The financial network channel of monetary policy transmission: An agent-based model

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Abstract

The purpose of this paper is to explore the impact of monetary policy shocks on a financial network, which we dub the "financial network channel of monetary policy transmission". To this aim, we develop a agent-based model (ABM) in which banks extend loans to firms. The resulting bank-firm credit network is structured as determined by plausible behavioral assumptions, with both firms and banks being always willing to close a credit deal with the network partner perceived to be less risky. As our ABM succeeds in reproducing several key stylized facts of bank-firm credit networks, we then assess through simulations how exogenous shocks to the policy interest rate affect some key topological measures of the bank-firm credit network (density, assortativity, size of largest component, and degree distribution). Our simulations show that such topological features of the bank-firm credit network are significantly affected by shocks to the policy interest rate, with such an impact varying quantitatively and qualitatively with the sign, magnitude, and duration of the shocks.

Keywords: Financial network, monetary policy shocks, agent-based modeling.

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1 Introduction

The intrinsically 'robust-yet-fragile' nature of a financial network (FN) has been long recognized as a key feature requiring due and careful consideration when analyzing the dynamic stability of the economy. In fact, complex market interconnections among heterogeneous and uncoordinated agents acting in a decentralized way, by their very nature, inevitably perform as both shock-absorbers and shock-amplifiers (Chinazzi and Fagiolo (2015)). Throughout this paper, by the notion of financial interconnection we mean the existence of direct contractual financial obligations between agents, such as loans extended by banks to firms and debt obligations in the interbank market. Our focus, in this paper, is on the impact of shocks to the base interest rate that propagate through direct and indirect network linkages between economic agents – here, firms and banks.[1]

In an influential paper, Allen and Gale (2000) argue that the benefits of risk diversification generated by a more interconnected FN more than offset the perils of risk propagation. However, this view has been subject to various criticisms (e.g., Brusco and Castiglionesi (2007); Freixas et al. (2000)). The *coup de grâce*, so to speak, came with the 2007-2008 financial crisis, which has clearly (and costly) shown that a localized shock may spread to a large part of the economy through complex financial linkages. As a result, policymakers and academic researchers have become considerably more aware that the role played by network interconnectedness in the propagation of a localized shock should not be neglected. Nevertheless, the ways in (and more precisely yet the mechanisms through) which network interconnectedness affect the 'resilience-cum-fragility' of the economy as a complex adaptive system is understandably still an open issue.

Direct interconnections in a FN can lead to shock propagation through two main risk channels. The first one – the so-called *counterparty risk* – refers to the risk of creditors not recovering at least part of their investment in agents affected by a negative shock. This channel is present in many network-based models of financial contagion (e.g., Battiston et al. (2012); Bech and Garratt (2012); Gatti et al. (2010); Upper (2011)). The second one is the so-called *funding risk*. This channel affects debtors and can operate in two ways when agents hit by, say, a negative shock either refuse to roll-over short-term sources of funding, such as loans and repo lending (e.g., López-Espinosa et al. (2012)), or anticipate the liquidation of assets (e.g., Allen and Gale (2000)). Notice the inherent asymmetry involved in the operation of these channels: in the case of the counterparty risk, a creditor will not recover more than what was specified in the respective financial contract if the agent she had invested in is hit by a same-size but now positive shock; in the case of the funding risk, a debtor hit by a same-size but instead positive shock will not necessarily be willing or capable to either roll-over (or contract new) short-term sources of funding or anticipate the acquisition of assets.

An important question raised by many studies is what topological features of the financial net-

[1] There are other types of indirect interconnections that give rise to the operation of other mechanisms of shock propagation but are not our object of study here. For instance, when agents are interconnected through common asset exposures, shock propagation is engendered by fire sales (Acharya (2009)). We neglect these mechanisms for simplicity, in order to keep the model clearly understandable. Our choice can be justified by the fact that most of the existing literature even neglects bank-firm linkages, being restricted to the interbank market (Battiston et al. (2016)). For a thorough review on financial contagion mechanisms, see Riccetti (2019)

work are mostly related to its resilience to shock propagation and how such a relation works. Interconnectedness is often pointed as playing the most important role in determining the financial network resilience. However, there is a relative consensus on some points about this relationship: i) there are some topological features which are important predictors of the financial network resilience, such as the degree distribution and the assortativity, ii) it is not linear (e.g., it seems that shock transmission rather than shock absorption dominates at low levels of connectivity), and iii) it depends on other elements, as the size of the shock (Acemoglu et al. (2015)) (more on this in Section 4.1).

Network models have been largely used both in the measurement of systemic risk and the assessment of supervision and regulation policies intended to mitigate it. In effect, macroprudential policy tools have been usually employed for such purpose. Although monetary policy is primarily concerned with achieving and maintaining macroeconomic stability, its impact on financial stability has been extensively studied, especially after the 2007-2008 crisis (e.g., Alexandre and Lima (2017); Riccetti et al. (2013); Stein (2012)). But only a few financial network models have incorporated monetary policy issues to their analytical framework. In Georg (2013) and Bluhm et al. (2014), for instance, the central bank provides liquidity in the interbank market. Meanwhile, Silva et al. (2020) estimate both direct and indirect impacts of monetary policy shocks (as measured by changes in the policy interest rate) on the economy by applying a multi-layer network model to a unique Brazilian data set.

Yet policy-oriented network models of financial contagion typically assume that shocks propagate through an exogenously given network. In effect, little is known about how shock propagation affects the topology of a FN, although there is robust evidence that the topology of a FN is sensitive to economic or regulation policy. Halaj and Kok (2015) calibrated a model for a sample of eighty European banks and showed that the topology of the interbank network generated by the model can be affected by different types of regulation. For instance, when high exposure limits are lowered as a regulation policy, banks reduce the size of their exposure and increase the number of connections in the interbank market. Bluhm et al. (2014) found that liquidity provision increases banks' resilience to shocks, although it is detrimental to financial stability through two different but considerably interrelated channels: it encourages risk-taking behavior and increases interconnectedness, thus facilitating the propagation of shocks. Given that the topology of a FN plays a key role in the propagation of shocks through the financial and the real sides of the economy, which are themselves interrelated in a complex way, a proper assessment of how the manipulation of a policy instrument such as the interest rate impacts on systemic risk requires that the intermediating effects operating by means of topological features of the FN are duly considered. These intermediating effects constitute what we dub here the *financial network channel of monetary policy transmission*. Using an analogy with the Lucas critique (Lucas (1976)) originally applied to macroeconomic stabilization policy, it seems reasonable to conjecture that the topology of a FN, by virtue of it being to a great extent affected in a complex manner by the decentralized and uncoordinated decisions and actions of its heterogeneous participants, is highly unlikely, to be invariant to monetary policy shocks.

