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Robust-less-fragile: Tackling systemic risk and financial contagion in a macro agent-based model

Gianluca Pallante [a,1,*], Mattia Guerini [c,d,b,e], Mauro Napoletano [e,f,b], Andrea Roventini [a]

[a] Institute of Economics and l'EMbeDS, Scuola Superiore Sant'Anna, Pisa, Italy
[b] Institute of Economics, Scuola Superiore Sant'Anna, Pisa, Italy
[c] University of Brescia, Department of Economics and Management, Brescia, Italy
[d] Fondazione ENI Enrico Mattei, Milano, Italy
[e] Université Côte d'Azur, CNRS, GREDEG, SOPHIA ANTIPOLIS, France
[f] Sciences Po, OFCE, France

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ABSTRACT

We extend the *Schumpeter meeting Keynes* (K+S) agent-based model by introducing an evolving interbank network in the money market. Banks are exposed to counterparty risk and evaluate interbank positions using a network valuation (NEVA) clearing mechanism, which ensures systemic risk minimization with minimal assumptions on banks' behavior. The model can replicate several stylized facts about the topology of the interbank network and the dynamics of banks' balance sheets. The model encompasses financial contagion and systemic risk, allowing us to study the interactions between micro- and macro-prudential policies. Our results suggest that the introduction of a micro-prudential regulation also accounting for the network structure can reduce the incidence of systemic risk events. We also find that, in presence of a two-pillar regulatory framework – grounded on a *Basel III macro-prudential* regulation and a *NEVA-based micro-prudential* one –, there is no trade-off between financial stability and macroeconomic performance. This points towards the possibility of designing a regulatory framework able to achieve financial stability without overly stringent capital requirements.

1. Introduction

In this paper we extend the *Schumpeter meeting Keynes* (K+S) agent-based model (Dosi et al., 2010, 2013, 2015) to account for the endogenous formation of an interbank market and to study the emergence of systemic risk, financial crises, and the possible interactions between micro-prudential and macro-prudential policies.

The complex interactions in financial networks among economic agents have a fundamental role in the building up of systemic risk and the emergence of financial crises. Indeed, *network interconnectedness* – which was substantially underestimated before 2008 – has amplified the negative effects of the sub-prime mortgage bubble, paving the way to the Great Recession (Haldane, 2012; Battiston et al., 2016; Dosi and Roventini, 2019; Chen, 2022). Understanding the relationship between interconnectedness, financial system stability, and macroeconomic resilience remains a paramount area of interest in the research agenda. However, a consensus has not yet been consolidated regarding the mechanisms, as well as the policy measures required to address the prevailing challenges arising from asymmetric information, moral hazard, and neglected network externalities inherent to interbank markets (Altinoglu and Stiglitz, 2023; Sigmund and Siebenbrunner, 2024). More precisely, the interplay between different micro-prudential and macro-prudential policies in limiting the emergence of financial crises

* Correspondence to: Institute of Economics and l'EMbeDS, Scuola Superiore Sant'Anna, piazza Martiri della Libertà 33, 56127, Pisa, Italy.
E-mail addresses: gianluca.pallante@santannapisa.it (G. Pallante), mattia.guerini@unibs.it (M. Guerini), mauro.napoletano@univ-cotedazur.fr (M. Napoletano), andrea.roventini@santannapisa.it (A. Roventini).

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and taming their negative effects is not yet fully understood. An increasingly connected financial system may favor risk diversification and so resilience to micro shocks, but it can also turn out to be more exposed to shocks' diffusion (Battiston et al., 2012; Glasserman and Young, 2016).

Agent-based models can be employed to study these issues, as they allow for the modeling of direct interaction between heterogeneous agents, the emergence of macroeconomic outcomes from simple behavioral rules, and the use of the simulated economic system as a laboratory to test the aggregate and distributional consequences of alternative policies (see Farmer and Foley, 2009; Fagiolo and Roventini, 2017; Dawid and Delli Gatti, 2018; Dosi and Roventini, 2019, among the others).

We contribute to these debates by modeling the evolution of an interbank network in the medium-scale *K+S* agent-based model, which can be used to *jointly* analyze short- and long-run macroeconomic dynamics as it generates both endogenous growth and business cycles punctuated by financial crises as emergent properties. In particular, to account for contagion effects and systemic risk, we exploit the network of connections between banks embedded in the *K+S* model, assuming that the payment flows among different firms must be managed by the commercial banks. This allows us to create a multilayered network where the shocks can originate either in the real or the financial sector, and they can propagate both within and between the two domains. Furthermore, to evaluate new policies, we endow banks in the model with a network-based micro-prudential tool called *Network Valuation* (NEVA, see Barucca et al., 2020). Generalizing the Eisenberg and Noe (2001) framework, NEVA is a model for the balance-sheet consistent valuation of interbank claims that ensures systemic risk minimization with minimal assumptions on banks' behavior and rationality. This is possible because the generality of the NEVA allows for an *ex-ante* (before maturity) valuation of interbank claims, requiring each bank to have only information about their own interbank exposure, and providing a unique clearing vector for interbank transactions. These properties hold as long as all institutions assess their interbank exposures using NEVA, making it a suitable micro-prudential tool for mitigating systemic risk. However, a regulation like NEVA has never been adopted in real practice, making an empirical counterfactual estimation of its efficacy impossible. Primarily discussed within models of contagion (see Bardoscia et al., 2021), NEVA has been employed in few empirical settings, in order to perform macro-stress testing that exploited detailed confidential datasets, usually provided by central banks (Roncoroni et al., 2021; Jin et al., 2024; Carro and Stupariu, 2024). Our paper complements these findings, by providing a model-based counterfactual evidence that could be valuable to policy-makers.

This paper is the first medium-scale macroeconomic agent-based model that studies the macro-financial effects stemming from the common adoption of a micro-prudential tool (NEVA) that evaluates banks' interbank exposures in order to minimize systemic risk. Moreover, the extended *K+S* model enables one to analyze, in a unified framework, the interactions between micro- and macro-prudential policies and their joint impact on financial stability and economic dynamics. This is particularly relevant because, even if these two policies are often modeled as separate tools, they inevitably share objectives, transmission channels and possible complementary features, which can be exploited by policy-makers (Altunbas et al., 2018; Osinski et al., 2013) .

Simulation results show that the model can account for a rich list of stylized fact concerning the network structure of the interbank market (sizable volume of interbank linkages, dissassortativity, vertex centrality and bank size relationship) and the co-movements of macro-financial variables. Regarding the policy implementation, we find that the economic system at large can benefit from the introduction of a micro-prudential regulation that takes into account the interbank network relationships. Indeed, the use of the NEVA framework decreases the incidence of systemic risk events and of bankruptcy episodes of financial institutions, notwithstanding the tightness of mandatory capital requirements. In addition, a trade-off between financial stability and macroeconomic performance does not emerge in a two-pillar regulatory framework grounded on a Basel III macro-prudential regulation and a NEVA micro-prudential policy. All in all, the NEVA loosens the constraints on credit supply resulting from a too stringent macro-prudential regulation, which could otherwise negatively impact macroeconomic performances, without threatening financial stability. In other words, NEVA allows the economic system to achieve financial and macroeconomic stability without relying on overly stringent capital requirements.

The rest of the paper is structured as follows. Section 2 provides a snapshot of the literature addressing financial contagion and systemic risk through the lenses of statistical physics and agent-based modeling. Section 3 describes the model and it focuses on the mechanisms underlying the formation and the evolution of interbank linkages, as well as the functioning of the NEVA micro-prudential tool. Section 4 presents the results of our simulations experiments. Section 5 concludes.

2. Literature review

The literature has identified three main channels through which shocks can percolate and undermine the overall financial stability of an economic system. The first one concerns shocks arising within the financial markets and that propagates therein. A typical case is the so-called balance sheet contagion, which arises when a shock to one bank's balance sheet negatively affects the balance sheets of all the other financial institutions holding that bank's assets. This might even trigger an avalanche of losses among interbank counterparts (Allen and Gale, 2000; Kiyotaki and Moore, 2002; Luu et al., 2021). The second channel concerns shocks that originate in the financial sector, but that in turn affect the real economy. It is the case of shocks to the leverage of a commercial bank, which impairs its lending ability and increases the likelihood that non-financial corporations will face credit rationing (Adrian and Shin, 2008; Brunnermeier and Pedersen, 2009; Laeven and Valencia, 2012; Gross et al., 2018). The third channel concerns shocks emerging in the real economy and hitting the financial sector. This may occur when competitive pressures, demand shocks, or supply-chain disruptions induce the default of very large corporations to which a bank is heavily exposed. The default can lead to non-performing loans, ultimately eroding the lenders' equity, which in turn becomes a riskier asset for all its counterparts across the financial system (Kiyotaki and Moore, 1997; Boissay, 2006; Battiston et al., 2007; Luu and Lux, 2019; Popoyan et al., 2020).

All these three mechanisms may contribute to the build-up of systemic risk. While seminal contributions on financial contagion primarily focused on interbank network transactions (Angelini et al., 1996; Iori et al., 2008; Gai et al., 2011), the recent literature explored financial contagion from a multi-layered perspective, illustrating how common asset holdings, overlapping portfolios, collateral rehypothecation and borrowing-lending relations contribute to the spread of systemic risk (Huang et al., 2013; Aldasoro et al., 2022; Luu et al., 2021; Cappelletti and Mistrulli, 2023). Empirically measuring financial contagion in its multi-dimensional form remains a demanding task, due to the limited availability of detailed financial transactions data. Yet, recent studies have highlighted the role of indirect connections in fueling systemic risk (see, for instance, Silva et al., 2018; Luu and Lux, 2019; del Rio-Chanona et al., 2020; Poledna et al., 2021; Tabachová et al., 2024; Alexandre et al., 2024).

However, a full identification of each of those forces is difficult because they are often connected in complex and non-linear ways. To overcome these challenges, an increasing number of small-scale agent-based models have studied the interaction between contagion effects and systemic risk (Georg, 2013; Montagna and Kok, 2016; Liu et al., 2020; Reale, 2024). From a macroeconomic point of view, most of the agent-based models abstract from an interbank market, although there are notable exceptions in which interbank networks are nested into larger agent-based models to draw and analyze the macroeconomics consequences of systemic risk (Delli Gatti et al., 2010; Tedeschi et al., 2012; Poledna and Thurner, 2016; Popoyan et al., 2017; Poledna et al., 2017; Gurgone et al., 2018; Popoyan et al., 2020; Catullo et al., 2021). At the same time, these models typically focus their interest on the business cycles frequencies and they abstract from endogenous growth and technical change. The incorporation of the interbank network into the K+S model, instead, allows us to study also the long-run consequences of financial instability.

3. The K+S model with an interbank market

The model belongs to the *Schumpeter meeting Keynes* family of models model (Dosi et al., 2010, 2013, 2015). It features vertically differentiated enterprises producing either a final consumption good or a capital good. Capital-good firms (indexed by $i = 1, \ldots, F_K$), produce vintages of machines, whose technology is defined by heterogeneous levels of labor productivity and energy efficiency.[2] These three dimensions analogously define the technology behind the production process of capital-good firms. The technology of both production processes and machines results from a process of endogenous technical change, the Schumpeterian growth engine of the model, primarily fueled by R&D expenditures, financed by a share of F_K firms' sales.

Machines are eventually sold as an input for production to downstream consumption-good firms (indexed by $j = 1, \ldots, F_C$). The Keynesian source of endogenous business cycles of the model is driven by the dynamics of investment in machines by consumption-good firms. This investment depends on consumption-good firms' expected final demand. In case internal funds are not sufficient to meet their desired levels of investments, consumption-good firms rely on an external source of finance, applying for loans from the banking sector.

The model also incorporates a household sector that consumes the final good out of wage income. The public sector collects taxes on incomes, i.e., on firm profits and wages, and when unemployment rises consumers are paid a subsidy, proportional to the current wage level. Finally, given the inflation and the unemployment rate target, the central bank implements its monetary policy by setting the main interest rate following a Taylor-type rule. All agents are heterogeneous in their state variables (e.g., number of clients, technology in use, productivity, R&D intensity, market shares, profits, net-worth, etc.). Moreover, agents are boundedly rational and use simple heuristics to make their decisions and they do not have complete knowledge of the network of economic relationships emerging in each market.

We extend the *K+S* model by introducing an interbank market where banks can directly interact by exchanging funds. This allows us to obtain a more realistic representation of the determination of credit supply, and to better account for counterparty risk and systemic risk. Indeed, the supply of credit of each bank does not depend only on its balance sheet and the creditworthiness of its clients, but also on the overall risk perception (possibly related to the business cycle phase), as well as on the possibility of exchanging liquidity with other financial institutions over the money market.

We model direct banks' interactions by exploiting the relationships (i) between consumption-good firms (clients) and capital-good firms (suppliers) in the market for machines; and (ii) between the banks and both types of firms (see Fig. 1). This approach is grounded on the fact that a key role of the banking sector is to handle the system of payments among firms.[3]

In the model, whenever a consumption-good firm buys a new machine, it transfers the corresponding money value of the transaction to a capital-good firm. We rule out the possibility of a direct cash transfer between firms, and we assume that the payment occurs through a deposit transfer from the bank where the consumption-good firm holds its bank account to the one where the capital-good firm holds its own account. This payment operation puts the two banks in direct connection. In Section 3.3, we shall also describe in detail how the payment system endogenously generates an endogenous network of interbank linkages. In this network, each bank represents a node/vertex, and a payment represents a link/edge. All links are directed and weighted. The direction of the link depends on the buyer-seller relationship between the two banks' clients. The weights of the links are instead defined by the amount of the payment between the two parties.

Given the focus of this paper, in the following sections, we provide a detailed description of the functioning of the banking sector. Specifically, we describe how credit supply is determined, the generation and evolution of the interbank network, and the characteristics of micro- and macro-prudential policies. The other elements of the model, such as technical change, investment decisions of the firms, households' consumption, and government's behavior, are detailed in Appendix B.

3.1. Banks' lending and macro-prudential regulation

Modern banking institutions do not just intermediate funds between savers and borrowers. They can create money *ex-nihilo* and play a central role in the system of payments in the economy (McLeay et al., 2014). Today, most of the money in circulation is endogenously created by private commercial banks in the form of loans granted to the private sector, a pillar for post-Keynesian theories of economic growth and fluctuations (Palley, 1996; Lavoie, 2014). This happens because every time a bank lends out new funds, e.g., loans to firms, a deposit of the same amount is automatically created on the liability side of the bank's balance sheet to match the new asset. This deposit corresponds to the funds that the borrower has obtained from the bank and which have been contingently deposited at the bank itself. Most deposits are therefore liabilities created by banks themselves rather than already existing funds provided by saving agents and ready to be lent out to firms.

