.765
net.worth	−0.255	0.972	1	−0.452	−0.484	0.934	−0.658	0.904	0.270	0.676
deposits	−0.147	−0.506	−0.452	1	0.973	−0.680	0.888	−0.729	−0.699	−0.773
ib.supply	−0.235	−0.541	−0.484	0.973	1	−0.709	0.921	−0.753	−0.667	−0.852
loans	−0.158	0.973	0.934	−0.680	−0.709	1	−0.835	0.996	0.383	0.848
ib.lending	−0.173	−0.717	−0.658	0.888	0.921	−0.835	1	−0.863	−0.650	−0.926
ib.borrowing	−0.132	0.953	0.904	−0.729	−0.753	0.996	−0.863	1	0.408	0.872
betweenness	−0.023	0.276	0.270	−0.699	−0.667	0.383	−0.650	0.408	1	0.472
RWA.CET1	0.189	0.765	0.676	−0.773	−0.852	0.848	−0.926	0.872	0.472	1

Table A9. Correlation Matrix (VUL-m).

	y	tot.assets	net.worth	deposits	ib.supply	loans	ib.lending	ib.borrowing	betweenness	RWA.CET1
y	1	−0.264	−0.333	−0.117	−0.184	−0.129	−0.158	−0.118	0.039	0.254
tot.assets	−0.264	1	0.898	0.165	−0.008	0.773	−0.292	0.645	−0.191	0.401
net.worth	−0.333	0.898	1	0.148	0.025	0.681	−0.207	0.550	−0.153	0.199
deposits	−0.117	0.165	0.148	1	0.963	−0.489	0.824	−0.632	−0.644	−0.676
ib.supply	−0.184	−0.008	0.025	0.963	1	−0.631	0.901	−0.741	−0.615	−0.814
loans	−0.129	0.773	0.681	−0.489	−0.631	1	−0.801	0.979	0.216	0.808
ib.lending	−0.158	−0.292	−0.207	0.824	0.901	−0.801	1	−0.863	−0.559	−0.907
ib.borrowing	−0.118	0.645	0.550	−0.632	−0.741	0.979	−0.863	1	0.281	0.842
betweenness	0.039	−0.191	−0.153	−0.644	−0.615	0.216	−0.559	0.281	1	0.378
RWA.CET1	0.254	0.401	0.199	−0.676	−0.814	0.808	−0.907	0.842	0.378	1

Table A10. Correlation Matrix (VUL-l).

	y	tot.assets	net.worth	deposits	ib.supply	loans	ib.lending	ib.borrowing	betweenness	RWA.CET1
y	1	−0.263	−0.378	−0.137	−0.182	−0.154	−0.195	−0.154	0.093	0.287
tot.assets	−0.263	1	0.851	0.729	0.517	0.493	0.116	0.151	−0.525	−0.037
net.worth	−0.378	0.851	1	0.617	0.483	0.394	0.173	0.082	−0.451	−0.243
deposits	−0.137	0.729	0.617	1	0.945	−0.224	0.665	−0.529	−0.603	−0.607
ib.supply	−0.182	0.517	0.483	0.945	1	−0.474	0.787	−0.698	−0.545	−0.797
loans	−0.154	0.493	0.394	−0.224	−0.474	1	−0.703	0.909	−0.030	0.742
ib.lending	−0.195	0.116	0.173	0.665	0.787	−0.703	1	−0.793	−0.459	−0.876
ib.borrowing	−0.154	0.151	0.082	−0.529	−0.698	0.909	−0.793	1	0.082	0.788
betweenness	0.093	−0.525	−0.451	−0.603	−0.545	−0.030	−0.459	0.082	1	0.334
RWA.CET1	0.287	−0.037	−0.243	−0.607	−0.797	0.742	−0.876	0.788	0.334	1

Table A11. Summary statistics (EBA-h).

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
y	41,672	0.198	0.399	0	0	0	1
tot.assets	41,672	2.176	1.860	0.274	1.205	2.457	27.644
net.worth	41,672	2.112	0.934	0.131	1.600	2.409	13.205
deposits	41,672	2.162	2.094	0.013	0.909	2.666	26.960
ib.supply	41,672	2.122	2.383	0.006	0.725	2.603	25.913
loans	41,672	2.308	4.523	0.000	0.784	2.279	81.126
ib.lending	41,672	2.152	2.158	0.000	0.615	3.028	21.832
ib.borrowing	41,672	2.340	7.683	0	0	1.5	99
betweenness	41,672	0.201	0.463	0	0	0.2	10
RWA.CET1	41,672	1.261	1.227	0.100	0.641	1.570	91.017

Table A12. Summary statistics (EBA-m).