The purpose of this paper is in contributing to a further understanding of the working of the financial network channel of monetary policy. To this aim, we develop an agent-based model (ABM) in which banks extend loans to consumption-good firms. The bank-firm credit network is topologically structured as determined by plausible and realistic behavioral assumptions, with both firms and banks being always willing (but not always able) to close a credit deal with the network partner perceived to be less risky. Our ABM succeeds in reproducing a handful of key stylized facts of bipartite bank-firm credit networks documented in the related literature. We then assess through simulation how exogenous shocks to the policy interest rate affect some key topological measures of the bank-firm credit network (density, assortativity, size of largest component, and degree distribution). In particular, we will focus our novel simulation analyses on the timely issue of how positive and negative shocks to the base interest rate that vary in terms of magnitude and duration operate through the financial network channel of monetary policy to affect the above-mentioned topological features of the bank-firm credit network.

Our main results can be summarized as follows: i) a positive (negative) interest rate shock decreases (increases) the density of the network. Therefore, when the flow of credit between banks and firms increases as a result of a negative interest rate shock, there is the creation of new links rather than a more intense flow through the existing ones. On the other hand, a decrease in the flow of credit leads to the destruction of links. That is, the flow of credit increases/decreases mainly along the extensive margin (i.e., creation/destruction of links) rather than the intensive one (i.e., more/less intense flow in the existing links); ii) negative shocks make the financial network more disassortative, as the links created in this case are mostly between highly-connected agents and poorly-connected agents of the oppositive type. Similarly, the impact of positive shocks to the base interest rate is mostly to destroy the links between highly-connected agents and those with less connections of the opposite type, decreasing the disassortativity of the financial network; and iii) interest rate shocks have a long-term impact in the kurtosis of the degree distribution of both banks and firms. Temporary shocks lead to a decrease (in most of the cases) in the kurtosis of the degree distribution, suggesting an asymmetry in the impact of negative and positive shocks. On the other hand, permanent negative (positive) shocks decrease (increase) the kurtosis of banks' degree distribution. In the case of the firms, this relationship is the opposite. A possible explanation for these results is that a higher supply of credit, caused by a negative interest rate shock, takes the form of more banks supplying credit to the more credit-demanding firms.

Besides this introduction, the paper is organized as follows. Section 2 presents the structure of the model, while Section 3 reports and discusses several simulation results. In particular, this section shows that our model is able to reproduce some key stylized facts of the financial network studied in this paper. After discussing the relationship between network topology and resilience, Section 4 shows the impact of monetary policy shocks in key topological features of the bank-firm credit network. Finally, Section 5 offers concluding remarks.

2 Structure of the model

2.1 Firms: technology, wage costs and demand for bank credit

Many firms, indexed by $i = 1, \ldots, N^F$, the number of which remains constant, produce a homogenous consumption good using homogeneous labor as the only physical input. The production function faced by all firms is given by $y = \eta L$, where L is hired labor and $\eta > 0$ is the labor productivity parameter, which for simplicity is assumed to be exogenously given and constant due to the focus of this paper on the financial network channel of monetary policy instead of technological change. The supply of labor is perfectly elastic so that firms can hire as much available labor as they need and want by paying the current nominal wage w_t, which is uniform across firms. However, the nominal wage varies over time according to the following expression:

$$w_t = \begin{cases} w_{t-1} & \text{if } g_{t-2} \leq 0 \\ w_{t-1}(1 + adjwg_{t-1}) & \text{if } g_{t-2} > 0 \end{cases}, \tag{1}$$

where $g_{t-2} = (Y_{t-1}/Y_{t-3})^{0.5} - 1$, with $Y = \sum_i y$, denotes the average growth rate of the aggregate real output in the last two periods, and $adjw \sim U(\psi_w^{min}, \psi_w^{max})$, with ψ_w^{min} and ψ_w^{max} being exogenously given and constant. Therefore, when the growth rate of the real output is positive, the nominal wage increases by a random percentage of that growth rate. However, the growth rate of the nominal wage is limited to a maximum value equal to 2% in each period. Meanwhile, the formal specification in equation 1 implies that the nominal wage is rigid downward.

At each time period, firms have a desired stock of debt $B_{i,t}^*$ determined by the product between their net worth $NW_{i,t}$ and their target leverage $l_{i,t}^*$ (debt-to-net worth ratio). Therefore, the flow of demand for bank credit of each firm at t $B_{i,t}^F$ is equal to the difference between $B_{i,t}^*$ and the stock of debt of firm i in the previous period ($B_{i,t-1}^S$), being zero if this difference is negative:

$$B_{i,t}^F = max(0, l_{i,t}^* NW_{i,t} - B_{i,t-1}^S). \tag{2}$$

Firms' target leverage is defined by the following equation:

$$l_{i,t}^* = \begin{cases} l_{i,t-1}^*(1 + adjl) & \text{if } \pi_{i,t-1} > 0 \\ l_{i,t-1}^*(1 - adjl) & \text{if } \pi_{i,t-1} \leq 0 \end{cases}, \tag{3}$$

where $adjl \sim U(0, \psi_l^{max})$, with ψ_l^{max} being exogenously given and constant, and $\pi_{i,t}$ is the nominal profit of firm i at period t. The target leverage of each firm will never be greater than l^{max} or smaller than l^{min}, which are exogenously given and remain constant.

2.2 The bank-firm matching process

Once the demand for bank credit of each firm is determined, the matching process between firms and banks, where the latter are indexed by $j = 1, \dots, N^B$, takes place. The number of banks remains constant. Here we adopt two plausible assumptions. First, banks are more prone to lend to less leveraged firms. Although there are competing theories on banks' lending behavior, such as the relationship lending (Berger and Udell (2002); Elsas and Krahnen (1998); Sette and Gobbi (2015)), it is widely recognized that leverage is an important driver of corporate distress (Altman and Sabato (2013); Giordani et al. (2014); Traczynski (2017)). Moreover, banks may be willing to act as relationship lenders only if borrowers are sound (Banerjee et al. (2021)).

The second assumption is that firms in turn prefer to borrow from less leveraged banks. The rationale behind this assumption is the following: a high leverage level is risky for banks. Therefore, as far as their leverage increases, banks are willing to increase it further at a higher cost to the borrowers (see Eq. 5). The idea is to discourage new borrowers so that leverage is kept at a safe level. Alternatively, a bank with a small leverage is willing to close more credit deals, and will try to fulfill this goal by charging a lower interest rate.[2]Therefore, credit deals will be closed preferentially between less leveraged firms and banks.