Our model comprises B heterogeneous commercial banks that can create money endogenously along the lines outlined above. Moreover, in line with the empirical evidence, the size of each bank, as measured by the number of clients, is drawn from a Pareto distribution – under the constraint that the total number of clients of all banks adds up to the total number of firms in the system (Berger et al., 1995).

As in Dosi et al. (2015), banks provide loans only to consumption-good firms and are subject to macro-prudential regulation.[4] We assume that for a generic bank k, the total credit supply $TC_{k,t}$ depends on three main factors: (i) the bank's past equity, $E_{k,t-1}$; (ii) the bank's past ratio of non-performing loans to total assets, $Bda_{k,t-1}$; and (iii) a macro-prudential counter-cyclical capital buffer CCB_t. Formally, a bank's credit supply is defined as:

$$TC_{k,t} = \frac{E_{k,t-1}}{\tau^B(1 + CCB_t + \beta Bda_{k,t-1})} \tag{1}$$

The macro-prudential setting in the model is in line with the Basel III regulatory framework. In particular, we assume that the authority fixes two types of constraints, which are both present in Eq. (1): a fixed *capital requirement* captured by the parameter $\tau^B \in (0, 1]$ that we

[2] Our model nests into an agent-based integrated assessment model (Lamperti et al., 2018, 2019, 2021), where the economy features a stylized energy sector and can interact with a climate box. In this version of the model, we keep the modeling of the energy sector as simple as possible (see Appendix B.3) and we do not allow the climate box to interact with the economic system. However, as we point out in the concluding remarks of the paper, our model can be easily extended to account for climate-induced systemic risk (Battiston et al., 2021).

[3] In line with Galbiati and Soramäki (2011), we model payments through a decentralized mechanism.

[4] Consistently with all previous versions of the K+S models, the loans to consumption-good firms are paid back in three periods.

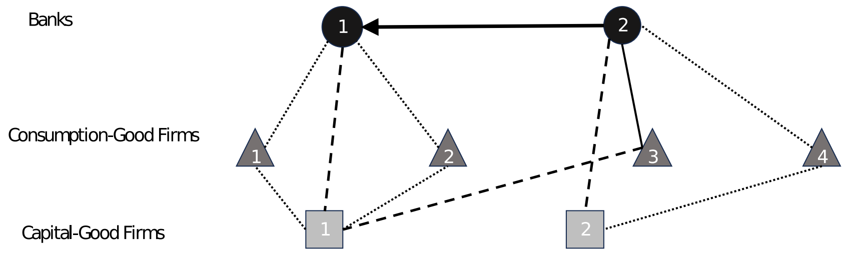

Fig. 1. Multi-layered network structure in the model. The solid arrow displays a representative transaction that occurs in the interbank market from Bank 2 to Bank 1. Capital-good firm 1 (a client of Bank 1) supplies a machine to consumption-good firm 3 (a client of Bank 2) and must receive deposits in exchange. As banks are responsible for arranging payments between the firms, our reduced form representation of the interbank market shows a mechanism for the formation of a direct payment link from Bank 2 (which takes deposits from the bank account of consumption-good firm 3) to Bank 1 (which use the received deposits and place them in the bank account of capital-good firm 1).

set equal to 4.5% as within the Basel III framework; a time-varying *counter-cyclical capital buffer* captured by the variable CCB_t. Similarly to Popoyan et al. (2017), the counter-cyclical buffer depends non-linearly on the aggregate credit-to-GDP gap CG_t, measured as the deviation of the credit-to-GDP ratio from its 5-year moving average trend. More specifically, the buffer writes:

$$CCB_t = \begin{cases} 0, & \text{if } CG_t < J \\ \frac{(CG_t - J)}{(H-J)} 0.025, & \text{if } J \leq CG_t \leq H \\ 0.025, & \text{if } CG_t > H \end{cases} \tag{2}$$

where $J = 2\%$ and $H = 10\%$ measure the adjustment factors based on historical evidence about banking crises (see BIS, 2010, pag.13). Overall, a tighter macro-prudential regulation, as measured by a higher value of τ^B, decreases the credit supply for all banks. However, the aggregate effects on the macroeconomic and financial systems are non-trivial. On the one hand, the lower credit supply might limit growth possibilities for firms. On the other hand, the regulation can also prevent the formation of *boom-and-bust credit cycles*, thereby stabilizing the economy (Schularick and Taylor, 2012).

Bank equity $E_{k,t-1}$ also plays a prominent role in determining the credit supply, as specified in Eq. (1). In banks' balance sheets, equity is a residual claim measuring the difference between assets and liabilities. In our model, it will consequently depend on the value of each bank's interbank claims. In Section 3.5 we shall discuss how the valuation of the interbank claims affects the equity value of the bank and indirectly the supply of credit in the economy.

3.2. The interest rates structure

The model features several interest rates because of the various activities banks perform. Let us begin by determining the interest rate charged by a bank to its client asking for a new loan (r_t^{deb}). This rate depends on two components: a mark-up common to all banks, (μ^{deb}) applied on the Central Bank interest rate (r_t^{cb}); a client-specific risk-premium that is associated with the fragility of the borrowing client cl. The latter is constructed by classifying clients into four credit classes that correspond to the four quartiles (i.e., $q^{cl} = \{1, 2, 3, 4\}$) of the distribution of firm financial fragility (see Dosi et al., 2015, for a similar approach). For each client cl belonging to the quartile q^{cl} at time t the bank k applies a risk-premium that is defined as follows:

$$r_{k,cl,t}^{deb} = r_t^{cb}(1 + \mu^{deb}) \left[1 + (q^{cl} - 1)k_{const}\right], \tag{3}$$

where $k_{const} > 0$ is a scaling parameter.

Furthermore, interbank assets (see Section 3.3 for a description of their determination) yield an interest rate r_t^{IB} equal to:

$$r_t^{IB} = (1 - md^{IB})r_t^{cb} \tag{4}$$

where md^{IB} is a mark-down on r_t^{cb} in line with the empirical evidence showing that in most economies, the money market rate is often highly correlated to the main refinancing rate, but slightly lower.

The deposit rate r_t^D that banks pay on the deposits from their clients is determined similarly, i.e., by applying a mark-down md^{dep} on the central bank main refinancing rate. The same approach is used to set the interest rate on government bonds r_t^{bonds} and the rate r_t^{res} at which bank reserves at the central bank are rewarded (see Table A.2 for the values of the mark-down applied to set these interest rates in the model).

Finally, the main refinancing operation rate is set by the central bank according to a dual-mandate Taylor rule:

$$r_t^{cb} = r^T + \gamma_\pi(\pi_t - \pi^T) + \gamma_U(U_t - U^T) \quad \text{with} \quad \gamma_\pi > 1, \quad \gamma_U \geq 0 \tag{5}$$

where the terms in parentheses represent inflation rate and unemployment rate gaps, while the parameters (γ_π, γ_U) measure the aggressiveness of the central bank with respect to each objective.

Overall, the interest rate structure in the model is such that the following inequalities hold (see also Table A.2):

$$r_t^D \leq r_t^{res} \leq r_t^{IB} < r_t^{cb} \leq r_t^{bonds} \leq r_t^{deb}. \tag{6}$$

3.3. Link creation in the interbank network

A key working assumption of our model is that banks manage payments between consumption-good and capital-good firms. This generates an endogenous network of interbank claims that evolves as time goes by. In this section, we describe the creation of new links in the foregoing interbank network. The next section describes instead how links can be destroyed.

To explain the process of link formation in the model, let us consider the case where a capital-good firm f_k sells a new machinery to a consumption-good firm f_c. The two firms are, respectively, clients of the banks b_k and b_c. Let us also consider a situation in which the f_c firm does not have enough internal funds to buy the new machine and asks for a loan from its associated bank, which endogenously creates new money in the system (Fig. 2 Panel A). The new loan is an asset for b_c and a liability for f_c. Given the assumption that all payments are managed by banks, the payment between the firms originates a transfer of deposits and an exchange of interbank funds between the two banks b_c and b_k. The transaction, therefore, implies a change in the level of deposits and the creation of an interbank relationship between the two banks.

At this stage, two alternative possibilities can emerge in our model according to the ability of the firm f_c to collect enough funds to repay the debt or, instead, to default (partially or totally) on its outstanding debt. Let us start from the first case (Fig. 2 Panel B). In such a situation, the consumption-good firm f_c has collected enough funds from its sales and, at the end of the period, it has a sufficient amount of liquidity to repay the loan. Thus, the firm f_c deposits its profits at its bank b_c and, consequently, this bank can immediately close the interbank liability position towards the other bank b_k. Hence, the interbank link is immediately closed and our interbank network is characterized only

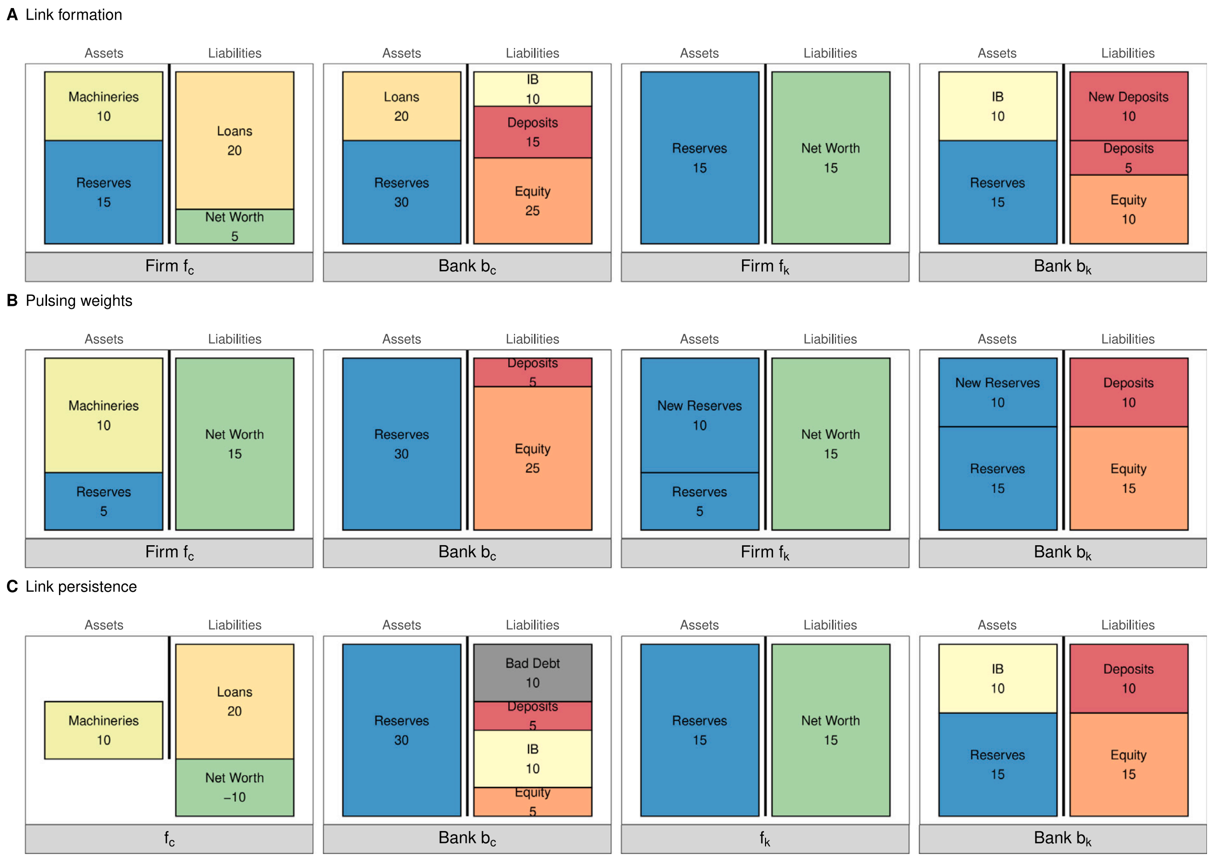

Fig. 2. Stylized examples of interbank network: link formation (**Panel A**), pulsing weights (**Panel B**) and link persistence (**Panel C**). *Notes*: The figure shows the T-account plot for representative balance sheets of consumption- and capital-good firms (f_c and f_k, respectively) and the banks to which they are connected (b_c and b_k). The figure depicts the evolution in the balance sheet composition and highlights how interbank linkages emerges within the system of payments embedded in the model. See text, Sections 3.3–3.4, for a more detailed description.

by *pulsing weights*. If this occurs for all firms, then all payments are settled and all the interbank claims are cleared. The interbank network would be represented by a null adjacency matrix. When firm f_c defaults instead, the bank b_c experiences a loss on the loan previously granted to f_c – i.e., a bad debt (Fig. 2 Panel C). In this case, a fraction of the credit loss is transmitted to the payment that the bank b_c would have done to the other bank b_k to close its interbank liability, if the firm f_c had not defaulted. The remaining fraction of the loss is absorbed by a reduction in the equity of b_c. Hence, in this situation, the link between the two banks survives over time since the interbank payment did not occur yet.

This simple mechanism for the creation of connections among banks is sufficient to characterize the interbank system by means of an adjacency matrix of the form:

$$L = \begin{bmatrix} 0 & \ell_{1,2} & \cdots & \ell_{1,B} \\ \ell_{2,1} & 0 & & \vdots \\ \vdots & & \ddots & \vdots \\ \ell_{B,1} & \cdots & \cdots & 0 \end{bmatrix} = A' \tag{7}$$

where the matrix L is the *interbank liability matrix*.[5] Each entry $\ell_{k,b}$ measures the nominal value of the interbank debt that a generic bank k has towards another generic bank b and that is not regulated within a period. The stock of interbank liabilities of a bank k is $IB_k^L = \sum_{b=1}^{B} \ell_{k,b}$ (i.e., the sum of the kth row of the matrix L); the total amount of interbank assets of a bank k is instead $IB_k^A = \sum_{b=1}^{B} \ell_{b,k}$ (i.e., the sum of the kth column of the matrix L).

[5] $L = A'$ implies that A is the corresponding *interbank asset matrix*.