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
y	46,852	0.159	0.366	0	0	0	1
tot.assets	46,852	2.070	1.489	0.162	1.127	2.506	17.165
net.worth	46,852	2.069	0.848	0.104	1.537	2.467	9.284
deposits	46,852	2.060	2.203	0.013	0.738	2.528	25.832
ib.supply	46,852	2.066	2.392	0.007	0.728	2.471	36.944
loans	46,852	2.112	2.326	0.000	0.735	2.623	31.910
ib.lending	46,852	2.084	2.034	0.000	0.684	2.876	28.518
ib.borrowing	46,852	2.106	4.316	0.000	0.015	2.325	60.084
betweenness	46,852	0.340	0.615	0.000	0.000	0.393	8.324
RWA.CET1	46,852	1.325	1.224	0.100	0.583	1.741	61.258

Table A13. Summary statistics (EBA-l).

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
y	46,808	0.139	0.346	0	0	0	1
tot.assets	46,808	2.073	1.411	0.209	1.204	2.479	17.873
net.worth	46,808	2.076	0.773	0.103	1.594	2.482	9.470
deposits	46,808	2.065	2.116	0.013	0.819	2.516	25.588
ib.supply	46,808	2.081	2.218	0.006	0.812	2.513	32.867
loans	46,808	2.113	1.781	0.000	0.911	2.750	19.791
ib.lending	46,808	2.079	2.050	0.000	0.666	2.878	30.325
ib.borrowing	46,808	2.092	3.838	0.000	0.000	2.669	73.184
betweenness	46,808	0.294	0.580	0.000	0.000	0.315	8.382
RWA.CET1	46,808	1.267	1.012	0.100	0.577	1.709	44.881

Table A14. Summary statistics (IMP-h).

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
y	34,041	0.305	0.461	0	0	1	1
tot.assets	34,041	1.769	1.627	0.176	1.027	1.937	25.515
net.worth	34,041	2.071	0.937	0.196	1.536	2.344	12.442
deposits	34,041	1.405	1.062	0.018	0.722	1.768	13.835
ib.supply	34,041	1.366	1.061	0.008	0.655	1.749	14.414
loans	34,041	2.392	4.623	0.000	0.616	2.282	74.238
ib.lending	34,041	1.570	1.446	0.000	0.547	2.197	25.929
ib.borrowing	34,041	2.751	8.127	0.000	0.023	1.667	97.926
betweenness	34,041	0.219	0.469	0.000	0.000	0.205	7.577
RWA.CET1	34,041	1.158	1.230	0.100	0.517	1.431	94.152

Table A15. Summary statistics (IMP-m).

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
y	31,914	0.324	0.468	0	0	1	1
tot.assets	31,914	1.716	1.039	0.175	1.114	2.012	15.108
net.worth	31,914	2.112	0.773	0.131	1.624	2.466	8.855
deposits	31,914	1.386	0.985	0.011	0.745	1.750	14.730
ib.supply	31,914	1.385	1.025	0.010	0.698	1.796	14.823
loans	31,914	2.235	2.569	0.000	0.844	2.676	31.460
ib.lending	31,914	1.643	1.542	0.000	0.568	2.300	21.248
ib.borrowing	31,914	2.681	5.794	0.000	0.036	2.810	83.401
betweenness	31,914	0.293	0.576	0.000	0.000	0.307	8.195
RWA.CET1	31,914	1.241	1.005	0.100	0.561	1.646	41.440

Table A16. Summary statistics (IMP-l).

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
y	35,507	0.383	0.486	0	0	1	1
tot.assets	35,507	1.654	0.871	0.086	1.063	2.034	9.825
net.worth	35,507	2.022	0.678	0.141	1.561	2.419	6.783
deposits	35,507	1.348	1.082	0.015	0.591	1.772	12.414
ib.supply	35,507	1.373	1.063	0.012	0.661	1.769	12.707
loans	35,507	2.036	1.663	0.000	0.895	2.676	17.532
ib.lending	35,507	1.620	1.433	0.000	0.628	2.230	19.852
ib.borrowing	35,507	2.410	3.732	0.000	0.156	3.185	65.186
betweenness	35,507	0.369	0.592	0	0.01	0.5	6
RWA.CET1	35,507	1.241	0.822	0.100	0.628	1.669	13.201

Table A17. Summary statistics (VUL-h).