In addition to setting the base interest rate in its role as monetary policymaker, the central bank also acts as a regulation authority by exogenously setting the maximum leverage ratio κ applicable to all banks, where $0 < \kappa < 1$. Additionally, each bank sets a capital buffer that is a function of $bda_{j,t-1}$, the non-performing loans-to-net worth ratio of the previous period (the concept of non-performing loans is properly explained in Section 2.4). Therefore, the amount of credit supplied by each bank cannot be greater than $NW_{j,t}/[\kappa(1+\alpha bda_{j,t-1})]$, where $NW_{j,t}$ is the net worth of bank j at period t and $\alpha > 0$ is an exogenously given and constant parameter. The maximum flow of credit of bank j at period t is set by:

$$B^{MAX}_{j,t} = max[NW_{j,t}/\kappa(1+\alpha bda_{j,t-1}) - B^S_{j,t-1}, 0]. \tag{4}$$

Thus, the flow in equation 4 is equal to the maximum credit supply minus the previous stock of loans $B^S_{j,t-1}$. Debt lasts for t_D periods, the value of which is exogenously given and constant, and is paid in periodic installments. Suppose a debt of value X is originated at period t. An amount equal to X/t_D should be paid back by the firm to the bank between $t+1$ and $t+t_D$. The interest to be paid at each period is computed on the residual amount.

As incumbent firms are deemed as less risky than the newly entrant ones, bank credit is granted only to the former. The incumbent firms with a positive demand for bank credit and the banks which are capable of supplying credit are sorted in ascending order according to their leverage. In this pattern

[2] A firm does not strategically and deliberately demand credit from a highly leveraged bank betting on the prospect that the bank is likely or about to go bankrupt, so that the respective debt will not have to be paid back in full. The reason is that the government is openly and credibly committed to bail out a bank if its net worth becomes negative, as described later.

of interaction, the less leveraged firm is prone to approach the less leveraged bank. However, with a small probability λ, which is exogenously and constant, it will choose a bank at random. The deal is closed only if the bank can supply at least a fraction equal to f^{min} of the bank credit demanded by the firm. This fraction f^{min} is an exogenously given constant. The value of the loan is the minimum between $B^{*}_{i,t}$ and $B^{MAX}_{j,t}$. Moreover, in order to ensure risk diversification, the bank never grants to a single firm a loan that is worth more than 25% of its net worth, as set by the Basel Committee on Banking Supervision (BCBS (2014)). If a bank is approached, it is removed from the list, even if a deal has not been closed. Thus, at each time step, a firm does not approach the same bank more than once. If this firm is still willing to borrow more funds, it approaches the next bank of the list with probability $1-\lambda$ and a random bank with probability λ. This process is repeated until the fulfillment of all demand for bank credit placed by firms or the exhaustion of the banks' available supply of credit.

The flow of funds lent by bank j to firm i at period t is represented by $B^{F}_{i,j,t}$. The stock of debt of firm i at period t, $B^{S}_{i,t}$, evolves according to the flow of loans and the debt payments made by the firm (interest plus periodic installments). The total loan of bank j, $B^{S}_{j,t}$, is updated in a similar fashion. The nominal interest rate charged by bank j on firm i, $i_{i,j,t}$, is set by applying a variable markup, $h_{i,j,t}$, on the base interest rate, $i^{B}(1+h_{i,j,t})$, where the base interest rate i^{B} is set exogenously by the central bank in its institutional role as monetary policymaker. Following Gatti et al. (2010), the banking markup is given by:

$$h_{i,j,t} = \beta[(l_{j,t})^{\gamma} + (l_{i,t})^{\gamma}]. \tag{5}$$

In the expression above, $l_{j,t}$ is bank j's leverage, $l_{i,t}$ is firm i's leverage, β is a parameter between 0 and 1, and γ is a positive risk premium parameter ranging from 0 to 1. These two parameters are exogenously given and constant. The relationship between the variable banking markup and the leverage as formally expressed in equation 5 implies that more leveraged firms and banks are perceived as less financially robust and hence riskier financial partners with whom to close a credit deal, as discussed earlier.

2.3 Firms: investment, production, profits, and net worth dynamics

At the beginning of each period, households invest in the firms the resources they saved for this purpose in the previous period. The total amount of the financial investment is I_t[3], and how this amount is determined is explained below. The fraction of the financial investment received by each firm is represented by:

$$I_{i,t} = I_t[(1-f_{RI})z_{i,t-1} + f_{RI}RI_{i,t-1}], \tag{6}$$

[3]We use the term "financial investment" to stress the difference with respect to the most common use of I as real investment. However, despite being a financial variable, this amount is used for real investment and production.

where $0 < f_{RI} < 1$ is an exogenously given and constant parameter and $RI_{i,t}$ is a random number, with $\sum_i RI_i = 1$. The variable $z_{i,t}$ is equal to $v_{i,t}/(\sum_i v_{i,t})$, where $v_{i,t} = 1/[1+exp(-\varepsilon op_{i,t})]$, with $\varepsilon \geq 1$ being an exogenously given and constant parameter. Therefore, a fraction f_{RI} of the total investment is shared randomly among firms. The remaining fraction is reasonably invested in each firm according to an increasing function of its operating profitability $op_{i,t} = (\pi_{i,t} + D_{i,t})/(NW_{i,t} + B^S_{i,t})$, which in turn is equal to the nominal profit without excluding the debt service $(\pi_{i,t} + D_{i,t})$ over total assets – net worth plus loans (see equation 13). The debt service $D_{i,t} = \sum_j \sum_t i_{i,j,t} B^F_{i,j,t}$ denotes the total amount of interest paid on the outstanding debt commitment of firm i.

After the interaction with banks in the credit market, as described in the preceding subsection, each firm will have its total capital, composed by its net worth plus loans. Recalling that the production function faced by all firms is given by $y = \eta L$, the real output production of an individual firm i at period t will be equal to:

$$y_{i,t} = (\eta/w_t)(NW_{i,t} + B^S_{i,t}). \tag{7}$$

Therefore, firms will spend their funds – net worth and debt – to hire labor and produce the consumption good according to a linear production function. The amount of labor hired by an individual firm i at period t is given by $L_{i,t} = (NW_{i,t} + B^S_{i,t})/w_t$.

The individual price of the consumption good $p_{i,t}$ is set by a firm i at period t by applying a variable markup, $\mu_{i,t}$, on the unit cost $\omega_{i,t}$, which is the sum of labor and debt service costs per unit of real output:

$$\omega_{i,t} = \frac{w_t L_{i,t} + D_{i,t}}{y_{i,t}}. \tag{8}$$

The variable markup applied by an individual firm follows a behavioral rule adapted from Dosi et al. (2013):

$$\mu_{i,t} = \mu_{i,t-1}\left(1 + \phi \frac{s_{i,t-1} - s_{i,t-2}}{s_{i,t-2}}\right), \tag{9}$$

where $0 < \phi < 1$ is an exogenously given and constant parameter and $s_{i,t}$ is firm i's market share at period t. The specification in equation 9 implies that firms that lost market share try to recover at least part of it through a reduction of their markup (as specified in equation 14 below).