3.4. Link destruction in the interbank network

After an interbank link between two banks is created, one bank becomes a creditor of another bank – in our previous example, the bank b_k is the creditor of bank b_c. A creditor bank is the holder of an interbank asset and it can demand the reimbursement of the deposit from the debtor bank at any time. We assume that the creditor bank decides to close (or not to close) the interbank position according to a relatively simple heuristic that involves the opportunity cost of holding the asset for another period. More in detail, we assume that a bank holding the interbank asset has two options. The first one consists in the rollover of the interbank credit for another period, which is a risky asset and pays the interbank rate r_t^{IB}, with a probability $(1 - p_{b,t})$ – that is, the probability that the debtor bank will not default. The second one is a risk-free alternative according to which the bank immediately closes the interbank position, obtains the liquidity, and deposits it at the central bank. This alternative pays the risk-free rate r_t^{res}. In a nutshell, the choice corresponds to an investment decision between a risky asset and a risk-free one. Formally, the decision by the creditor bank k to destroy the interbank with bank b at time t reads:

$$Pr(CLOSE_{k,b,t} = 1) = Pr\left(r_t^{res} - r_t^{IB}(1 - p_t^b) > \xi_{k,b,t}\right) \tag{8}$$

$$\xi_{k,b,t} = \begin{cases} 1 & \text{if} \quad IB_k^A / (\sum_k IB_k^A) \leq \Upsilon \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

with Υ being a random variable with a uniform distribution $\mathcal{U}[m_t, n_t]$. The support of this distribution is denoted by m_t and n_t. These are, respectively, the minimum and maximum interbank exposures as a share of total interbank exposure at time t. Comparative statics of Eq. (8) suggests that, if the default probability of the borrower ($p_{b,t}$) is too large to compensate the spread between the returns on the interbank market (r_t^{IB}) and on the central bank deposits (r_t^{res}), then it is preferable for bank k to close the risky position towards bank b. However, if $p_{b,t} = 1$, bank k can still decide to keep the interbank position open. This event occurs whenever the variable $\xi_{k,b,t} = 1$, namely when the share of interbank assets that bank k holds, is not higher than the random realization of Υ.[6]

Following Gai et al. (2011), in our baseline specification the probability of default $p_{b,t}$ of bank b is fully exogenous and drawn from a uniformly distributed random variable $\mathcal{U}(0, 2h_0)$ whose expected value $h_0 \in (0, 0.5]$ can be interpreted as the haircut rate, which is usually defined as the percentage deduction from the value of the collateral required to obtain financing.[7] In this setting, realizations of $\mathcal{U}(0, 2h_0)$ reflect idiosyncratic shocks to the perceived underlying risk of the interbank debtor. In our equation, therefore, a smaller haircut maps into a reduction in the perceived risk associated to the bankruptcy of the counterpart and to a lower probability of closing the interbank position. Therefore the counterparty's probability of default is an important trigger for the banks' actions and can have relevant consequences on the profitability and the credit supply of each single bank. At the aggregate level, instead, it can affect the overall interbank network topology and systemic risk.

3.5. Banks' equity

The credit supply of a bank does not only depend upon the macroprudential regulation, but also on banks' equity (see Section 3.1). We now introduce the law of motion of a bank's equity and we carefully describe how micro-prudential regulation can impact on equity and, in turn, on credit supply and macroeconomic fundamentals.

At the end of each period, the profit of a generic bank k is determined as:

$$\Pi_{k,t} = \left(\sum_{cl=1}^{Cl_k} r_{k,cl,t}^{deb} Loans_{k,cl,t} \right) + r_t^{res} Res_{k,t} + r_t^{bonds} Bonds_{k,t} - r_t^{D} Depo_{k,t} - Bad\,Debt_{k,t} + r_t^{IB} Net\,IB_{k,t} \quad (10)$$

where Cl_k indicates the number of clients of the bank k, and the $Bad\,Debt_{k,t}$ is strictly positive only in those periods in which the bank experiences some losses on its outstanding loans due to the bankruptcy of some of its clients. Banks earn profits on the outstanding loans to consumption-good firms ($Loans_{k,t}$), on the stock of reserves at the central bank ($Res_{k,t}$), on the yields provided by sovereign bonds ($Bonds_{k,t}$), and on the interbank assets ($IB_{k,t}^{A}$). At the same time, banks pay an interest rate on firms' deposits ($Depo_{k,t}$) and on the interbank liabilities ($IB_{k,t}^{L}$).[8]

At the end of the period, the after-tax profits of banks – i.e., $Net\Pi_{k,t} = (1-tr)\Pi_{k,t}$ – are stockpiled to the bank's net worth. Thus, the equity of the generic bank k evolves accordingly to the following law of motion:

$$E_{k,t} = Loans_{k,t} + Res_{k,t} + Bonds_{k,t} + IB_{k,t}^{A} - IB_{k,t}^{L} - Depo_{k,t} + Net\Pi_{k,t} \quad (11)$$

If the equity of the bank is negative, the bank goes bankrupt and the interconnected banks in the interbank network L may only partially recover their interbank claims (i.e., $\ell_{b,k}$) up to a fraction ρ^{IB} of their original claims. In our baseline scenario, we set $\rho^{IB} = 0$. Moreover, to keep the number of banks constant within a simulation, we assume that when a bank goes bankrupt the government steps in by providing fresh capital to the defaulted bank. The equity of the bank after the government bailout is a fraction $\vartheta \sim \mathcal{U}(0.1, 0.9)$ of the smallest incumbent banks equity, provided it meets the regulatory capital requirements.

In our baseline scenario equity is evaluated at its book value, as calculated in Eq. (11). However, such a formulation does not take into account the fact that all the other banks with whom the generic bank k has direct or indirect interconnections in interbank network can default. Therefore, the book value provides only an imperfect representation of the market value of the bank.

A well-designed micro-prudential regulation provides banks with the tools to better evaluate their interbank claims. If appropriately evaluated, the equity value of banks can systematically vary from the book value. This difference might give rise to sizable impact on the credit supply of each bank, limiting their exposure to counterparty and systemic risks. In particular, in this model we investigate the properties of the NEVA mechanism (Barucca et al., 2020), which can be employed as a behavioral and micro-prudential device aimed at protecting the banks from the counterparty default risk, as well as from credit risk. The next section describes the implementation of such a mechanism in our model.

3.6. The NEVA clearing mechanism and micro-prudential regulation

Persistent interbank links between two banks endogenously emerge in the model when a consumption-good firm defaults on its debt. As time goes by, the owner of an interbank claim that decides not to close the position remains the holder of an interbank asset which is valued at its historical nominal value. However, this value could be misleading as it does not take into account two relevant risk factors: the counterparty risk and the credit risk.

If one accounts for these two sources of risk, the market value of an interbank asset may change over time also impacting on the final value of a bank's equity, as in Eq. (11). By introducing in the model a clearing mechanism that allows all banks to constantly update the market evaluation of their interbank claims, we thus allow firms to constantly update also the value of their equity.

An example of the above interbank clearing mechanism is the proposed by Eisenberg and Noe (2001). Under some regularity conditions, this mechanism provides a unique evaluation vector of the outstanding interbank claims based upon the probability of default of all banks. However, the Eisenberg and Noe (2001) evaluation model relies on two strong assumptions. First, it assumes that the evaluation of the interbank claims by each bank is carried out only at the maturity (i.e., ex-post) rather than at each period (i.e., ex-ante). Second, it assumes that all banks have a complete knowledge of the underlying network structure and the financial conditions of all the other banks. These two issues are solved by Barucca et al. (2020) with the development of the NEVA (Network Valuation), which generalizes the Eisenberg and Noe (2001) framework. More specifically, the NEVA model allows banks to evaluate their claims at any time (not only at maturity) with a local knowledge of the network. In particular, all banks are assumed to have information about their own financial situation and about those of their first neighbors, i.e., the banks with whom they have a direct interbank link.

Following Barucca et al. (2020), we thus aggregate all assets and liabilities outside the interbank market (i.e., loans, bonds, reserves and deposits) into a unique balance sheet item which we label the *"Net External Asset"* and we denote it by $\Theta_{k,t}$. The book value of the generic bank's equity presented in Eq. (11) can be reformulated as:

$$E_{k,t} = \Theta_{k,t} + \sum_{b=1}^{B} \ell_{k,b,t} - \sum_{b=1}^{B} \ell_{b,k,t} = \Theta_{k,t} + IB_{k,t}^{A} - IB_{k,t}^{L} \quad (12)$$

[6] In the simplest case in which $\Upsilon \sim \mathcal{U}[\bar{m}, \bar{n}]$, and the share of bank's k interbank asset $IB_k^A/(\sum_k IB_k^A) = (\bar{n} + \bar{m})/2$, then $\xi_{k,b,t} = 1$ with 50% probability. However, since the support of Υ changes over time according to the minimum and maximum share of interbank exposure of the system (m_t and n_t, respectively), the probability of keeping the position open anyway *regardless* the estimated counterparty's probability of default $p_{b,t}$ changes accordingly. Hence, a bank with a relatively lower interbank exposure will tend to keep the position open towards the debtor bank b.

[7] See Section 3.6 for scenarios in which $p_{b,t}$ is endogenously determined.

[8] For sake of brevity, in Eq. (10) we have directly reported the net interbank position $Net\,IB_{k,t}$.

When the NEVA framework is implemented at each time step, a bank's interbank claims are evaluated in a way that potential losses associated with the bankruptcy of other banks are taken into account.

This above evaluation mechanism replaces the historical book value of equity in our model. To account for this new element, the equity Eq. (12) becomes:

$$E^{NEVA}_{k,t} = \Theta_{k,t} + \sum_{b=1}^{B} \ell_{k,b,t} V^{NEVA}_{k,b,t} - \sum_{b=1}^{B} \ell_{b,k,t} = \Theta_{k,t} + IB^{A,NEVA}_{k,t} - IB^{L}_{k,t} \tag{13}$$

where $V^{NEVA}_{k,b,t}$ is the evaluation vector that bank k associates to all the direct links with other b banks in the interbank market at time t, and it is computed using the clearing mechanism described in Barucca et al. (2020). In short, this corresponds to the expected value of a valuation function that depends, on the one side, upon the expected value of the counterparty b's equity, and, on the other side, upon the expected value of b's assets under the circumstance that b defaults. Following Barucca et al. (2020), the vector $V^{NEVA}_{k,b,t}$ can be expressed as:

$$V^{NEVA}_{k,b,t} = 1 - p^{NEVA}_{b,t} - \rho^{NEVA}_{b,t}, \quad \forall\ k. \tag{14}$$

The term $p^{NEVA}_{b,t}$ measures the default probability of a bank b and measures the counterparty risk. The term $\rho^{NEVA}_{b,t}$, instead, is an endogenously-determined recovery rate on the assets of b, in the case b shall default. The two variables are determined as follows:

$$p_{b,t} \simeq \mathbb{E}\left[\mathbb{1}_{\Delta\Theta_{b,t}<E_{b}t} | \Theta_{b,t}\right] \tag{15}$$

$$\rho_{b,t} \simeq \mathbb{E}\left[\left(\frac{E_{b,t} + \Delta\Theta_{b,k} + IB^{L}_{b,t}}{IB^{L}_{b,t}}\right)\mathbb{1}_{-IB^{L}_{b,t}-E_{b,t}\le\Delta\Theta_{b,t}<-E_{b,t}} | \Theta_{b,t}\right] \tag{16}$$

where $\Delta\Theta_{b,t}$ is an unexpected change in net external assets that in our model refers to the increase in the bad debt, which might unexpectedly occur at time t.[9]

In our model, the NEVA can be used for two different purposes, which will characterize two different scenarios. First, it can be used by each bank as a device to evaluate counterparty risk. Using the NEVA to evaluate the probability of default of its counterparts, a bank might be more careful in its decision to close or not to close a persistent interbank link, see Eq. (8). Second, the NEVA can be used as a micro-prudential tool by a regulatory authority that tries to limit the credit exposure of the banking industry. We assume that the regulatory authority asks to all the banks that have an interbank claim to another bank b to reduce their leverage whenever the evaluation of the bank b is below unity – i.e., if $V^{NEVA}_{.,b} < 1$. In particular, we assume that under this micro-prudential regulatory settings, the banks should always take into account a fall in the evaluation of $V^{NEVA}_{.,b}$ in their measure of financial fragility, which is captured by the variable $Bda_{k,t}$. More specifically, for all banks holding a credit with b the prudential buffer writes:

$$Bda_{k,t} = \frac{\gamma_{BD}\, Bad\, Debt_{k,t}}{\Theta_{k,t} + \sum_{b=1}^{B} \ell_{k,b,t} V^{NEVA}_{k,b,t}} \tag{17}$$

If equity were evaluated at its book value, then the supply of credit (see Eq. (1)) would be completely inelastic to the evolution of risk in the interbank market. The introduction of the NEVA relaxes this feature.

3.7. Risk evaluation scenarios

The decision of a creditor bank to close an interbank position in the model depends upon the probability of default of the borrower bank, measured by $p_{b,t}$, as well as on the relative interbank exposure of the lender, captured by $\xi_{k,b,t}$, (see Eq. (8) and Section 3.4). We can use these two variables to define four alternative interbank risk evaluation scenarios. The details of these scenarios are summarized in Table 1

Table 1
Interbank market scenarios.

Scenario	Probability of default $p_{b,t}$	Valuation of Interbank claims
BASE	$\mathcal{U}(0, 2h_0)$	✗
SEMI	$\mathcal{U}(0, 2h_0)$, for Bank b: $\arg\max_{b\in B} Bda_{b,t}$	✗
NEVA	$p^{NEVA}_{b,t}$	✗
NEVA^2	$p^{NEVA}_{b,t}$	$\sum_{b=1}^{B} \ell_{k,b,t} V^{NEVA}_{k,b,t}$

Baseline scenario (BASE). In our baseline specification, the NEVA is switched off. In this scenario, $p_{b,t}$ is exogenous and drawn from a Uniform distribution $\mathcal{U}(0, 2h_0)$, where the expected value h_0 can be interpreted as the average of idiosyncratic shocks to the haircut on the collateral that the creditor can obtain in case of default of a debtor bank.

Semi-endogenous (SEMI). This scenario is similar to the baseline, except that now the creditor banks can close the riskiest positions in the interbank market. More specifically, banks apply the previous decision rule based on the haircut and a draw from a uniform distribution, only if they have an open interbank claim towards the riskiest bank in the system, as measured by the firm with the largest share of non-performing loans.

NEVA. In this scenario, a creditor bank in the interbank market decides to close a position according to Eq. (13) and hence it employs the NEVA clearing vector for better evaluating the counterpart risk.

NEVA^2. This last scenario is characterized by the presence of NEVA, employed both to guide the banks' decision about closing or not interbank claims according to Eq. (13), as well as to fix the supply of credit for the next period, by evaluating interbank exposures according to Eq. (17).