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
y	33,205	0.362	0.480	0	0	1	1
tot.assets	33,205	1.768	1.633	0.197	1.022	1.965	25.156
net.worth	33,205	2.048	0.924	0.169	1.520	2.335	12.819
deposits	33,205	1.388	1.046	0.015	0.691	1.803	16.611
ib.supply	33,205	1.304	1.072	0.002	0.584	1.705	13.468
loans	33,205	2.367	4.395	0.000	0.751	2.346	81.329
ib.lending	33,205	1.523	1.401	0.000	0.500	2.154	18.885
ib.borrowing	33,205	2.781	7.745	0.000	0.072	2.014	98.405
betweenness	33,205	0.225	0.460	0	0.01	0.2	8
RWA.CET1	33,205	1.272	1.021	0.100	0.662	1.563	53.130

Table A18. Summary statistics (VUL-m).

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
y	33,205	0.362	0.480	0	0	1	1
tot.assets	33,205	1.768	1.633	0.197	1.022	1.965	25.156
net.worth	33,205	2.048	0.924	0.169	1.520	2.335	12.819
deposits	33,205	1.388	1.046	0.015	0.691	1.803	16.611
ib.supply	33,205	1.304	1.072	0.002	0.584	1.705	13.468
loans	33,205	2.367	4.395	0.000	0.751	2.346	81.329
ib.lending	33,205	1.523	1.401	0.000	0.500	2.154	18.885
ib.borrowing	33,205	2.781	7.745	0.000	0.072	2.014	98.405
betweenness	33,205	0.225	0.460	0	0.01	0.2	8
RWA.CET1	33,205	1.272	1.021	0.100	0.662	1.563	53.130

Table A19. Summary statistics (VUL-l).

Statistic	*N*	Mean	St. dev.	Min	Pctl(25)	Pctl(75)	Max
y	33,205	0.362	0.480	0	0	1	1
tot.assets	33,205	1.768	1.633	0.197	1.022	1.965	25.156
net.worth	33,205	2.048	0.924	0.169	1.520	2.335	12.819
deposits	33,205	1.388	1.046	0.015	0.691	1.803	16.611
ib.supply	33,205	1.304	1.072	0.002	0.584	1.705	13.468
loans	33,205	2.367	4.395	0.000	0.751	2.346	81.329
ib.lending	33,205	1.523	1.401	0.000	0.500	2.154	18.885
ib.borrowing	33,205	2.781	7.745	0.000	0.072	2.014	98.405
betweenness	33,205	0.225	0.460	0	0.01	0.2	8
RWA.CET1	33,205	1.272	1.021	0.100	0.662	1.563	53.130