The nominal aggregate demand, C_t, is represented by the following equation:

$$C_t = \rho_t(R^H_{t-1} + w_t L_t) - NWF_{t-1} + E_t. \tag{10}$$

The expression above represents the total resources that can be spent by the agents (households and government). The nominal aggregate demand includes two positive components: i) household consumption, which is equal to the household cash in hand, R^H_{t-1}, not spent in and hence accumulated from the previous period, plus the aggregate wage bill paid by the population of firms, $w_t L_t$, where $L_t = \sum_i L_{i,t}$, multiplied by the uniform propensity to consume ρ_t, which is endogenously time-varying, and ii) the government spending E_t. The amount given by $(1-\rho_t)(R^H_{t-1} + w_t L_t)$ is saved by households to be invested in the firms in the next period, as described earlier, thus corresponding to I_{t+1}. The uniform propensity to consume evolves over time according to the following expression:

$$\rho_{i,t} = \begin{cases} 0.95 - U(0, \psi_\rho) & \text{if } g_{t-2} > 0 \\ 0.95 + U(0, \psi_\rho) & \text{if } g_{t-2} \leq 0 \end{cases}, \tag{11}$$

where $0 < \psi_\rho < 0.05$ is an exogenously given and constant parameter. In our model, households are assumed to be "hand-to-mouth" (HtM) consumers, which explains their high marginal propensity to consume.[4] A positive output growth rate impacts positively on expected profits, so that households will be willing to consume less and invest more to receive more dividends, which add to their cash in hand. An opposite effect operates when the output growth rate is negative.

In equation 10, any positive net worth of new firms created in the previous period (NWF_{t-1}), up to the limit of 50% of households' previous funds ($R^H_{t-1} + w_t L_t$), will be subtracted from the nominal aggregate demand, in order to guarantee the stock-flow consistency of the model. Any possible amount of money still needed to finance the new entrants is included in the government spending (more on this in subsection 2.5). The nominal aggregate output can be equal to, smaller than or greater than C. In the latter case, as the consumption good is fully perishable, the amount of unsold output will not be accumulated as inventory by the respective firm(s) for the next period.

An exogenously given and constant fraction f_{RD} of the nominal aggregate demand is uniformly distributed among firms. This is mostly due to imperfect information on the part of households, as they do not know precisely which firm is charging the smallest price. The remaining nominal aggregate demand is distributed according to each firm's market share $s_{i,t}$, which is proportional to the firm's price competitiveness (as specified in equation 14 below). Therefore, the potential nominal revenue of an individual firm i is equal to:

$$S_{i,t} = C_t[(1 - f_{RD})s_{i,t} + f_{RD}u_{i,t}], \tag{12}$$

where $u_{i,t} = p_{i,t}y_{i,t} / \sum p_{i,t}y_{i,t}$. The nominal profit of an individual firm i is given by:

$$\pi_{i,t} = min(p_{i,t}y_{i,t}, S_{i,t}) - w_t L_{i,t} - D_{i,t}. \tag{13}$$

[4]HtM consumers allocate almost all, if not all, their current income to consumption due to unsophisticated behavior (of the non-optimizing or rule-of-thumb variety) or inability to trade in asset markets because of high transaction costs (Weil (1992)). There is robust empirical evidence that HtM consumers correspond to a large fraction of households in developed countries and have a high marginal propensity to consume even out of temporary income shocks (Attanasio et al. (2020); Kaplan et al. (2014)). Another feature of our model that further validates the assumption that households behave as HtM consumers, and which is in keeping with the evidence offered in Kaplan and Violante (2010), is that households do not have access to consumer credit.

Firms' nominal revenue cannot be greater than their nominal output. Their expenses include the wage bill and the debt service. The initial market share of an individual firm i is set as proportional to its net worth and evolves according to the following expression:

$$s_{i,t} = s_{i,t-1}\left(1+\theta\frac{p^M_{t-1}-p_{i,t-1}}{p^M_{t-1}}\right), \tag{14}$$

where $0 < \theta \leq 1$ is an exogenously given and constant parameter and p^M_t is the average price at period t. The individual market share has an upper bound equal to s^{max}, which is exogenously given and constant. Thus, firms setting a price below (above) the average price will increase (reduce) their market share.

Firms pay taxes and dividends on positive profits. Consequently, the net worth of an individual firm i evolves according to $NW_{i,t+1} = NW_{i,t} + (1-\delta-\tau)\pi_{i,t}$ if $\pi_{i,t} > 0$, or $NW_{i,t+1} = NW_{i,t} + \pi_{i,t}$ otherwise. The exogenously given and constant parameters δ and τ are strictly between 0 and 1 and correspond to the dividends rate and the tax rate, respectively.

In any given period, firms with a negative net worth go bankrupt and are expelled from the model. For simplicity, the number of firms is kept constant. The sum of the market share of bankrupt firms is randomly distributed among entrant firms, whose number is equal to that of bankrupted firms. The target leverage of entrant firms is set according to the uniform distribution $U(1.5,2)$. The net worth and markup of entrant firms are set according to the uniform distribution $U(0.9,1)M^I$, where M^I is the average value of the respective attribute of incumbent firms.

2.4 The banking system

The nominal profit of an individual bank j is given by:

$$\pi_{j,t} = D_{j,t} - NPL_{j,t}. \tag{15}$$

In the expression above, $D_{j,t} = \sum_i \sum_t i_{i,j,t} B^F_{i,j,t}$ is the receivable interest on the nominal stock of granted bank credit. The non-performing loans $NPL_{j,t}$ corresponds to the concept of bad debt presented in Gatti et al. (2007): $\sum_{i\in H} \chi_{j,i,t}(-NW_{i,t})$, where $\chi_{j,i,t} = B^S_{i,j,t}/B^S_{i,t}$ is the proportional credit granted by bank j to firm i at period t, and H corresponds to the set of expelled firms with negative net worth. Thus, if a firm fails due to it having a negative net worth, the correspondent loss $(-NW_{i,t})$ is distributed among the firm's creditors (the banks), proportionally to the loan granted by each bank to the firm.