3.8. Timeline of events

At each time step t of our simulations, agents take the following decisions:

1. Policy variables (e.g., capital requirement, tax rate, central bank interest rate, etc.) are fixed.
2. Machines ordered by consumption-good firms in the previous period are delivered and will become part of the capital stock.
3. Capital and consumption-good firms calculate costs and set their prices.
4. The maximal amount of credit supplied by each bank to consumption-good firms is determined according to Eq. (1).
5. Capital-good firms signal the discovery of new machines, if any, to consumption-good firms.
6. Consumption-good firms fix their desired level of production and investment and eventually their demand for bank credit.
7. Banks rank firms' request and provide credit. Credit rationing may possibly arise.
8. Consumption-good firms receive the "brochures" of the brand new machines produced by capital-good firms and buy the most convenient.
9. Banks settle the payments between consumption-good and capital-good firms.
10. Both firms calculate the labor input necessary for production.
11. Production plans are undertaken.
12. Consumption-good firms' market shares are allocated based on their competitiveness.
13. Firms in both sectors compute profits. If profits are positive, consumption-good firms pay back their loans to their bank and deposit their net savings, if any. If some consumption-good

[9] Notice that the book value evaluation, can also be seen as a very particular case of the NEVA, in which $V_{k,b,t} = 1$ for all the interbank positions and for all periods. This will simply lead to Eq. (12). In addition under some regularity conditions (see Barucca et al., 2020, pag. 1189-1195) the solution for the vector of the default probabilities of the NEVA algorithm is unique and equivalent to the one by Eisenberg and Noe (2001).

Table 2
Summary statistics of the main aggregate macroeconomic and financial variables growth rates (unless otherwise stated). The average $\bar{\mu}$, median $\mu_{0.5}$ and standard deviation σ are computed across 1000 Monte Carlo experiments in the baseline configuration.

	$\bar{\mu}$	$\mu_{0.5}$	σ		$\bar{\mu}$	$\mu_{0.5}$	σ
GDP	0.029	0.030	0.003	*Deposits*	0.059	0.062	0.010
Consumption	0.029	0.030	0.003	*Bad Debt*	0.059	0.060	0.050
Investment	0.028	0.029	0.005	*Cash Reserves*	0.057	0.061	0.013
Unempl. rate	0.069	0.037	0.111	*Interbank Exposure*	0.060	0.062	0.018
Inflation	0.031	0.032	0.005	*Total Credit*	0.059	0.061	0.009
Debt/GDP	0.847	0.116	3.226	*Losses due to contagion*[c]	0.031	0.000	0.104
Bank defaults[a]	28.000	3.000	71.000	*Bank Fragility*[d]	0.083	0.070	0.066
Fin. constraints[b]	0.250	0.223	0.095	*Bank Equity*	0.057	0.061	0.013

[a] Number of bank defaults.

[b] Share of credit rationed firms.

[c] Interbank losses over interbank claims.

[d] Average financial fragility index Bda as in Eq. (1).

firms are unable to pay back their loans, banks involved in the payment system open an interbank position.

14. Banks evaluate their interbank exposures and decide whether to close their interbank claim according to Eq. (8). Firms' and banks' profits are taxed.
15. Entry and exit of consumption-good and capital-good firms takes place. In both sectors firms with market shares smaller than a minimum threshold and firms with negative net liquid assets exit from the market and are replaced by new entrants.
16. Bank profits are calculated. Banks pay taxes and dividends.
17. Government bails out banks with realized negative equity.
18. Government calculate its budget and, if negative, deficits are financed by banks.
19. Aggregate macroeconomic and financial variables are calculated.
20. Capital-good firms perform R&D, trying to discover new products and more efficient production techniques and to imitate the technologies and the products of their competitors.

4. Simulation results

In this section, we present the main results obtained from our extensive Monte Carlo simulations of our model in the baseline scenario. For this baseline simulation setting, we run 1000 Monte Carlo simulations in which only the pseudo-Random Number Generator has been modified. This allows us to obtain a sufficient set of observations to test the statistical significance of our claims. In addition, we discard the first 300 time observations for each batch run to ensure that the statistics are washed away by the noise due to initial conditions.

To broadly validate the model, we follow the indirect calibration approach, also employed by all the previous versions of the *Schumpeter meeting Keynes* family of models (see Windrum et al., 2007; Fagiolo and Roventini, 2017). In particular, we evaluate the ability of our model to replicate a wide range of stylized facts at the micro-, meso- and macroeconomic levels. Specifically focusing on this model, the indirect calibration process aims to qualitatively replicate observed data concerning macro-financial factors and several statistical characteristics of the interbank network involving borrowing and lending connections (see Fagiolo et al., 2019). Finally, we also verify the continued validity of the micro- and macro-properties reproduced by earlier versions of the $K+S$ models within our extended framework.

Table 2 presents a collection of key Monte Carlo statistics produced by our model in the baseline scenario. The results of the table show that our model can generate the following outcomes: (i) realistic growth rates for GDP, consumption, and investment, arranged in an accurate hierarchy of volatility; (ii) low unemployment rates; and (iii) consistent inflation stability. This indicates that in the baseline scenario, the model effectively emulates a healthy economic system characterized by endogenous growth and business cycles. Moreover, financial variables, which are significantly impacted by the extensions described in Section 3 exhibit, on average, higher rates of growth compared to real variables, but they are also much more volatile. This finding is compatible with the empirical evidence brought about by Jakab and Kumhof (2015).

In the next Section we will discuss in detail the ability of the model to account for a set of stylized facts related to the co-movements of financial aggregates and fundamental features inherent to interbank networks. Notoriously, $K+S$ models can account, jointly, for a wide ensemble of empirical regularities, making it suitable to deliver credible insights into policy scenarios (Dawid and Delli Gatti, 2018; Dosi and Roventini, 2019). For the full list of stylized facts replicated by the model, we refer to Table A.1 in Appendix A.

4.1. Empirical results of the model

Our model incorporates a process of firm financing that involves money creation by banks, wherein the lending decision depends on leverage and capital requirements (Godley and Lavoie, 2006; Caverzasi and Godin, 2015). In line with the working of modern financial markets, this framework implies a nearly one-to-one adjustment of the banks' debt to a variation in assets. On the other hand, equity remains relatively unresponsive to changes in assets. Indeed, equity will increase only if banks generate profits, which is not immediately related to assets' variation (Jakab and Kumhof, 2018; Ihrig et al., 2021).

This distinction in the sensitivity of debt and equity to fluctuations in assets has also been empirically recorded by both Adrian et al. (2013) and Jakab and Kumhof (2015). Our agent-based model replicates this empirical finding as an emergent property of the system. Panel A of Fig. 3 presents the relationship between the log-changes in banks' equity (red) and debt (blue) as a function of the log-changes in total assets. It is immediate to observe that the elasticity of debt to assets is high and slightly larger than one. Conversely, the response of equity to changes in assets is rather flat.

Panel B of Fig. 3 shows instead the distribution of the two elasticity parameters, estimated with simulated bank-level data. It is easy to observe that the estimate for the Debt-to-Assets elasticity is centered around 1, while the Equity-to-Assets elasticity is centered around 0. Models utilizing the loanable funds approach, in which banks solely serve as intermediaries for private sector savings, often fail to replicate such empirical patterns (examples are, but not limited to Bernanke et al., 1999; Gertler and Kiyotaki, 2010; Adrian and Boyarchenko, 2012). Our results suggest that a financing mechanism driven by endogenous money creation offers a more credible description of banking industry behavior.

Next, we focus on the composition of the asset and liability sides of individual banks' balance sheets over time in a typical Monte Carlo simulation (cf., Fig. 4). First, coherently with Jakab and Kumhof (2018), our model predicts that banks' balance sheets experience frequent

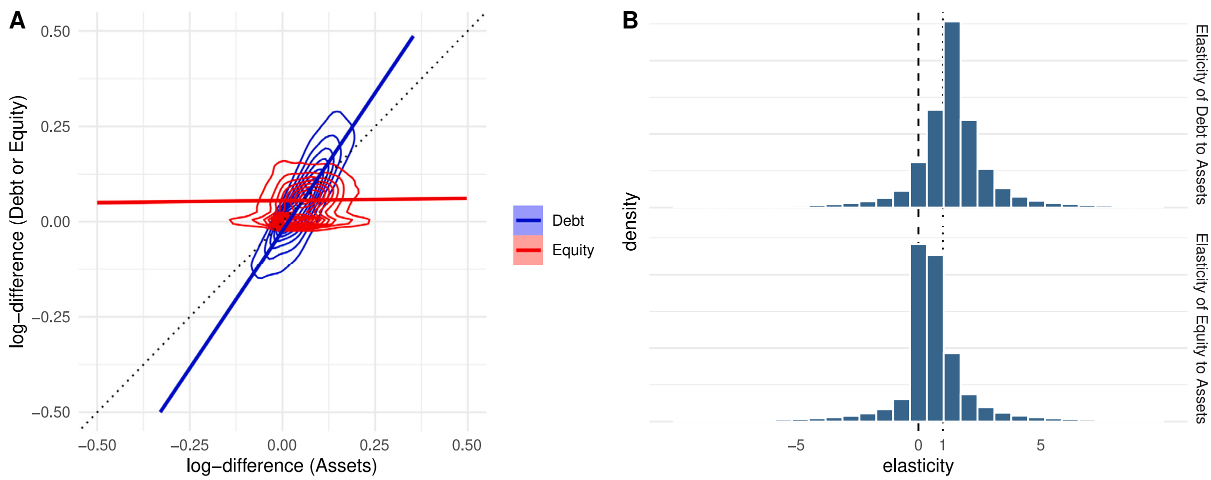

Fig. 3. Panel A. A 2-dimensional density plot of (log)changes in bank Debt/Equity (y-axis) vs Bank Assets (x-axis), along with a 45 degrees line (dotted). **Panel B.** Univariate distribution of the bank-level elasticities of Debt to Assets (top) are centered around one (dotted vertical line). Univariate distribution of the bank-level elasticities of Equity to Assets (bottom) are centered around zero (dashed vertical line). All observations are at bank-level, pooled across all time periods for all Monte Carlo iterations. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

oscillations in the level of their interbank assets and liabilities. Second, the asset side (Panel A of the figure) shows that the loans granted to the consumption-good firms and reserves constitute the most relevant components of the asset side of the balance sheet. Pooling all bank-level observations, these two components, on average, represent 58% and 33% of the whole amount of assets. Loans to consumption-good firms and interbank positions are the components determining banks' heterogeneity in the assets' and liabilities composition.[10]

To analyze how the creation and destruction of interbank claims affect balance sheet adjustments, let us consider the example of a representative bank (bank 5 in the simulation) in the last interval of a Monte Carlo iteration (few time steps before period 450). Looking at its liabilities (cf., Panel B of Fig. 4), we observe that the bank records a sudden increase in the share of its interbank debt, which emerges due to the default of at least one of its consumption-good firm clients. Part of this loan corresponds to the payment made in advance to buy the machinery of capital-good firms, which are in turn connected to banks that would experience sudden increases in the share of interbank assets (in the example, the increase is visible in the asset side of bank 1 and 2).

Up to now our discussion focused on the model's ability to mimic the empirical properties of the macro-financial sector and of individual banks' balance sheet. Let us now examine the observed statistical properties of the interbank network that the model can replicate. More specifically, we examine network assortativity and network density.[11] In addition, we study node-specific features of the network, like the centrality and exposure of the single banks, split by their size class.

Empirical studies show that the network of interbank credit-debit relationship is disassortative and has a low density, recorded to be about 0.3% on average (Soramäki et al., 2007; Cocco et al., 2009, among others). Moreover, the network typically features a high-density core – a group of few densely connected banks – and a low-density periphery, i.e., banks with few connections (Alves et al., 2013; Aldasoro and Alves, 2018).

In particular, for the banking sector, disassortativity implies that small banks, whose size is measured by their number of clients, will tend to be connected to banks with large sizes. This feature can hardly be reproduced by scale-free networks generated via preferential attachment (Fricke et al., 2013). For instance, by specifying a simple rule for interbank borrower/lender choice, as in Lux (2015) or Liu et al. (2020), does not ensure that disassortativity is achieved. In contrast, we theoretically motivate a mechanism that explains the formation and persistence of interbank links without relying on rules of preferential attachment, also ensuring that the emerging interbank network is disassortative (cf., Sections 3.3 and 3.4).

Our mechanism of interbank link formation, despite its simplicity, reproduces all above-mentioned stylized facts about the structure of an interbank network. Indeed, our model generates a network with a density that remains quite stable over time and averages 15% for the overall network (see Panel A of Fig. 5).In addition, consistent with empirical evidence, we can identify a core of the network with high density (around 35%) and a periphery with lower density (slightly below 10%). Panel B of Fig. 5 presents instead the Monte Carlo average of the assortativity index over time. This is always negative, thus confirming that the interbank network generated by our model is disassortative.

Let us now consider node-specific network statistics. In this respect, a major role is played by measures of centrality which capture the relative importance of each node in the network.[12] The results are also disaggregated by bank size classes (see Fig. 6). In particular, for each size class, we report the average centrality of the banks belonging to that specific class.[13] A standard result in the empirical interbank network literature is that big banks are significantly more central, especially when the outgoing links are considered (Craig and von Peter, 2014; Fricke and Lux, 2015). Furthermore, empirical evidence suggests that larger banks tend to borrow cash reserves in the interbank market (see Müller, 2006, for the Swiss interbank market). The results from our simulations are consistent with this evidence (see Fig. 6). The result

[10] Similarly to Dosi et al. (2015), the government bonds are bought in proportion to the bank's size and play a marginal role in our model.

[11] A network is said to be assortative (disassortative) if there is a higher likelihood that a network's node is connected to other nodes with similar (different) characteristics. Newman (For the definition of assortativity indexes see Section 3.E of 2003).

[12] There is a plethora of centrality measures that can be employed. In what follows we focus on of the most popular measures: the overall centrality accounting for incoming and outgoing links; the in-degree centrality accounting only for the incoming ones; and the out-degree centrality taking into account only the outgoing links. See Newman (2018).

[13] Taking into account that the distribution of banks' clients is Pareto, the size-class categories are constructed as follows: big banks are those in top 20% of the distribution, medium-sized banks are between the 30-th and 80-th percentiles, small banks are below the 30-th percentile.