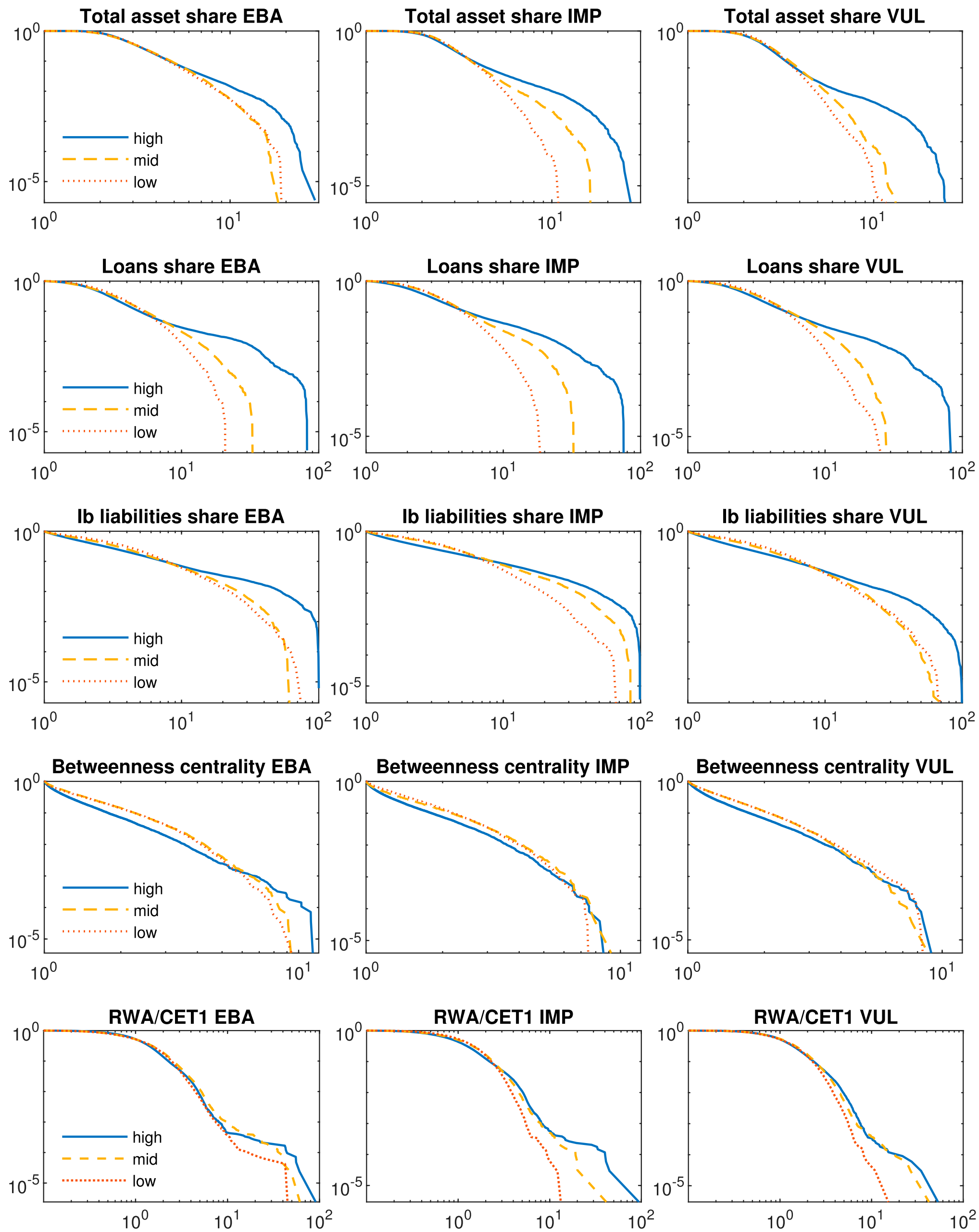

Figure A1. Distribution of selected variables (ccdf) for high (blue line), mid (yellow dotted line), and low (red dashed line) heterogeneity.

A.3. Parameters and initialization

Table A20. Main parameters and initialization of variables.

Parameter	Description	Value
T	Length of the simulation	850
N^F	Number of firms	500
N^H	Number of households	1500
N^B	Number of banks	50
α	Labor productivity	2
a	Calibration of the score quantiles, Equation (A6)	0.8
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
Fh	Share of firms observed on the goods market	0.25
lev^*	Calibration parameter, Equation (15)	$\lambda/2$
r^L	Interest rate on reserves	0.005
r^D	Interest rate on deposits	0.005
r^B	Interest rate on bills	0.01
r^H	Interest rate on advances	0.1
rr	Reserve coefficient	0.1
σ_1	Sensitivity of the wage rate to unemployment	0.1
σ_2	Sensitivity of the wage rate to hysteresis	0.05
u^f	Calibration parameter, Equation (8)	$1-\dfrac{1+r^D}{1+r^H}$
u^B	Calibration parameter, Equation (15)	$1-\dfrac{1+r^L}{1+r^H}$
u^*	Full-employment rate of unemployment	0.1
v_B	Calibration parameter, Equation (15)	2
v_f	Calibration parameter, Equation (8)	2
λ	Minimum capital requirements	0.07
ℓ^*	Calibration parameter, Equation (8)	4
μ	Initial mark-up rate	0.01
f^{bills}	Share of banks' deposits invested in bills	0.25
$\bar{d}$	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	3500
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
ϵ^{loans}	price elasticity of loans, Equation (18)	-0.8
ϵ^{bills}	price elasticity of bills, Equation (18)	-1.0
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	$\left(\sum Dep_{0j}^F + \sum Dep_{0i}^H\right)/N^B$
nw_0^B	Initial net worth per bank	$700\dfrac{N_b^{sh}}{\sum_{i=1}^{N^B} N_i^{sh}}$
R_0	Initial liquidity of banks	$Dep_0^B + nw_0^B$
G_0	Equation (1) 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.3.1 Robustness check

The scope of Figure A2 is providing robustness checks to the results in Sections 3.4.2 and 3.5 by a different and more general definition of a systemic event, that is the simultaneous failure of at least 25% of banks.