Meanwhile, the net worth of an individual bank j evolves according to $NW_{j,t+1} = NW_{j,t} + (1-\tau)\pi_{j,t}$ if $\pi_{j,t} > 0$, or $NW_{j,t+1} = NW_{j,t} + \pi_{j,t}$ otherwise. In order to sharpen our focus on the impact of shocks to the base interest rate on the topology of the bank-firm network, we abstract from the possibility that banks on the brink of or already in bankruptcy can rely on an interbank market. However, also in keeping with the main focus of this paper, we assume that the government bails out the banks in trouble, covering any difference between the bank's net worth and its minimum level.[5]

2.5 The government

The fiscal balance of the government evolves according to:

$$\Gamma_{t+1} = \Gamma_t + \tau\left(\sum_{\pi>0}\pi_{i,t} + \sum_{\pi>0}\pi_{j,t}\right) - E_t - \sum_j BO_{j,t}. \tag{16}$$

The variable Γ_t represents the stock of resources (or debt, if negative) of the government in a given period. Government revenues are made up of the taxes collected from firms and banks with positive profits. In addition to disbursements with the bailing out of banks (see equation 15), government spending E_t has two components:

$$E_t = max\left[0, NWF_{t-1} - 0.5\left(R^H_{t-1} + W_t Lt\right)\right] + \zeta_t \sum p_{i,t} y_{i,t}. \tag{17}$$

Following Riccetti et al. (2015), the government plays a role in financing the new entrants. The net worth of new firms will be subtracted from households' funds (see equation 10), up to the limit of 50% of these funds. Any amount of money still needed to finance the new entrants will correspond to the first component of the government spending. Moreover, the government spends a value that is equal to a fraction ζ_t of the total nominal output, defined according to the following equation:

$$\zeta_t = \begin{cases} \zeta_{t-1}[1 - U(0, \psi_\zeta)] & \text{if } g_{t-2} > g^* \\ \zeta_{t-1}[1 + U(0, \psi_\zeta)] & \text{if } g_{t-2} \leq g^* \end{cases}, \tag{18}$$

where $g^* \geq 0$ is the growth rate target and $0 < \psi_\zeta < 1$ is an exogenously given and constant parameter. Therefore, the government adopts an anticyclical fiscal policy, spending a fraction of the total nominal output greater (smaller) than that of the previous period when the growth rate of aggregate output is below (above) its target. This fraction is never smaller than ζ^{min}, which is exogenously given and constant.

3 Simulations

In this section, we run 50 simulations of 3,000 periods of the baseline model. The time interval composed by the first 1000 periods is disregarded as the transient interval. The parameters and initial conditions specified for running the simulations are reported in the Appendix A.

[5] This minimum level is equal to the maximum between i) the net worth necessary to meet the maximum leverage ratio: $BO_{j,t} = max(0, \kappa B^S_{j,t} - NPL_{j,t})$, and ii) 5% of the firms' average net worth.

3.1 Time series

Table 1 provides statistics of the main series considering the 50 simulations of 3,000 periods. One can observe that the variables oscillate considerably around a long-run mean, and take values which are comparable to real time series and to those generated by other agent-based models (e.g., Riccetti et al. (2021)). The output growth rate, the inflation rate, and the non-performing loans oscillate more (with the coefficient of variation given by the standard deviation-to-mean ratio being above 0.25), and the other variables, less (with a coefficient of variation below 0.1). This oscillation seems to be mainly explained by the two countercyclical mechanisms at work in the system: the fiscal policy and the households' financial investment in firms. Regarding the operation of the fiscal policy, the government increases (decreases) its expenditures when the growth rate of the economy is below (above) its target, pushing up (down) aggregate demand. Concerning the second mechanism, the households increase their financial investment in firms when the growth rate of the economy is positive. However, this comes at the expense of a lower demand for consumption goods in the next period (equation 11). Thus, this causes a subsequent decrease in aggregate demand, pushing the economy down in the following periods. In the boom period, higher profits lead firms to revise upward their target leverage. The resulting growth of output and aggregate demand sustains the firms' satisfactory profitability. The non-performing loans are kept at a low level, enhancing the supply of credit by the banks. In the descending phase, firms reduce their markup in order to compete for market share. Firms' target leverage is brought down. Aggregate demand decreases, causing the non-performing loans to increase. As a consequence, banks reduce the supply of credit, thus accentuating the descending phase of the cycle.

Table 1: *Statistics of some variables considering 50 simulations.*

	Average	Standard dev. (simulations)[1]	Standard dev. (periods)[2]
Output growth rate	0.0299	0.0088	0.0088
Price variation	0.0239	0.0067	0.0067
Firms' leverage	0.9990	0.0344	0.0365
Banks' leverage	4.1420	0.2814	0.2934
Nominal credit[3]	0.4415	0.0079	0.0081
NPL[4]	1.7919	0.4527	0.4548
Public debt[3]	0.5424	0.0077	0.0080
Density	0.1629	0.0157	0.0157

1: Average over 50 standard deviation values computed for each simulation.

2: Average over 2,000 standard deviation values computed for each time period.

3: As a proportion of nominal output.

4: As % of total credit.

We applied the Hodrick-Prescott (HP) filter to two of our artificial series – real output and real consumption – in order to isolate the cyclical component. Figure 1 depicts the autocorrelation function (ACF) of the cyclical component of these variables. These results bear some similarities with those generated by other agent-based models (e.g., Alexandre and Lima (2017); Assenza et al. (2015)), as well as with real time series – e.g., the shape of the ACF and a high, positive first lag autocorrelation (e.g., Collard (1998)).

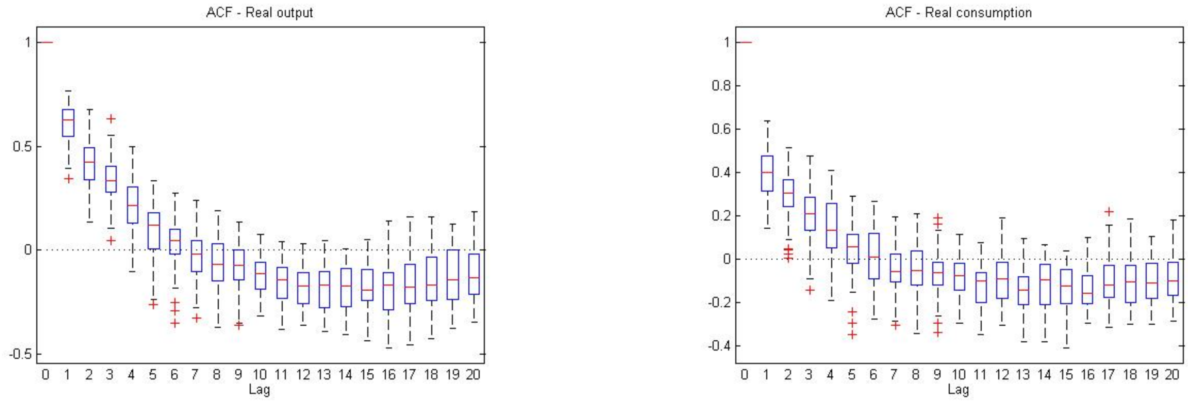

Figure 1: *ACF of the real output (left) and real consumption (right).*

3.2 Stylized facts of the bipartite bank-firm credit network

In this section, we show that the model is also able to reproduce a handful of key stylized facts of bipartite bank-firm credit networks reported in the related literature (Bottazzi et al. (2020); De Masi et al. (2011); De Masi and Gallegati (2012); Freund (2017); Luu and Lux (2019)):

- The degree distributions are fat-tailed.
- The bipartite bank-firm credit network is characterized by a disassortative behavior.
- The correlation between the size of the node and its degree is positive.