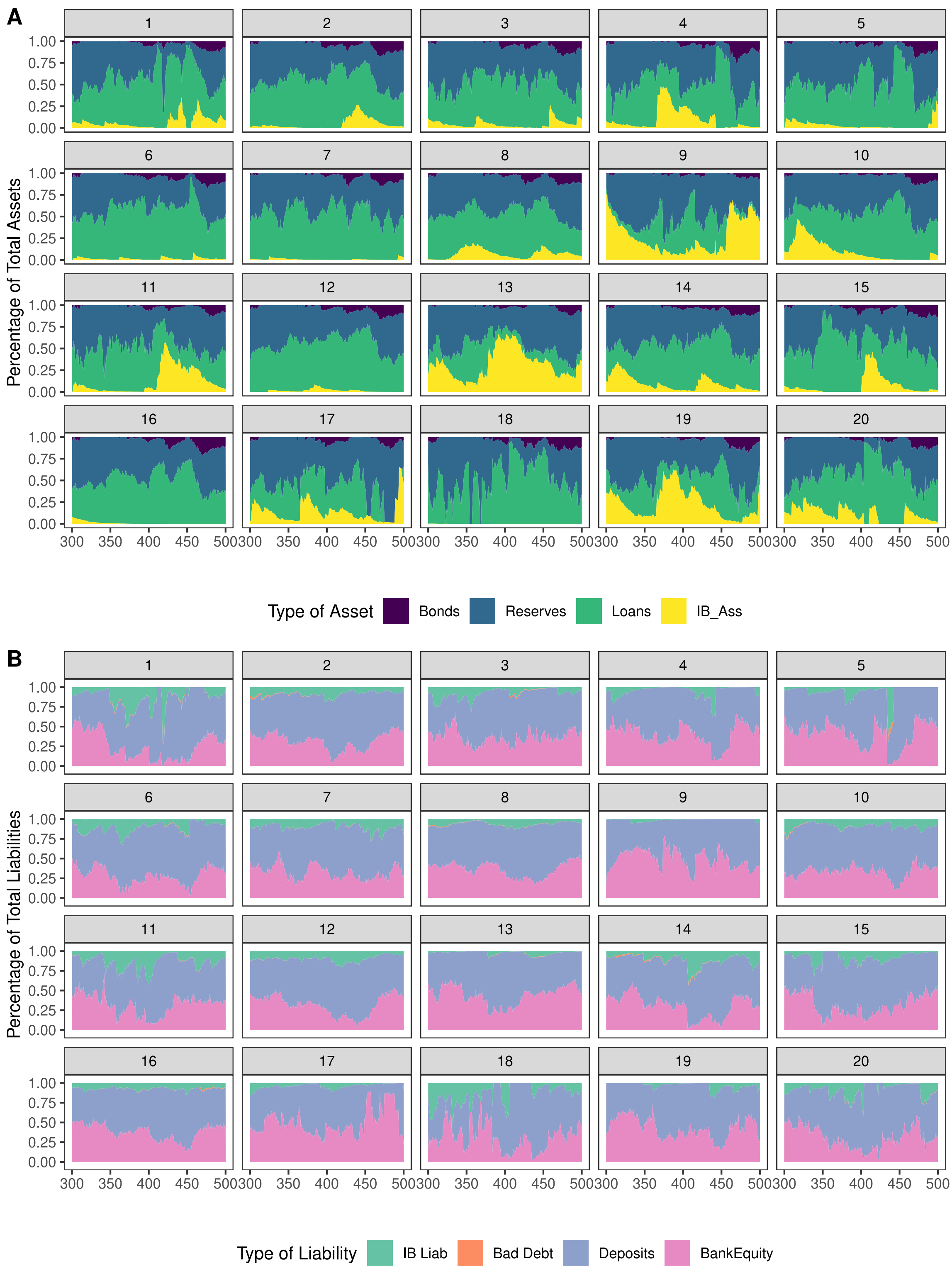

Fig. 4. Composition of the assets (**Panel A**) and liability (**Panel B**) sides of individual banks' balance sheets in a representative Monte Carlo simulation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

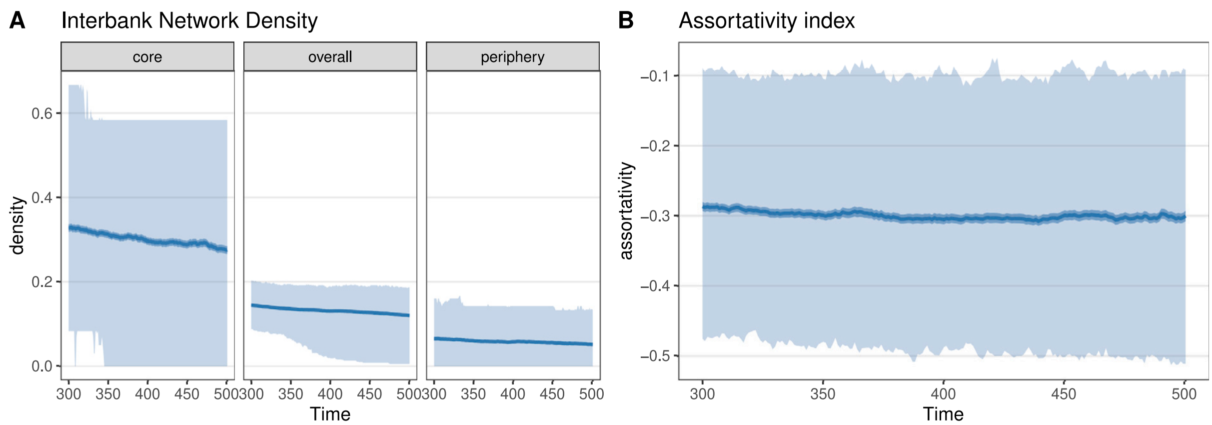

Fig. 5. Density (A) and assortativity (B) indexes of the emergent interbank network. The indexes are computed as averages of the 1000 Monte Carlo simulations at each time step along with the 5-th and 95-th percentiles confidence bands (light color). We also report a 90% confidence interval for the sample mean (dark color).

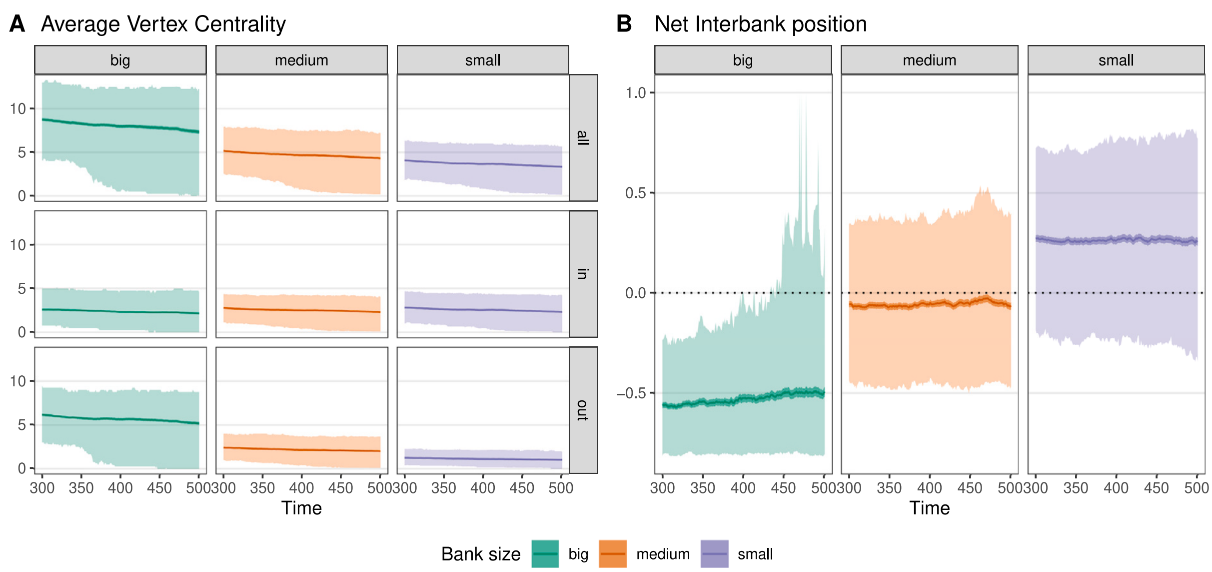

Fig. 6. Panel A shows the Monte Carlo average number of links by type and bank size. **Panel B** plots the evolution of the Monte Carlo average value of net interbank assets as a percentage of total interbank exposures (breakdown by size). Confidence bands denote the 5% and 95% percentiles and the 90% confidence interval for the sample mean (lighter and darker colors, respectively).

is explained by the fact that big banks have many more consumption-good firm clients who can default on their debts. And when such clients default, these banks become borrowers in the interbank market.

Finally, the simulation results indicate that our model generates a banking structure wherein small banks are liquidity providers; medium-sized banks are liquidity neutral; and large banks are liquidity borrowers (see the right panel of Fig. 6).[14] This is also a prominent feature observed in real interbank networks (see Liu et al., 2020).[15]

4.2. The effects of a network-based micro-prudential regulation

Given the good empirical performance of the model, in this section we present the results of policy evaluation exercises, where we compare the performance of the economy and the banking sector in the four different scenarios described in Section 3.7 and summarized in Table 1. These exercises aim to test whether the NEVA clearing mechanism can dampen systemic risk, as measured by the total number of banks' defaults and by the losses experienced by non-defaulting banks because of the contagion from defaulted ones.

Table 3 compares the simulation results about the variables capturing systemic risk (first horizontal block), the banking sector (second block), and overall macroeconomic performance (third block) in the semi-endogenous, NEVA and NEVA^2 scenario with respect to the baseline one.

First, none of the above alternative scenarios involves a significant variation in credit supply, as well as on variables measuring macroeconomic performance (like GDP growth, the unemployment rate, investment growth, etc.). In addition, also average bank performance (captured by bank profits, bank equity, bad debt and bank fragility) is not significantly affected.

[14] The net interbank positions are measured for each bank k as the difference between the bank's total interbank assets IB_k^A and its total interbank liabilities IB_k^L. At each period t, we then average the net interbank position of each bank in the specific size class and we compute the share, as a percentage of the total interbank exposure of the system.

[15] At this stage, the model cannot yet replicate empirical regularities associated by considering additional layer analysis of financial networks: for instance, those implied by a varying maturity structure or by the different types of financial instrument exposure (Aldasoro and Alves, 2018).

Table 3
Comparison of systemic risk mitigation scenarios to the baseline. Main indicators for systemic risk, financial and macroeconomic performances.

Scenario	Bank defaults	Loss due to contagion	Interbank exposure	Bailout costs	Credit Supply
SEMI	0.866	0.832*	1	0.849	1.011
NEVA	0.508***	0.269***	0.992	0.572***	1
NEVA^2	0.483***	0.263***	0.992	0.542***	1.006
	Total Loans	Bank Profits	Bank Equity	Bad Debt	Bank Fragility (Bda)
SEMI	1.005	1.042	1.01	0.952	0.976
NEVA	0.996	0.992	0.999	0.986	0.999
NEVA^2	0.996	1.012	1.005	0.972	1.018
	GDP growth	Unempl. rate	Deb/GDP ratio	Investment growth	Financial constraints
SEMI	1.002	0.937	0.806	1.009	0.988
NEVA	1.004	0.893	0.806	1.002	0.99
NEVA^2	1.003	0.897	0.815	1.002	0.99

Notes. The table reports the ratio of the average values of economic indicators of a particular scenario relative to the baseline scenario. Values higher than one implies that the average value of the economic variable is higher than in the baseline scenario. The null hypothesis is that there is no statistical difference in the means calculated in the two scenarios.
*p<0.1; **p<0.05; ***p<0.01.

The significant effects mostly concern the systemic risk in the interbank market. In particular, the semi-endogenous scenario (SEMI) does not yield significant improvements in performance in terms of systemic risk mitigation. In contrast, when the NEVA framework is applied *solely* to compute the probability of default of banks' counterparties (NEVA scenario), we find that the number of bank defaults decreases by 48.2%. In addition, losses due to contagion effects contract by 73.1%, and bailout costs are lowered by 42.8%, without significantly affecting exposure in interbank markets.

Moreover, if NEVA's micro-prudential potential is fully exploited and it is used *also* for an internal assessment for bank credit provision (NEVA^2 scenario), we observe a further reduction in the number of bank defaults, losses due to contagion and bailout costs by 51.7%, 73.7% and 45.8%, respectively. Hence, the NEVA is extremely effective in taming the perilous effects of systemic risk.

The results discussed indicate that the use of the NEVA has significant effects in terms of systemic risk mitigation while not having any negative impact either on banks or macroeconomic performance. Accordingly, they suggest that the use of such a micro-prudential tool is not characterized by a trade-off between financial stability and macroeconomic performance. Encouraged by this finding, in the following section we explore whether this trade-off shows up instead for banks of different sizes, thus offering insights on the possible distributional impacts of NEVA. Furthermore, we investigate the possible interactions between a micro-prudential tool, like the NEVA framework, and macro-prudential regulatory conditions, represented by the Basel III macro-prudential regulation.

4.3. Heterogeneity analysis

To detect the possible heterogeneous impact of the NEVA, we study the effects brought about by the introduction of the NEVA on different categories of banks. In particular, for each category of bank size (big, medium, small), we compute the instances of bank defaults, the losses due to contagion, the growth rate of the total loans to consumption-good firms and the growth rate of firms' investments. This exercise allows us to understand whether the NEVA affects some banks and their credit transmission more than others. As usual, we run t-tests to assess whether there are, on average, statistically significant differences across the scenarios.

Fig. 7 illustrates the findings of our study, which reveal the heterogeneity underlying the aggregate patterns discussed in the previous section. We first focus on systemic risk indicators (first and second row of Fig. 7). Our results suggest that the use of both NEVA and NEVA^2 yields advantages to all banks regardless of their size. However, larger banks get a more pronounced benefit. This is because large banks are also more connected in the interbank network (see Section 4.1). Accordingly, a better evaluation of their counterparties' assets yields larger reductions in contagion-related losses for these banks and as a consequence, in their default rate.

The last two rows of Fig. 7 illustrate the distributional impact of the NEVA on the real sector by showing, respectively, the variation in the loans to firms of banks on different size classes (third row) and the variation in the investment of firms connected to banks of different sizes (fourth row). The two panels indicate that the more prudential behavior implied by the NEVA does not bring significant reductions either in the amount of loans that banks of different sizes grant to consumption-good firms or in the investment of the firms connected to them (cf., the NEVA and NEVA^2 scenarios with the BASE one). Accordingly, the absence of a significant impact of the NEVA on the real sector that we highlighted in the previous section is not generated by a composition effect.

4.4. Micro-prudential and macro-prudential interactions

In the previous sections we highlighted that the introduction of the NEVA allows a significant mitigation of systemic risk in interbank markets while not generating credit-crunch effects and/or a worse macroeconomic performance.

However, how does the NEVA micro-prudential tool interact with the Basel III macro-prudential regulation? In particular, we want to study whether a trade-off between financial stability and macroeconomic performance emerges when these two different sets of regulatory instruments interact. Indeed, as micro- and macro-prudential policies inherently share objectives and transmission mechanisms, their simultaneous adoption could trigger non-trivial effects on systemic-risk-related variables and the macro-financial outlook (Altunbas et al., 2018; Osinski et al., 2013).