A.4 Sensitivity analysis

A.4.1 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

$$q_n = q_{n-1} + a^{n-1}d \tag{A6}$$

where $n = \{0, \ldots, N\}$ is an index, N is the number of buckets, d is a distance set to ensure that $q_S = 1$, 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 SBCs meaningless. Therefore, we conduct a sensitivity analysis to find the optimal value of a. Based on results, we set $a = 0.8$. Figure A3 reports the results for EBA. Similar patterns hold for IMP and VUL.

A.4.2 Asset price elasticity

In Section 3.5, we introduced common asset holding contagion. To calibrate the asset price elasticity when assets are mark-to-market, we conduct a sensitivity analysis on ϵ^{bills} from Equation (18). Results are displayed in Figure A4. The case labeled as *bench* refers to simulations without any price impact, where elasticity is $\epsilon^{bills} = -1.0$. To avoid excessive variance or too weak effects, we set $\epsilon^{bills} = -1.6$.

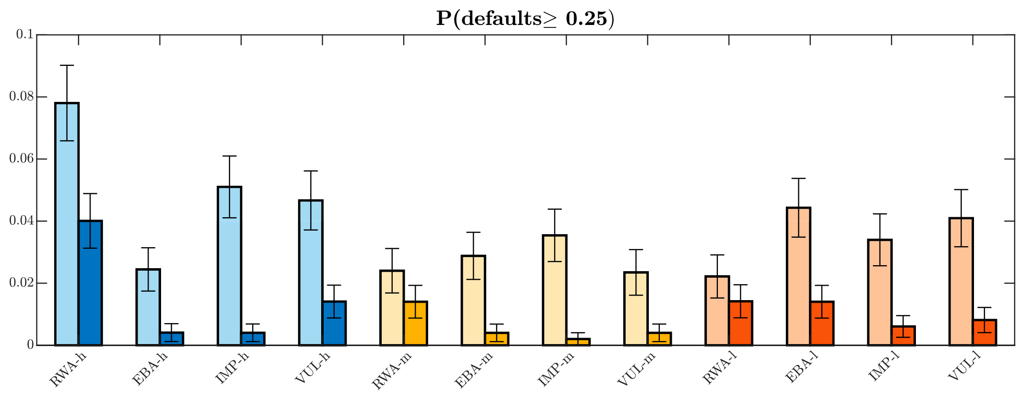

Figure A2. Frequency of simultaneous defaults of at least 25% of banks. High (blue), mid (yellow), and low (red) heterogeneity. Shaded colors refer to the case with the CAHC. Error bars are 95% confidence intervals.

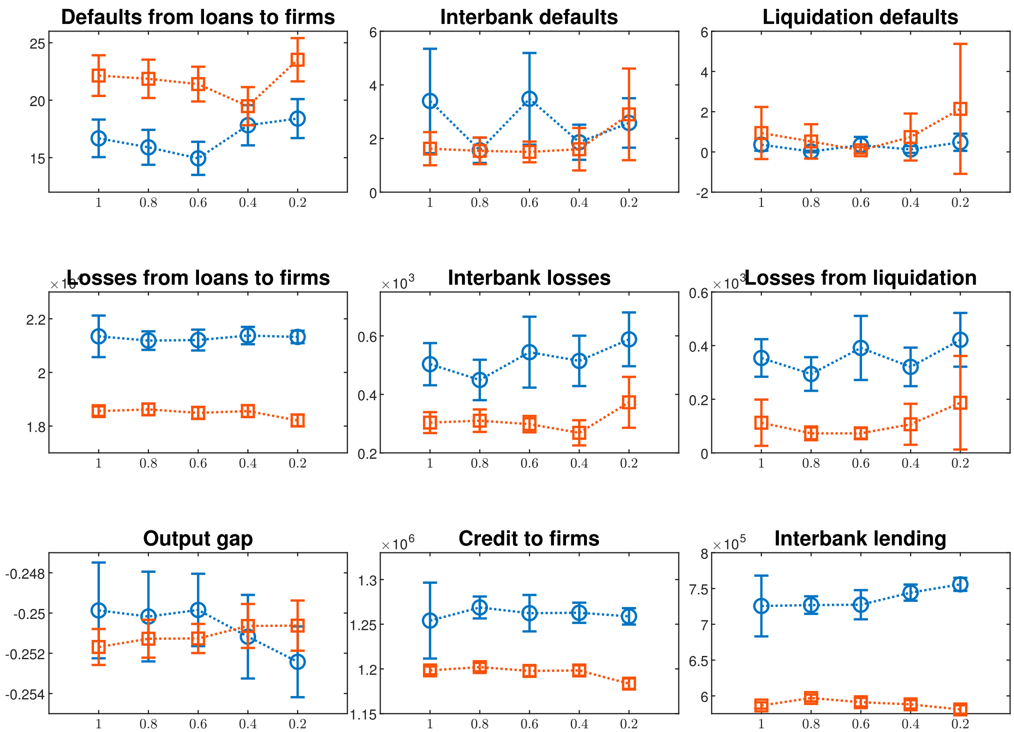

Figure A3. Sensitivity analysis on the values of a for EBA under high (blue circles) and low (red squares) heterogeneity. Error bars are 95% confidence intervals.