Figure 2 presents the empirical counter-cumulative distribution function (CCDF) of the degrees. In the top panel, we report the absolute number of links. In the bottom panel, we consider the sum of the weights of the links. This corresponds to the concept of strength presented in De Masi et al. (2011). For firms (banks), this is equal to the total amount borrowed (lent). One can clearly observe that the distributions are right-skewed, approximately fitted by a power law. Similar results have been reported in De Masi et al. (2011) using Japanese data, De Masi and Gallegati (2012) using Italian data, Miranda and Tabak (2013) using Brazilian data, Freund (2017) and Luu and Lux (2019) using Spanish data, Poledna et al. (2018) using Austrian data, and Bottazzi et al. (2020) using data from an international financial network. This finding implies that a few firms and banks have many connections, receiving (supplying) most of the credit, while most of them have few partners and negotiate a small proportion of the total credit.

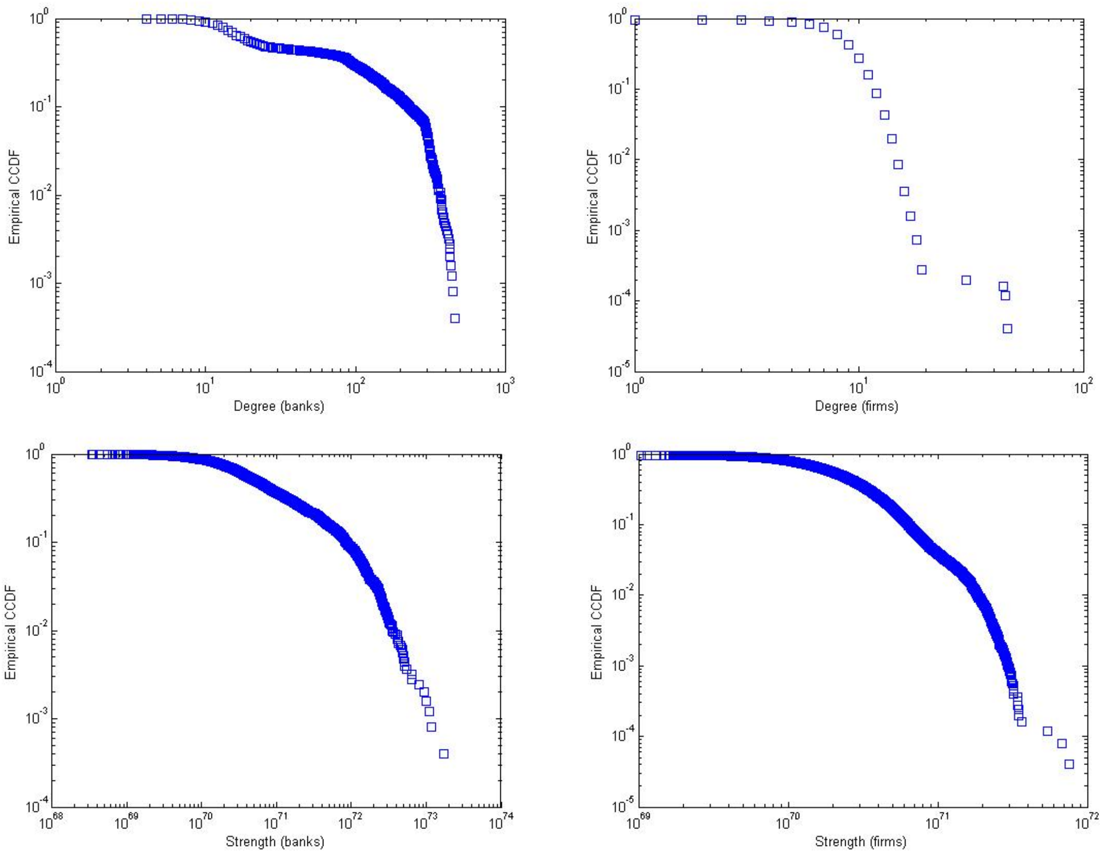

Figure 2: *Empirical CCDF of the degree (top) and node strength (bottom) in log-log scale. We considered the result of 50 simulations at period t=3,000 (25,000 firms and 2,500 banks).*

The disassortative behavior of the simulated bank-firm credit network is shown in Figure 3. Assortativity is the correlation between the node degree and the average degree of its direct neighbors. Despite oscillating considerably over time and across simulations, the assortativity is negative in most of the cases. This means that highly-connected nodes are more likely to connect with nodes of the opposite type (firm or bank) that have few connections. Empirical evidence on negative assortativity has been reported in Bottazzi et al. (2020) and Freund (2017).

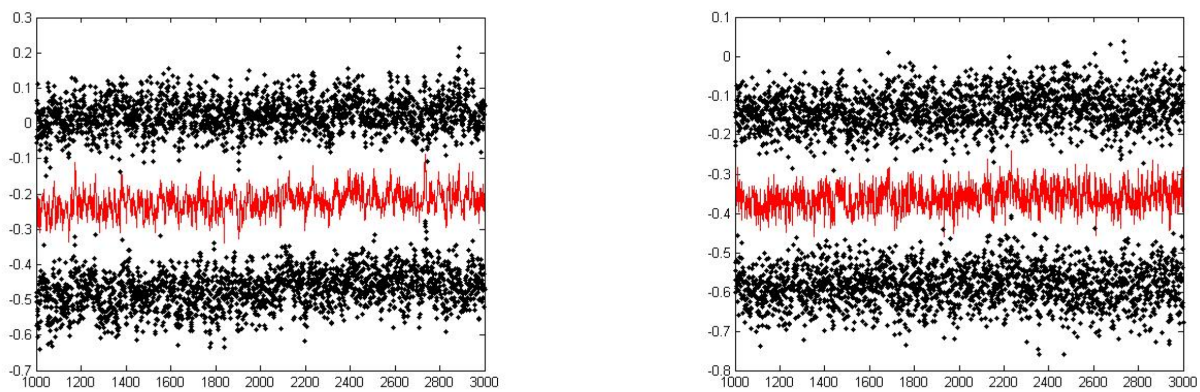

Figure 3: *Assortativity for banks (left) and firms (right). Red: median of 50 simulations. Dashed line above (below) the red line: median plus (minus) two median absolute deviations.*

The correlation between the size of the node (represented by its net worth) and its degree is positive (Figure 4 – top). The node size is also positively correlated to its strength (Figure 4 – bottom). Thus, large nodes tend to have more connections, as well as to lend (borrow) more resources in the case of banks (firms). This is in accordance with the empirical evidence provided in Bottazzi et al. (2020). Miranda and Tabak (2013) and De Masi and Gallegati (2012) reported a positive correlation between the size of the banks and their degree. However, the latter authors did not find a well-defined relationship between the firms' size and their degree.