For this purpose, we exploit the versatility of our agent-based model to perform Monte Carlo simulation experiments where we interact the

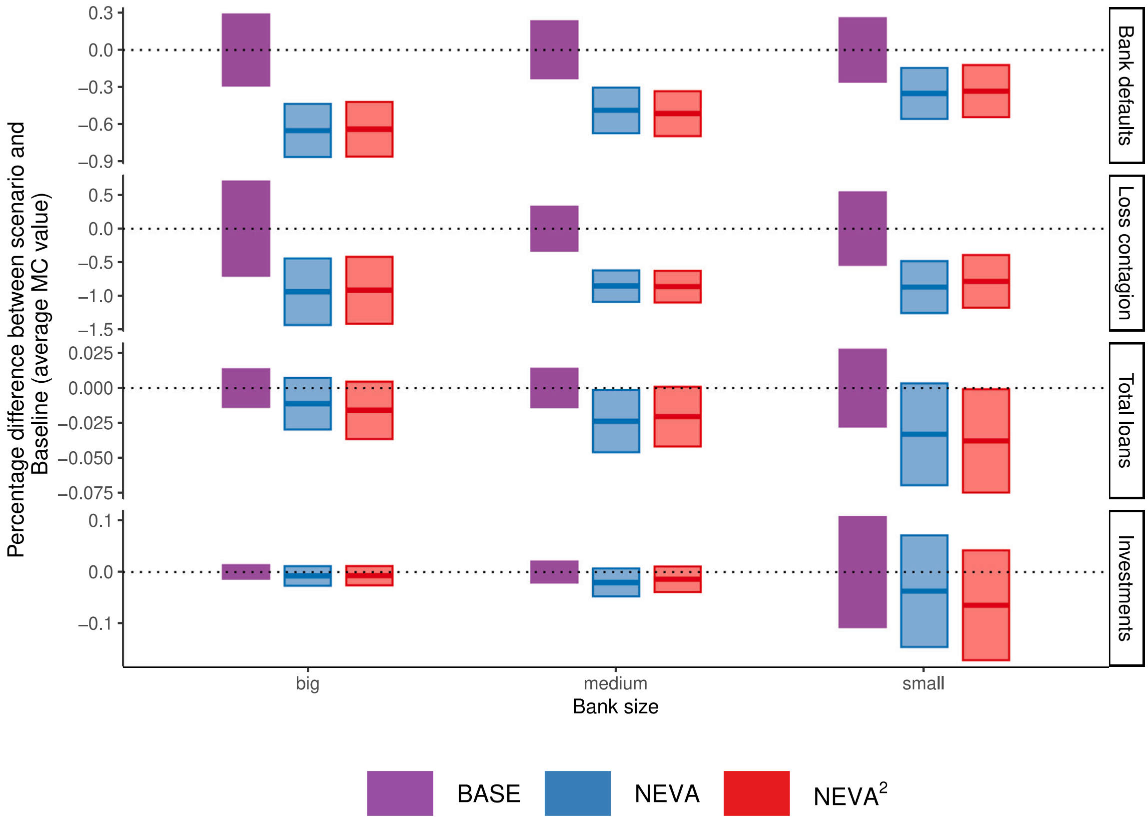

Fig. 7. The effects of the NEVA implementation on different categories of banks. *Notes*: The figure shows, for each category of bank size, the distribution of the 1000 Monte Carlo percentage difference between the value of statistic X under the scenario of interest s and a baseline scenario *base*, $(X_s - X_{base})/X_{base}$, with a 90% confidence level. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

NEVA and NEVA^2 micro-prudential tools with more or less stringent macro-prudential policy regimes identified by mandatory capital requirements, captured in our model by the parameter τ^B in Eq. (1). More specifically, we let the macro-prudential parameter τ^B to vary from 2% to 7% (higher values implies a more stringent macro-prudential regulation) and for each value of τ^B, we simulate the micro-prudential policy scenarios described in Section 3.7. We take as benchmark for this experiment the baseline scenario (BASE) with $\tau^B = 4.5\%$ (cf., Tables 2 and 3) to ease the comparability of the results.

The results of the above experiment are presented in Figs. 8 and 9 for all the analyzed combinations of the macro-prudential parameter (τ^B) and of the micro-prudential settings. Each bar of the plots in the two figures shows the difference between the value of a variable of interest in a given scenario and the value of the same variable in the benchmark scenario, along with a 90%-level confidence interval. The value of the variable in the benchmark scenario (BASE with $\tau^B = 4.5\%$) is centered on zero by construction.

The analysis of the bar plots in Figs. 8 and 9 confirms that the implementation of the NEVA brings a significant reduction in the values of the systemic risk-related variables (i.e., number of bank defaults, losses due to contagion and bailout costs approximately fall by 30%, 75% and 50%, respectively) *notwithstanding* the strength of macro-prudential policy (Fig. 8, top 3 panels). Such results are robust even in the NEVA^2 scenario, i.e., when the tool is implemented also for determining lending decisions. The NEVA thus appears to be invariant and orthogonal to the macro-prudential regime in terms of systemic risk mitigation.

However, two outcomes emerge when we examine the impact on credit and macroeconomic variables. First, we observe stronger credit crunch effects as the macro-prudential policy gets tighter (Fig. 8, bottom 3 panels). The mechanism is straightforward: an increase in capital requirements (higher τ^B) leads to a contraction in the supply of credit – see Eq. (1) – given the loans demand. This increases the share of credit-constrained firms (see Fig. 9, first panel from the top) that need to revise downward their investment and production plans, thus hampering economic growth.

Second, we observe *non-linear* interaction effects between micro- and macro-prudential policy tools. For instance, Figs. 8 and 9 show that for values of τ^B lower than 4.5%, none of the macroeconomic and financial variables are significantly affected by the introduction of the NEVA. This is because, in presence of looser capital requirements, the NEVA regulatory tool contributes to keep the credit supply steady, thus taming the risk associated to the formation of credit booms. In such a stable macro-financial environment, firms are generally not credit rationed (see also Fig. 9, top panel). They can therefore pursue their desired investment plans, which in turns sustain the pace of economic growth (cf., Fig. 9).

On the contrary, the credit crunch triggered by tighter macro-prudential requirements ($\tau^B > 4.5\%$) is reinforced by the presence of the NEVA micro-prudential tool. In this case, the total loans granted to firms decrease from −2.3% to −6.3% when τ^B is equal to 5% and 7%, respectively (see Fig. 8); in the more stringent macro-prudential scenario, as Fig. 9 highlights, financial constraints increase by 12.4%, while investment growth and GDP growth decrease by −4.8% and −2.4%, respectively.[16] Nonetheless, even in presence of tighter capital

[16] For detailed magnitudes of this effects see Table A.3 in Appendix A.

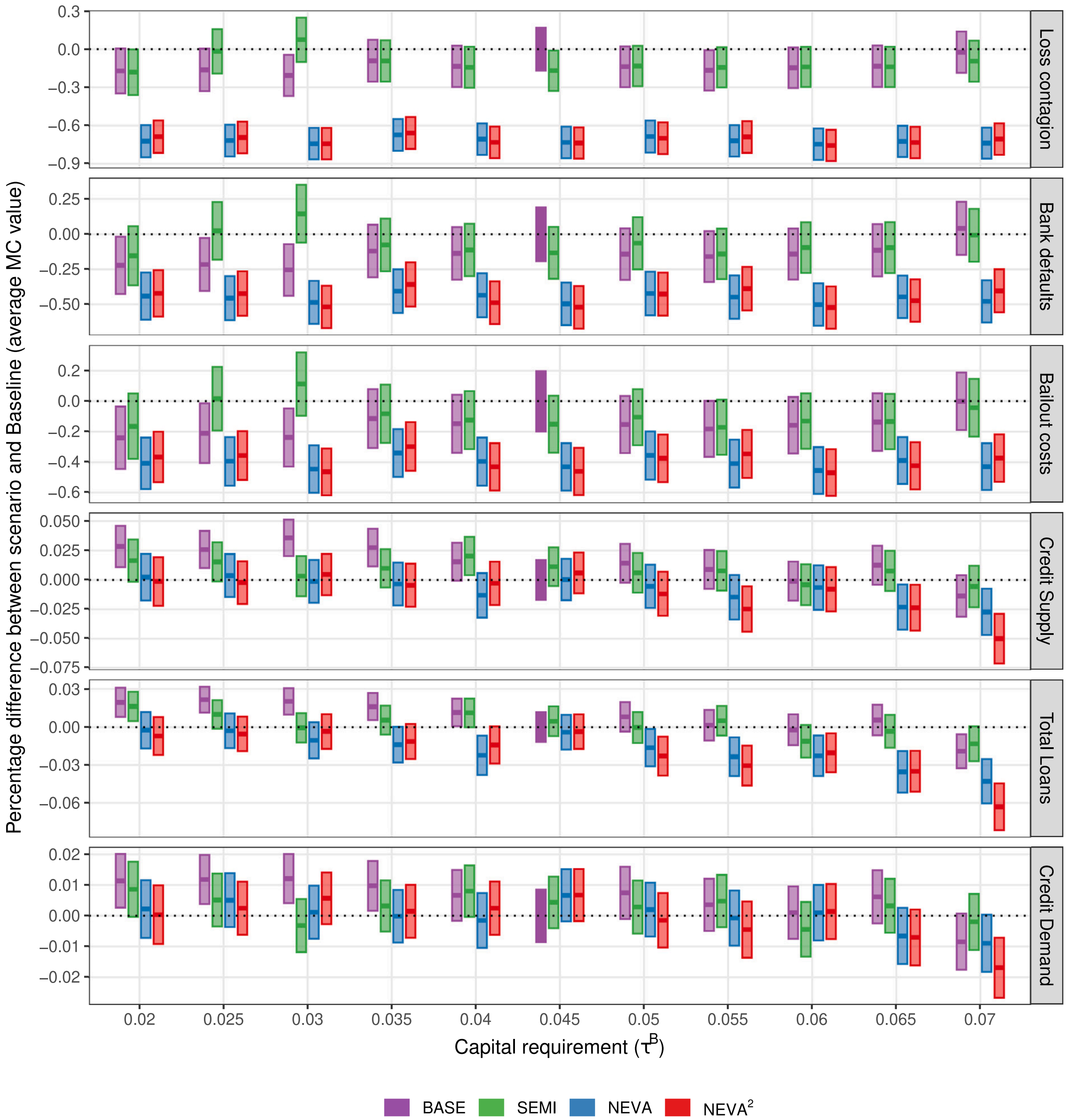

Fig. 8. Systemic-risk related and macrofinancial effects of NEVA implementation under different capital requirement regimes. *Notes*: The figure shows, for a set of financial indicators, the distribution of the 1000 Monte Carlo percentage difference between the value of statistic X under the scenario of interest s and a baseline scenario $base$, $(X_s - X_{base})/X_{base}$, with a 90% confidence level. In order to have statistics comparable across different capital requirement regimes, a reference-baseline scenario is fixed at $\tau^B = 0.045$, i.e., the baseline parametrization in Section 4, centered around 0 by construction (darker purple bars). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

requirements, the introduction of the NEVA brings significant improvements in the mitigation of systemic risk (see Fig. 8 top 2 panels).

Overall, our results suggest that there are strong complementarities between the NEVA micro-prudential tool and the BASEL III-like macro-prudential tools. More precisely, the introduction of the NEVA could allow policy makers to relax (or at least not to exacerbate) mandatory capital requirements. In particular, a mix represented by the adoption of the NEVA micro-prudential tool and a less stringent macro-prudential regulation successfully tames systemic risk without constraining the flow of bank credit to firms in the real economy.

4.5. Schumpeterian growth regimes and systemic risk mitigation

At last, we explore the interplay between the NEVA framework and the Schumpeterian growth engine of the model. In particular, we evaluate the NEVA performance, conditional upon different regimes of technological opportunities and firms' search capabilities, which prominently characterize the process of economic growth in the family of *K+S* models (Dosi et al., 2010). For a more detailed discussion we refer to Appendix B.1.

To model the presence of low (high) technological opportunities, we shift to the left (right) the density of the $Beta(\alpha, \beta)$ distribution, from which the technological productivity coefficients are drawn. As modeled in Eqs. (B.2)–(B.3), a more left (right)-skewed Beta distribution implies that technological opportunities are more rarefied (frequent).

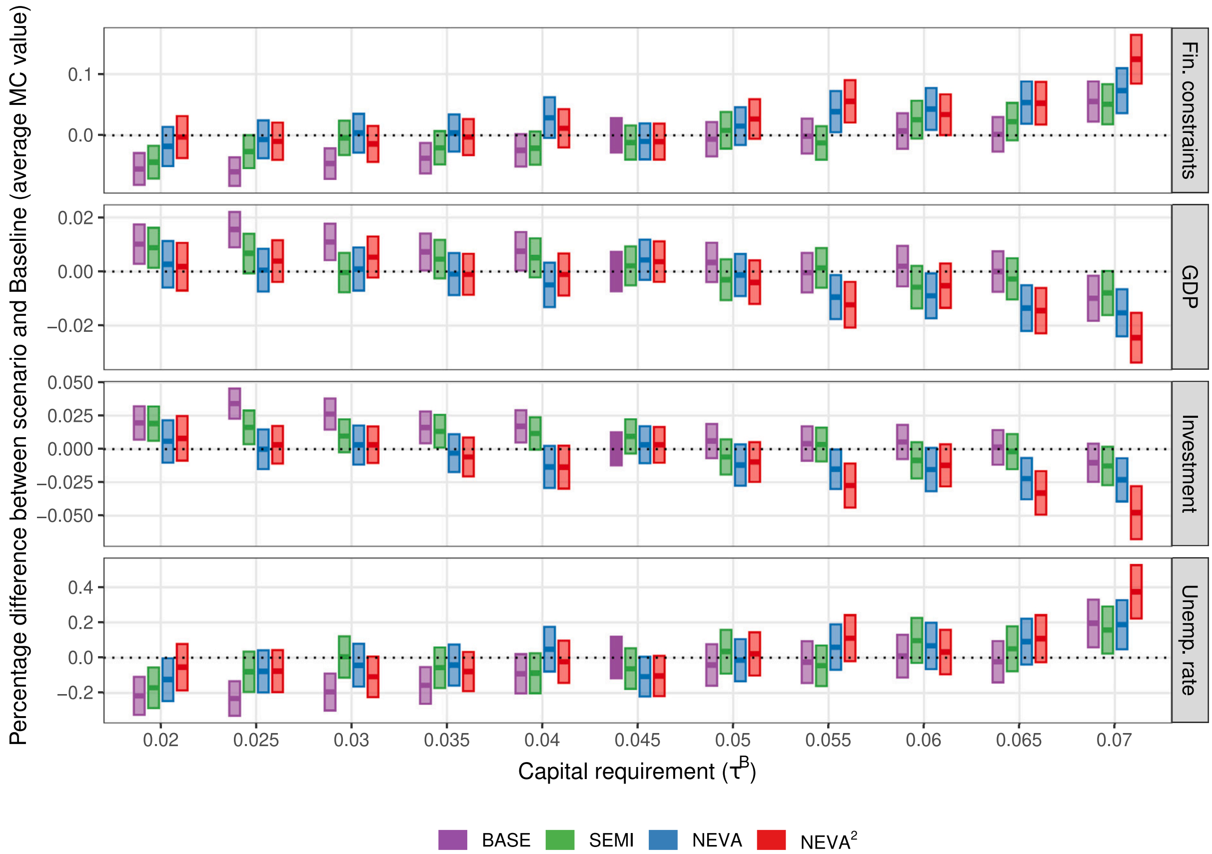

Fig. 9. Real effects of NEVA implementation under different capital requirement regimes. *Notes*: The figure shows, for a set of macroeconomic indicators, the distribution of the 1000 Monte Carlo percentage difference between the value of statistic X under the scenario of interest s and a baseline scenario *base*, $(X_s - X_{base})/X_{base}$, with a 90% confidence level. In order to have statistics comparable across different capital requirement regimes, a reference-baseline scenario is fixed at $\tau^B = 0.045$, i.e., the baseline parametrization in Section 4, centered around 0 by construction (darker purple bars). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

We also increase (decrease) firms' search capabilities (cf., Eq. (B.1)) by varying the parameter ζ, in order to increase (decrease) the chances of accessing innovations (Dosi et al., 2010, 2020).[17]

Table 4 shows the results of NEVA implementation in scenarios characterized by combinations of higher and lower technological opportunities, as well as higher and lower search capabilities.[18] We find that also within different technological scenarios, the adoption of NEVA robustly achieves systemic risk mitigation. NEVA becomes particularly effective in more turbulent times, where more technological opportunities are available and access to innovation is more widely spread.