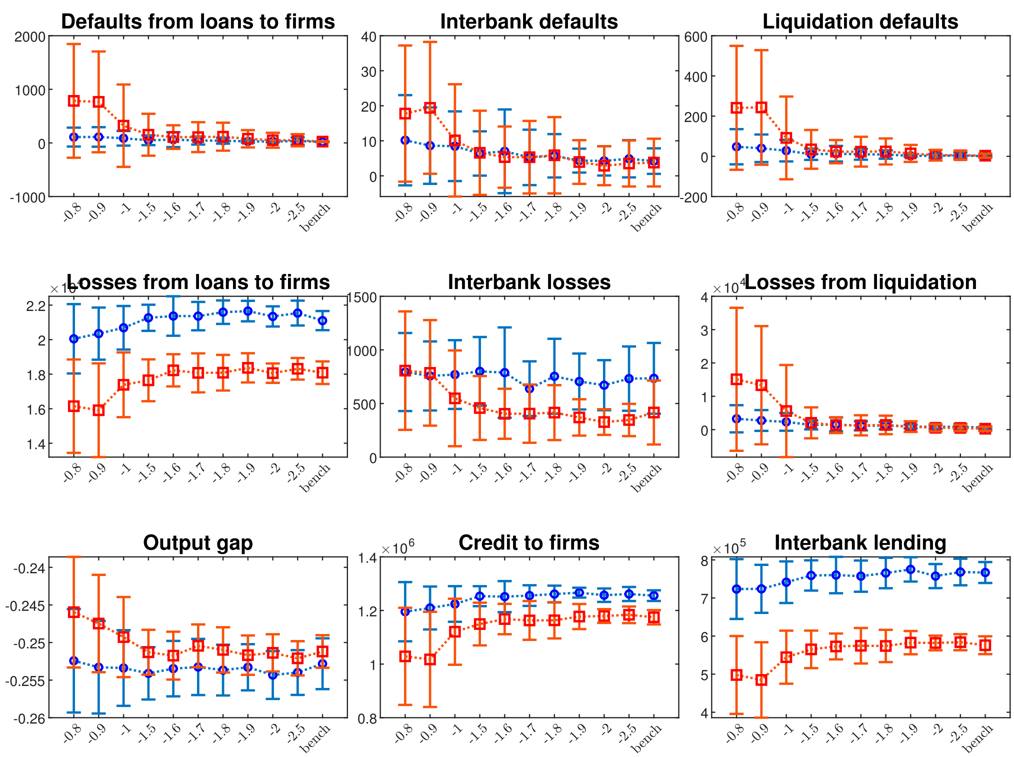

Figure A4. Sensitivity analysis on the values of ϵ^{bills} under high (blue circles) and low (red squares) heterogeneity. Error bars are 95% confidence intervals.

A.5. Differences with the original model

Table A21. Main differences in the macroeconomic model of this paper (GI) and that in Gurgone, Iori, and Jafarey (2018) (GIJ).

Differences	GI	GIJ
Interbank and credit networks	dynamic, heterogeneous (Section 2.1)	static, homogeneous (Section 2.1.2)
Depositors and shareholders' networks	static, heterogeneous (Section 2.1)	static, homogeneous (Section 2.1.2)
Mark-up rule	based on excess demand ($A^d - A^s$) $\mu_t = \begin{cases} \mu_{t-1}(1+0.1) & \textit{if } A^d_{t-1} > A^s_{t-1} \\ \mu_{t-1}(1-0.1) & \textit{otherwise} \end{cases}$	based on the change in market-share (Δy), Equation (15) $\mu_t = \mu_{t-1}(1+\Delta y_{t-1})$
Unitary cost of output	includes the cost of borrowing	does not include the cost of borrowing, Equation (17)
Money (bills)	G adjusts to keep the stock of bills constant, Equation (1)	G is fixed, the stock of bills varies, Equation (5)
Lender of last resort	no	yes, Equation (7)