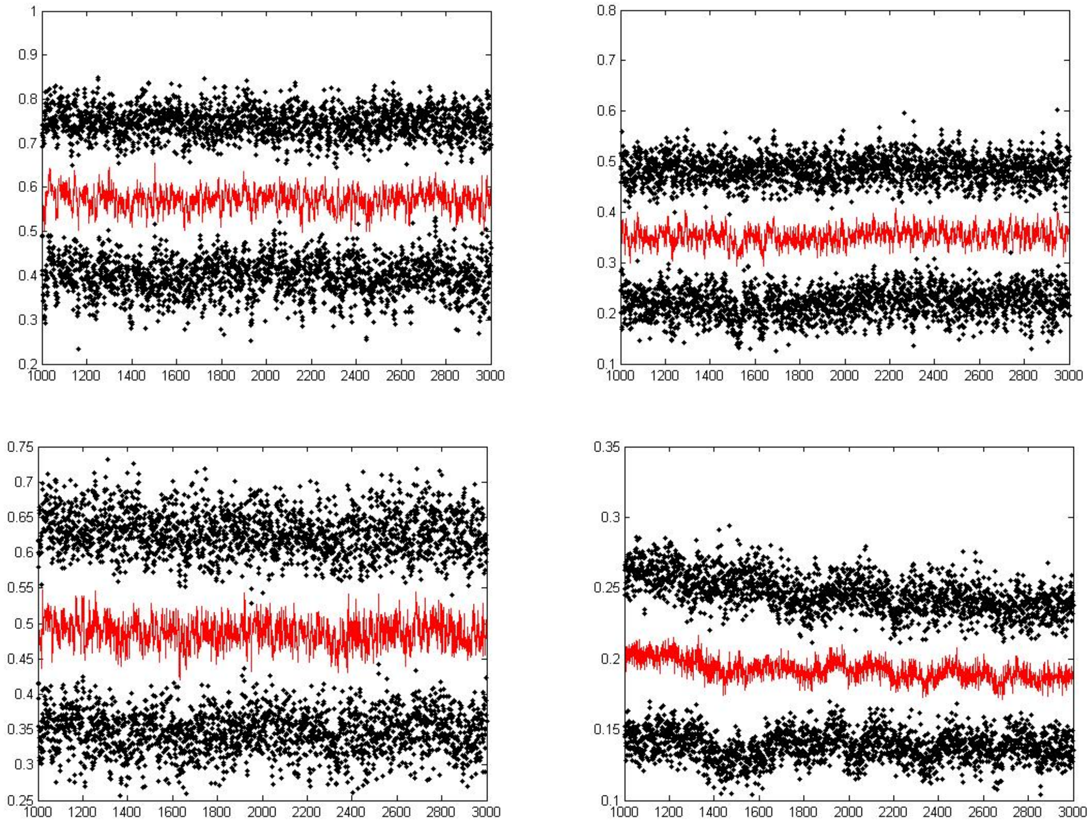

Figure 4: *Net worth-degree correlation (top) and net worth-strength correlation (bottom) of banks (left) and firms (right). Red: median of 50 simulations. Dashed line above (below) the red line: median plus (minus) two median absolute deviations.*

The degree also correlates positively with the strength, mainly in the case of the banks (Figure 5). As expected, nodes with more connections borrow/lend a larger amount of resources. Our simulations also nicely reproduce two empirical findings with respect to the degree-strength correlation reported in De Masi et al. (2011): i) it is positive, and ii) it is higher for banks than for firms. The largest component of the bank-firm credit network includes almost all nodes (Figure 6), as reported by the empirical study of Freund (2017) on the Spanish bank-firm network. This means that there are few isolated components in the network.

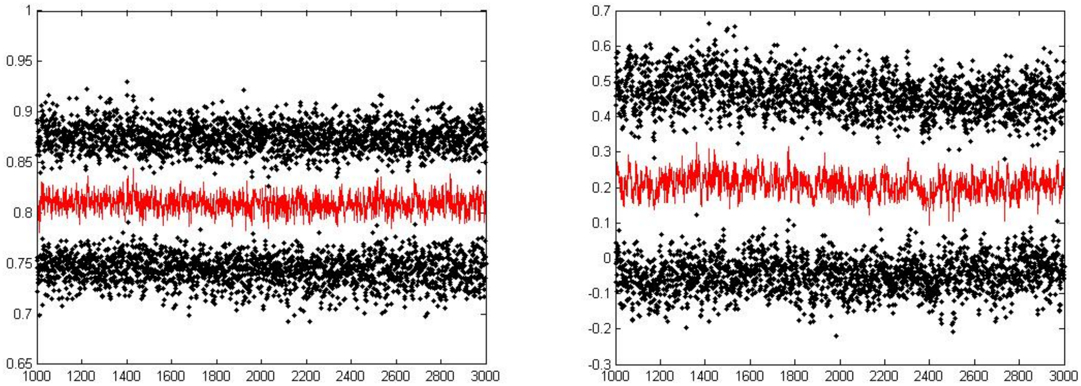

Figure 5: *Degree-strength correlation for banks (left) and firms (right). Red: median of 50 simulations. Dashed line above (below) the red line: median plus (minus) two median absolute deviations.*

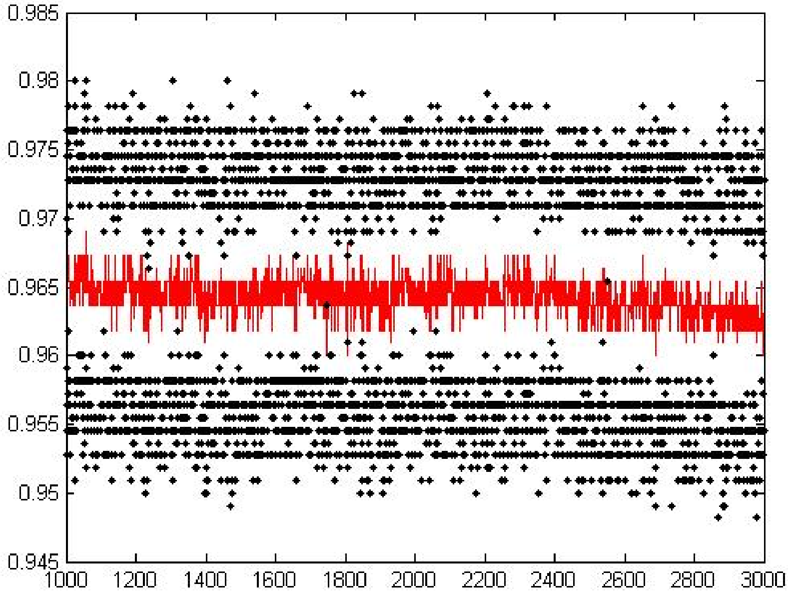

Figure 6: *Fraction of nodes in the largest component of the financial network. Red: median of 50 simulations. Dashed line above (below) the red line: median plus (minus) two median absolute deviations.*

4 The impact of shocks to the base interest rate on the financial network topology

In this section, we assess how interest rate shocks impact on the topology of the financial network. After carefully assessing which topological features of the financial network are important drivers of its resilience (Section 4.1), we investigate the effect of shocks to the base interest rate on these features (Section 4.2).