Only under a particular setting – i.e., when technological opportunities are high – we record a negative effect of NEVA on GDP growth. In this scenario, capital-good firms that exploit higher technological opportunities acquire a competitive advantage in terms of cost effectiveness of their products, leading to a tendency towards high market concentration in the capital-good sector. As a consequence, consumption-good firms are more likely to buy capital goods from the same market leaders, whose associated banks are more likely to become interbank lenders (i.e., they hold interbank assets). Introducing NEVA in such a scenario induces these banks to become more cautious about their interbank exposures. They will close interbank positions more often (in the NEVA scenario), and they also more prudently evaluate their exposures (in the NEVA^2 scenario). Accordingly, the other banks holding interbank liabilities must find financial resources to close their interbank positions, lowering their equity and, in turn, their supply of credit. This more prudent behavior is more likely to tighten the borrowing constraints, also hindering investments and, in turn, GDP growth. Though suggestive, this mechanism seems to be in tune with recent empirical evidence brought about by Tabachová et al. (2024) where the costs of reducing systemic risk are amplified by the higher likelihood of large supply chain cascades. We think that our result provides interesting evidence on the role of industry concentration for systemic risk mitigation.

5. Conclusion

This work extends the *Schumpeter meeting Keynes* model (Dosi et al., 2010, 2013, 2015), introducing an explicit payment system between the economic agents that leads to the endogenous formation of an interbank network. In the model, payments among firms for capital goods are mediated by deposits exchanges between their banks which are closed within a period. Indeed, under normal conditions, a bank

[17] Notice that, as reported in Table A.3 in Appendix A, our baseline scenario is characterized a technological opportunity regime with $Beta(3,3)$ and by a regime of the search capabilities with $\zeta = 0.3$.

[18] For sake of clarity, we have omitted scenarios combining high technological opportunities with low search capabilities (and vice versa), as these may represent less likely or interesting regimes. However, these scenarios do not significantly alter the overall findings of our experiments. Results are available from the authors upon request.

Table 4
Comparison of NEVA scenarios with different technological opportunities and search capabilities, relative to the baseline. Main indicators for systemic risk, financial and macroeconomic performances.

Technological Opportunities:		Low		Base			High	
Search Capabilities:		Low	Base	Low	Base	High	Base	High
NEVA	Loss contagion	0.288***	0.404***	0.314***	0.269***	0.296***	0.266***	0.286***
NEVA^2		0.273***	0.344***	0.304***	0.263***	0.303***	0.284***	0.273***
NEVA	Bank defaults	0.503*	0.827	0.62***	0.508***	0.507***	0.56***	0.565***
NEVA^2		0.503*	0.678	0.606***	0.483***	0.543***	0.581***	0.545***
NEVA	Bank Equity	0.998	0.991	0.996	0.999	0.996	0.921***	0.886***
NEVA^2		0.997	0.994	1.001	1.005	0.977*	0.92***	0.902***
NEVA	Credit Supply	0.998	0.991	0.996	1	0.997	0.921***	0.887***
NEVA^2		0.997	0.994	1.001	1.006	0.978*	0.919***	0.901***
NEVA	Fin. constraints	1.003	1.016	1.023	0.99	0.994	1.091***	1.111***
NEVA^2		1.003	1.016	1.015	0.99	1.022	1.076***	1.096***
NEVA	Investment	1	0.993	0.988	1.002	0.997	0.941***	0.956**
NEVA^2		1.002	0.998	0.99	1.002	0.996	0.954***	0.954**
NEVA	Unemp. rate	1.003	1.093	0.999	0.893	0.891	1.091	1.116**
NEVA^2		1.013	1.085	0.957	0.897	0.987	1.062	1.091
NEVA	GDP	1.003	0.998	0.995	1.004	1.004	0.978***	0.975***
NEVA^2		1.004	0.998	0.996	1.003	0.998	0.984**	0.983*

Notes. The table reports the ratio of the average values of economic indicators of a particular scenario relative to the baseline scenario for each combination of parameters governing the innovation regimes. For high, base and low technological opportunities we use a $Beta(\alpha,\beta)$ where $(\alpha,\beta) = \{(3.1, 2.9), (3.3), (2.9, 3.1)\}$, respectively. Related to the high, base and low search capabilities regime we let $\zeta = (0.25, 0.3, 0.35)$. Values higher than one implies that the average value of the economic variable is higher than in the baseline scenario. The null hypothesis is that there is no statistical difference in the means calculated in the two scenarios.
*p<0.1; **p<0.05; ***p<0.01.

advances resources for a consumption-good firm at the moment of the purchase of machines from a capital-good firm and recovers them at the end of the same period if the consumption-good firm is solvent, thereby closing the position in the interbank market. However, if the consumption-good firm is insolvent, the advances made by the buyer's bank to the seller's one result in an interbank position that cannot be immediately closed and thus persists over time. This simple mechanism endogenously generates a sizable volume of interbank assets and liabilities without imposing any restrictive assumptions on banks' behavior, and results in an endogenous interbank network whose features are consistent with recent empirical evidence.

By employing extensive Monte Carlo simulations, we show that our model is able to jointly replicate a wide ensemble of stylized facts concerning growth and business cycles, the properties of firm size distributions, and key features of empirically-observed interbank markets. It is therefore suitable to be used as a policy laboratory to test the financial and real impact of alternative regulatory mechanisms impacting on banks' behavior. In this respect, we study whether the NEVA clearing mechanism can be employed as a *micro-prudential* instrument to mitigate financial instability. NEVA equips banks with a tool for the endogenous evaluation of interbank claims. Such an evaluation considers the interconnectedness within the interbank network, effectively protecting banks from increasing systemic risk (Barucca et al., 2020). We study the effectiveness of this tool in different scenarios: in the NEVA scenario, banks evaluate the counterparty probability of default in order to decide whether to keep open (or not) the interbank claims; in NEVA^2 scenario, banks adopt the tool also to adjust their credit supply in a more prudent fashion when dealing with relatively risky interbank clients.

Simulation results show that NEVA helps mitigating the harmful effects of systemic risk, measured by the number of bank defaults and losses due to contagion effects. In addition, the foregoing mitigation effects are stronger whenever the NEVA is used both for evaluating the interbank counterparty's probability of default and for making lending decisions based on a prudent evaluation of interbank exposures. Moreover, we do not detect any distributional effects of the adoption of the NEVA across bank size. In other words, the benefits from systemic risk reduction are shared among all banks regardless of their size. Furthermore, we do not observe the emergence of a trade-off between financial stability and macroeconomic performance in our simulation, which suggests that the more cautious approach towards interbank interconnectedness implied by the NEVA does not result in a lower levels of credit provision to the real economy and therefore in worse short- and long-run macroeconomic performances.

We then further explore the interplay between micro- and macro-prudential policies. We find non-linear interactions between the NEVA and the Basel III tools. More specifically, in presence of looser capital requirement, the NEVA micro-prudential tool mitigates systemic risk, while not constraining the flow of credit to firms. On the contrary, when macro-prudential regulation becomes tighter, the NEVA still prevents the build-up of systemic risk but it exacerbates the fall of credit to the real side of the economy. The non-linear interaction between the NEVA and Basel III framework has two relevant policy implications. First, the NEVA is always able to mitigate systemic risk in more or less stringent Basel III framework. Second, the implementation of NEVA micro-prudential regulation allows to pursue financial stability with less stringent mandatory capital requirements, thus supporting a more abundant flow of bank credit to finance firms' investment and production plans.

The model could be extended in different ways. First, similarly to Guerini et al. (2022), one could enrich the dynamics of the interbank market by letting banks trade other financial instruments, e.g., government bonds, thus determining the creation of secured/unsecured transactions. Second, since our model is nested into an agent-based integrated assessment model, it could be employed to evaluate the financial risks related to the green energy transition (Lamperti et al., 2018, 2019, 2021). This would allow one to study the rising contagion and systemic risks related to the formation of stranded assets and the policies to be implemented in order to tame their destabilizing effects, thus contributing to a blossoming literature on climate-related financial risks (Battiston et al., 2021). Third, similarly to Popoyan et al. (2017, 2020), one could introduce in the model an explicit market for liquidity which is now automatically deposited at central bank facilities in the form of cash reserves. This would also introduce another source of financial instability in the model and allow the study of the impact of unconventional monetary policies.

CRediT authorship contribution statement

Gianluca Pallante: Writing – review & editing, Writing – original draft, Methodology, Investigation, Visualization, Formal analysis, Conceptualization. **Mattia Guerini:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Funding acquisition, Conceptualization. **Mauro Napoletano:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Funding acquisition, Conceptualization. **Andrea Roventini:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Funding acquisition, Conceptualization.

Appendix A. Tables and figures

See Tables A.1–A.3.

Appendix B. The model

This appendix contains the full formal structure of the model as originally developed by Dosi et al. (2010, 2013, 2015), Lamperti et al. (2018). The description of the original model and those parts that have not been modified, heavily draws on the latter references.

We begin with the description of the technological search processes and the determination of production and prices in the *capital-good sector* and the equations related to the determination of production, investment, prices and profits in the *consumption-good sector*, as well as those related to the *public sector*.

B.1. The capital-good sector

The economy is characterized by two vertically-integrated sectors, a upstream capital-intensive sector that sells machines to a downstream sector which produces an homogeneous bundle of goods.

In this version of the model, upstream firms use labor and energy as an input of production. Innovation and imitation activities are undertaken to boost productivity, and to cut production costs; moreover, they are carried on by firms' investments in R&D, which are ultimately a share of past revenues.

The technology of the machines of vintage τ is captured by their labor productivity (LP) and energy efficiency (EE) it is represented by a set of coefficients $(A^l_{i,\tau}, B^l_{i,\tau})$, where $l = \{LP, EE\}$.

The coefficient $A^{LP}_{i,\tau}$ represents the productivity of the machinery in the consumption-good industry; $B^{LP}_{i,\tau}$ is the productivity of the process leading to the manufacturing of the capital good. Similarly, $A^{EE}_{i,\tau}$ and $B^{EE}_{i,\tau}$ characterize the level of energy efficiency in the production processes of both type of goods.

Upstream firms, subject to market selection forces, need to improve their technology in order to increase their productivity and to gain market power. They can do it by means of innovation and imitation, which are both costly. Following Dosi et al. (2010), both innovation and imitation are modeled in two steps. In the first, the dynamics of technical change randomly determines the success of both innovation and imitation processes: this is modeled by realization of Bernoulli-distributed random variables in which the level of R&D investments positively determine the probability that the innovation is successful. In particular:

$$\theta_i^{\mathcal{IP}_i} = 1 - e^{\zeta \mathcal{IP}_i} \tag{B.1}$$

where $\mathcal{IP}_i$ is the share of R&D expenses devoted to innovate or imitate ($\mathcal{IP}_i = \{Inn, Imm\}$) and ζ is a parameter that governs firms' search capabilities. In a second step, the size of the technological improvement is stochastically determined:

$$A^l_{i,\tau+1} = A_{i,\tau}(1 + \chi^l_{A,i}) \qquad l = \{LP, EE\} \tag{B.2}$$

$$B^l_{i,\tau+1} = B_{i,\tau}(1 + \chi^l_{B,i}) \qquad l = \{LP, EE\} \tag{B.3}$$

where $\chi_{A,i}$ and $\chi_{B,i}$ are i.i.d. realization of $Beta(\alpha,\beta)$ random variable with support given by the interval $[\underline{x}^l, \overline{x}^l]$, which characterize

Table A.1
Main empirical stylized facts replicated by the model.

Stylized facts	Empirical studies (among others)
Macroeconomic stylized facts	
SF1 Endogenous self-sustained growth	Burns and Mitchell (1946), Kuznets and Murphy (1966)
with persistent fluctuations	Zarnowitz (1985), Stock and Watson (1999)
SF2 Fat-tailed GDP growth-rate distribution	Fagiolo et al. (2008), Castaldi and Dosi (2009)
SF3 Recession duration exponentially distributed	Ausloos et al. (2004), Wright (2005)
SF4 Relative volatility of GDP, consumption, investments and debt	Stock and Watson (1999), Napoletano et al. (2006)
SF5 Cross-correlations of macro variables	Stock and Watson (1999), Napoletano et al. (2006)
SF6 Pro-cyclical aggregate R&D investment	Wälde and Woitek (2004)
SF7 Cross-correlations of credit-related variables	Lown and Morgan (2006), Leary (2009)
SF8 Cross-correlation between firm debt and loan losses	Foos et al. (2010)
SF9 Cross-correlation financial aggregates	Adrian et al. (2013), Jakab and Kumhof (2015)
Interbank network stylized facts	
SF10 Disassortativity	Soramäki et al. (2007), Cocco et al. (2009)
SF11 Centrality-bank size relation	Craig and von Peter (2014), Fricke and Lux (2015)
SF12 Heterogeneous interbank network density	Alves et al. (2013), Aldasoro and Alves (2018)
SF13 Large (small) banks are net borrowers (lenders)	Müller (2006), Liu et al. (2020)
Microeconomic stylized facts	
SF14 Firm (log) size distribution is right-skewed	Dosi (2005)
SF15 Fat-tailed firm growth-rate distribution	Bottazzi and Secchi (2003, 2006)
SF16 Productivity heterogeneity across firms	Bartelsman and Doms (2000), Dosi (2005)
SF17 Persistent productivity differential across firms	Bartelsman and Doms (2000), Dosi (2005)
SF18 Lumpy investment rates at firm-level	Doms et al. (1998)

Notes: The table reports the full list of stylized facts that our model is able to replicate. In *italics*, we highlight those that are relative to our version.

Table A.2
Main parameters and initial conditions in the economic system. For previous parametrization of some subportions of the model and for model sensitivity to key parameters see Dosi et al. (2010), Dosi et al. (2015), Lamperti et al. (2018) and Martinoli et al. (2024).

Description	Symbol	Value
Monte Carlo replications	MC	1000
Time sample in economic system	T	500
Transient period (time sample)	T	300
Number of firms in capital-good industry	F_1	60
Number of firms in consumption-good industry	F_2	300
Number of bank	B	20
Capital-good firms' mark-up	μ_1	0.04
Consumption-good firm initial mark-up	$\bar{\mu}_0$	0.17
Initial bank mark-up	μ_0^{deb}	0.05
Uniform distribution supports	$[\varphi_1, \varphi_2]$	[0.10, 0.90]
Wage setting $\Delta\bar{AB}$ weight	ψ_1	1
Wage setting Δcpi weight	ψ_2	0.05
Wage setting ΔU weight	ψ_3	0.05
R&D investment propensity (industrial)	ν	0.04
R&D allocation to innovative search	ξ	0.5
Firms' search capabilities parameter	ζ	0.3
R&D investment propensity (energy)	ξ_e	0.01
Beta distribution parameters (innovation)	(α, β)	(3, 3)
Beta distribution support (innovation)	$[\chi_1, \bar{\chi}_1]$	[−0.2, 0.2]
Desired inventories	l	0.1
Physical scrapping age (industrial)	η	20
Payback period (industrial)	b	3
Proxy of bank's capital adequacy (fixed by regulator)	τ^B	0.045
Markdown on bank deposits interest rate	md^{dep}	0.78
Markdown on central bank deposits interest rate	md^{res}	0.41
Markdown on interbank interest rate	md^{IB}	0.31
Markdown on government bonds	md^{bonds}	0
Recovery rate on interbank claims	ρ^{IB}	0
Average idiosyncratic shock to haircut	h_0	0.2
Sensitivity to inflation gap (Taylor rule)	γ_π	1.1
Sensitivity to unemployment gap (Taylor rule)	γ_U	1.1

the technological opportunity space (Dosi, 1988). If an upstream firm successfully innovate, close competitors can increase the chances of being imitators.

B.2. The consumption-good sector

Downstream firms manufacture a homogeneous bundle of goods by using machineries bought from upstream firms, with constant returns to scale. Workers consumption determines the level of demand to be satisfied and accordingly, firms adaptively update their production plans Q_j^d (also considering desired inventories (N_j^d) and the actual stock (N_j)) according to the expected level of demand $D_j^e = f[D_{j,t-1}, D_{j,t-2}, \dots, D_{j,t-h}]$:

$$Q_{j,t}^d = D_{j,t}^e + N_{j,t}^d - N_{j,t}, \tag{B.4}$$

where $N_j(t) = \iota D_j^e(t),\ \iota \in [0, 1]$.

The production levels of downstream firms are constrained by the level of their capital stock (K^d). Accordingly, if production plans require more capital, firms undertake expansionary investments, namely that increase their production capacity.

$$EI_{j,t}^d = K_{j,t}^d - K_{j,t}. \tag{B.5}$$

Firms also undertake investments aimed at replacing machineries that are become technologically obsolete in terms of productivity performances that is, for a given set of capital goods $\Xi_i(t)$, the vintage τ is substituted with a more productive one if

$$\frac{p^{new}}{c_{j,t}^{con} - c^{new}} = \frac{p^{new}}{\frac{w_t}{A_{i,\tau}^{LP}} + \frac{c_t^{en}}{A_{i,\tau}^{EE}} - c_j^{new}} \le b \tag{B.6}$$

with p^{new} and c^{new} being the price of the machinery and its unitary cost of production, respectively. The parameter b discounts firms' "patience" on the rate of return on investments.

The choice of the upstream supplier is determined by a price/productivity ratio of those vintages that the downstream firm can observe. Being characterized by the presence of systematic information asymmetries, the choice of the consumption-good firm canis restricted to a subset of upstream producers. Since the production of machineries requires some time, consumption-good firms first order the capital good that delivered at the end of the period. The price of each machine-tool has a mark-up on its cost.

When comes at how to finance their investments, consumption-good firms operate in imperfect credit markets (in the spirit of Stiglitz and Weiss (1981)). Internal finance has priority: if are not able to fully cover production and investment costs, they will rely on external finance, by borrowing funds from a bank in the form of a credit line. Given the total credit (exposure) of a bank, the latter lends out money to firms on a pecking-order, determined by the ratio between equity and sales (see Dosi et al., 2013). If the credit demanded by consumption-good firms exceeds its supply, firms are credit-rationed. Also in the downstream sector, firms charge a markup over the unit cost of production according to the following rule:

$$p_{j,t}^{con} = c_{j,t}^{con}[1 + \mu_{j,t}]. \tag{B.7}$$

The choice of the markup is determined by selection processes of the markets in which firms operate. In particular, it depends on the evolution firms' market share, f_j:

$$\mu_{j,t} = \mu_{j,t-1}\left[1 + \upsilon\frac{f_{j,t-1} - f_{j,t-2}}{f_{j,t-2}}\right] \tag{B.8}$$

with $0 \le \upsilon \le 1$.

Moreover, market shares evolution is governed by a "quasi replicator" mechanism: less competitive firms are driven out from the market as the level of their competitiveness decreases.

At the end of every period, all firms' profits (net of taxes) are computed and the level of cash reserves is updated. If the latter is

Table A.3
Macroeconomic effects of NEVA implementation under different capital requirement regimes.

		Macro-prudential policy parameter τ^B										
		2%	2.5%	3%	3.5%	4%	4.5%	5%	5.5%	6%	6.5%	7%
Loss contagion	BASE	−0.17	−0.162	−0.206**	−0.091	−0.134	**0**	−0.137	−0.165*	−0.146	−0.133	−0.023
	SEMI	−0.18*	−0.015	0.076	−0.091	−0.142	−0.168*	−0.132	−0.143	−0.139	−0.138	−0.094
	NEVA	−0.724***	−0.718***	−0.743***	−0.674***	−0.707***	−0.733***	−0.687***	−0.72***	−0.747***	−0.726***	−0.739***
	NEVA^2	−0.688***	−0.694***	−0.744***	−0.659***	−0.732***	−0.738***	−0.7***	−0.69***	−0.758***	−0.733***	−0.706***
Bank defaults	BASE	−0.222*	−0.216*	−0.254**	−0.12	−0.138	**0**	−0.142	−0.16	−0.141	−0.114	0.041
	SEMI	−0.154	0.023	0.144	−0.076	−0.112	−0.133	−0.064	−0.141	−0.096	−0.096	−0.008
	NEVA	−0.441***	−0.455***	−0.485***	−0.405***	−0.434***	−0.495***	−0.422***	−0.448***	−0.501***	−0.446***	−0.477***
	NEVA^2	−0.421***	−0.423***	−0.517***	−0.358***	−0.488***	−0.52***	−0.426***	−0.387***	−0.522***	−0.473***	−0.403***
Bailout costs	BASE	−0.24*	−0.211*	−0.237**	−0.114	−0.147	**0**	−0.153	−0.182	−0.158	−0.137	−0.001
	SEMI	−0.165	0.016	0.113	−0.082	−0.124	−0.151	−0.105	−0.171	−0.13	−0.134	−0.043
	NEVA	−0.407***	−0.394***	−0.446***	−0.34***	−0.396***	−0.431***	−0.356***	−0.41***	−0.455***	−0.389***	−0.43***
	NEVA^2	−0.367***	−0.357***	−0.464***	−0.298***	−0.431***	−0.461***	−0.376***	−0.346***	−0.469***	−0.424***	−0.374***
Credit Supply	BASE	0.029***	0.026***	0.036***	0.028***	0.016	**0**	0.014	0.009	−0.001	0.013	−0.014
	SEMI	0.016	0.015	0.003	0.01	0.02**	0.011	0.006	0.008	−0.004	0.008	−0.006
	NEVA	0.002	0.004	−0.001	−0.003	−0.013	0	−0.005	−0.015	−0.006	−0.023**	−0.027**
	NEVA^2	−0.001	−0.002	0.005	−0.005	−0.003	0.006	−0.012	−0.025**	−0.008	−0.024**	−0.05***
Total Loans	BASE	0.02***	0.022***	0.02***	0.016**	0.012*	**0**	0.008	0.002	−0.002	0.006	−0.019**
	SEMI	0.016**	0.01	−0.001	0.006	0.011	0.005	0	0.005	−0.011	−0.003	−0.013
	NEVA	−0.002	−0.003	−0.01	−0.014	−0.022**	−0.004	−0.016*	−0.023**	−0.023**	−0.035***	−0.043***
	NEVA^2	−0.007	−0.005	−0.003	−0.011	−0.014	−0.004	−0.023**	−0.03***	−0.02**	−0.035***	−0.063***
Credit Demand	BASE	0.011**	0.012**	0.012**	0.01**	0.007	**0**	0.008	0.004	0.001	0.006	−0.008
	SEMI	0.009	0.005	−0.003	0.003	0.008	0.004	0.003	0.005	−0.004	0.003	−0.002
	NEVA	0.002	0.005	0.001	0	−0.001	0.007	0.002	−0.001	0.001	−0.007	−0.009
	NEVA^2	0	0.002	0.006	0.001	0.002	0.007	−0.001	−0.004	0.001	−0.007	−0.017***
Fin. constraints	BASE	−0.055***	−0.06***	−0.046***	−0.038**	−0.025	**0**	−0.007	−0.002	0.007	0.001	0.055***
	SEMI	−0.044***	−0.027	−0.004	−0.021	−0.021	−0.012	0.008	−0.013	0.025	0.022	0.051**
	NEVA	−0.018	−0.007	0.003	0.003	0.029	−0.01	0.015	0.038*	0.043**	0.053**	0.073***
	NEVA^2	−0.003	−0.01	−0.014	−0.003	0.011	−0.011	0.026	0.055***	0.034*	0.052**	0.124***
GDP growth	BASE	0.01**	0.016***	0.011***	0.007*	0.008*	**0**	0.003	0	0.002	0	−0.01*
	SEMI	0.009**	0.007	0	0.005	0.005	0.002	−0.003	0.001	−0.006	−0.003	−0.008
	NEVA	0.003	0.001	0.001	−0.001	−0.005	0.004	−0.001	−0.009*	−0.009*	−0.013***	−0.015***
	NEVA^2	0.002	0.004	0.005	−0.001	−0.001	0.004	−0.004	−0.012**	−0.005	−0.014***	−0.024***
Investment growth	BASE	0.02**	0.034***	0.026***	0.016**	0.017**	**0**	0.006	0.004	0.005	0.001	−0.01
	SEMI	0.019**	0.016**	0.01	0.013*	0.012	0.009	−0.006	0.003	−0.009	−0.002	−0.013
	NEVA	0.006	0	0.003	−0.003	−0.013	0.003	−0.012	−0.015*	−0.015	−0.022**	−0.023**
	NEVA^2	0.008	0.003	0.003	−0.006	−0.014	0.003	−0.01	−0.027***	−0.012	−0.033***	−0.048***
Unemp. rate	BASE	−0.218***	−0.232***	−0.195***	−0.158**	−0.092	**0**	−0.042	−0.026	0.008	−0.023	0.195**
	SEMI	−0.171**	−0.08	0.005	−0.057	−0.088	−0.063	0.034	−0.046	0.098	0.05	0.158*
	NEVA	−0.125*	−0.078	−0.044	−0.042	0.048	−0.108	−0.014	0.06	0.067	0.092	0.188**
	NEVA^2	−0.054	−0.077	−0.109	−0.079	−0.023	−0.104	0.022	0.111	0.032	0.108	0.375***

Notes: The table shows, for a set of macroeconomic real and financial indicators, the Monte Carlo average percentage difference between the value of statistic X under the scenario of interest s and a baseline scenario *base*, $(X_s - X_{base})/X_{base}$. In order to have statistics comparable across different capital requirement regimes, a reference-baseline scenario is fixed at $\tau^B = 0.045$, i.e., the baseline parametrization in Section 4, centered around 0 by construction.
We also test whether the difference in means is statistically significant or not between the two scenarios. The null hypothesis is that there is no statistical difference in the means calculated in the two scenarios: *p<0.1; **p<0.05; ***p<0.01.

negative or market share goes to zero, a firm exits the market and it is replaced by a new entrant.

B.3. The energy industry

The model relies on an energy sector (Lamperti et al., 2018). Upstream and downstream sectors produce their goods also using energy as input, which is produced by a vertically-integrated monopolist owning power plants. Interactions and feedbacks stemming from the energy sector that performs R&D for green and dirty technologies are not relevant for the macro-financial dynamics. The only feedback mechanism that we embed is on the dynamics of unit cost of production of the two competitive sectors, as the latter use energy for manufacturing their products. For a more detailed discussion of the functioning of this sector we refer to section 2.2.1 of Lamperti et al. (2018).

B.4. The public sector

The public sector collects taxes on incomes (firm profits and wages) and when unemployment rises consumers are paid a subsidy, proportional to the current level of market wage. As in other versions of the model, wages are determined by institutional, market-related and macroeconomic factors. Accordingly, they ultimately depend on the inflation gap, average productivity, and unemployment rate, as follows:

$$\frac{\Delta w_t}{w_{t-1}} = \pi^T + \psi_1(\pi_{t-1} - \pi^T) + \psi_2 \frac{\Delta \overline{AB}_t}{\overline{AB}_{t-1}} - \psi_3 \frac{\Delta U_t}{U_{t-1}}, \tag{B.9}$$

where $\overline{AB}$ stands for the economy-wide average productivity and $\psi_1, \psi_2, \psi_3 > 0$. The sum of all unemployment subsidies adds up to the level of Government expenditures $G_t = w_t^u(L^S - L_t^D)$. Since workers consume all their income, aggregate consumption is determined by the sum of all incomes, both from employed and unemployed: $C_t = w_t L_t^D + G_t$.

The tax rate is fixed at tr. Public expenditures also comprises the bank bailout costs. Public deficit is calculated accordingly and it set to be equal to $Def_t = Debt_t^{cost} + G_t^{bailout} + G_t - Tax_t$. Whenever the deficit is positive, the Government issues bonds that are acquired by banks according to their size.

All the aggregate variables are then the result of microeconomic behavior and interaction. Since there are not intermediate goods, aggregate production is the sum of firms' value added. National accounting entities are also met: the value of total production corresponds to the sum of aggregate consumption, investment and change in inventories (ΔN_t):

$$\sum_{i=1}^{F_1} Q_{i,t} + \sum_{j=1}^{F_2} Q_{j,t} = Y_t = C_t + I_t + \Delta N_t$$

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