4.1 Network topology and resilience

Some features of a financial network are related to its resilience to shocks. Several studies have carefully investigated the relationship between network interconnectedness and systemic risk – that is, the potential damage to or even collapse of a non-negligible part of a system caused by a shock (even if a small one) in some of its components. It is relatively consensual in the related literature that this relationship, by its very nature, is non-linear in the degree of interconnectedness. Some studies (e.g., Gai and Kapadia (2010); Haldane and May (2011); Nier et al. (2007)) point out that shock transmission dominates at low connectivity levels. However, once a certain threshold is crossed, shock absorption dominates, and higher interconnectedness is beneficial for the resilience of a highly networked system like the economy. Working on two different dimensions of network interconnectedness, Elliott et al. (2014) argue that higher integration (greater dependence on counterparties) decreases the probability of an initial failure but leads to a higher probability of contagion once this initial failure has occurred. Meanwhile, increasing diversification (more counterparties per organization) initially promotes contagion, but when a certain threshold is crossed, it protects organizations against each other's failures.

Another point largely accepted in the literature is that network interconnectedness alone is intuitively a poor predictor of systemic risk. In effect, the nature and magnitude of the impact of interconnections on shock propagation, shock absorption, and systemic risk does depend on other topological features of a financial network. It is intuitive that interconnectedness itself is highly connected in complex ways to other salient topological features of a financial network. Several empirical studies focus on degree heterogeneity. For instance, Amini et al. (2016) found through numerical simulations that heterogeneity in degree distribution negatively affects the resilience of a network, which explains why scale-free networks tend to be more fragile than random networks. Caccioli et al. (2012) point out that contagion is less likely in scale-free networks when attacks are random, but that such type of network is more fragile when attacks are targeted to high-degree banks. Roukny et al. (2013) argue that the optimal network structure depends on the underlying market conditions. For instance, scale-free networks are the most fragile when markets are illiquid. Georg (2013) finds that, while in normal times different network topologies have a similar performance regarding systemic risk, the network topology becomes quite important in times of crisis. In these circumstances, contagion seems to be stronger in random networks, whereas scale-free networks are more resilient.

Acemoglu et al. (2015) assessed three types of networks: a complete graph, a cycle graph (ring), and a γ-convex combination of the two (the highest the value of parameter γ, the closest is the graph to the cycle network). They concluded the following: (i) for small shocks, the cycle (complete) graph is the least (most) resilient; moreover, the system becomes less stable as γ increases; and (ii) for large shocks, the effect is non-linear: the cycle and complete graphs are the least stable structures, while the system is more resilient for intermediate values of γ.

Meanwhile, Loepfe et al. (2013) explored the impact of topological features other than degree heterogeneity on the resilience of a FN. In a thorough study combining both analytical models and empirical data, the authors assessed the role of the topology of the FN in affecting systemic risk. They found a transition from safe to risky regimes, with the critical range of which being located at a low level of link density and high levels of modularity and size heterogeneity. These authors also showed that degree heterogeneity increases vulnerability only when shocks are targeted to high-connected firms. Besides, the removal of links with the highest centrality betweenness can significantly increase the stability of the system.

Assortativity is also pointed as strongly related to the financial network resilience. Computational simulations performed by D'Agostino et al. (2012) show that assortativity has an ambiguous effect on network resilience. On the one hand, distress propagates more easily in assortative (i.e., with positive assortativity) networks. However, assortativity was found to enhance the effectiveness of a targeted immunization policy. Hurd et al. (2017) developed a measure which is a combination of edge- and node-assortativity, the *graph-assortativity*. This measure proved to be a better predictor of systemic vulnerability than the usual edge-assortativity measure. The study of Ramadiah et al. (2019) points out that, in an assortative structure, the network is more resilient when different blocks are scarcely connected. However, a disassortative network is more resilient when the structure moves away from a pure bipartite one. Assessing data taken from the Italian electronic broker market e-MID, Krause et al. (2021) did not find a correlation between assortativity and systemic risk. However, the authors found that the scalar assortativity measure with respect to the interbank leverage is positively correlated to the systemic risk level. That is, the systemic risk is intuitively higher when risky (i.e., highly leveraged) banks interacts mostly with other risky banks.

4.2 The impact of base interest rate shocks on the topological features of the financial network

As discussed in the preceding subsection, some of the topological features mostly related to shock propagation in financial networks are interconnectedness, assortativity, and degree distribution. In network models of systemic risk, the topology of the financial network is assumed to be exogenous. However, an interesting question is the following: what if the occurrence of the shock and its propagation impact on the topology of the financial network? In other words, is it possible that the topology of the financial network and the shock propagation mutually influence and affect each other? In this subsection, we investigate this issue by assessing how shocks to the base interest rate impact on the aforementioned topological features. As the largest component can reasonably be considered an important determinant of the financial network resilience, we include this measure among the topological features the impact on which will be assessed.[6]

We proceed as follows: at period $t = 1500$, we impose a shock of magnitude s on the base interest rate. This shock will last for D periods. Thus, during periods from 1501 to 1500+D, the base interest rate will be equal to $i^B(1+s)$. We considered two values of s (0.1 and 0.2) of both signs

[6]In general, the resilience or robustness of a network is related to the ability of its nodes to communicate being unaffected even by unrealistically high failure rates. In our case, it refers to the ability of firms (banks) to borrow from (extend loans to) banks (firms). In fragmented networks, in which the fraction of nodes belonging to the largest cluster is small, the removal of a link will create isolated nodes with a higher probability. For more details, see, for instance, Albert et al. (2000).

(positive and negative), and four values of D (50, 100, 200, and 1500). Note that in the latter case the considered shock can be interpreted as becoming permanent as far as the length of time of the model is concerned, in that it lasts for all the remaining periods of the whole set of 3,000 simulated periods.

A positive shock on the base interest rate increases the dispersion of the loan interest rates – as measured by the coefficient of variation – charged by the banks, while a negative shock engenders the opposite effect. This impact is observed when both all stock of loans (Figure 7 – left panel) and only new loans (Figure 7 – right panel) are considered. This result goes in hand with the literature on the interest rate pass-through (e.g., Cottarelli and Kourelis (1994); De Bondt (2002); Hofmann and Mizen (2004)). It is important to notice that, in the case of the interest rate pass-through when all the stock of loans is considered, a shock of any sign increases for a few periods the variation of the loan interest rates.

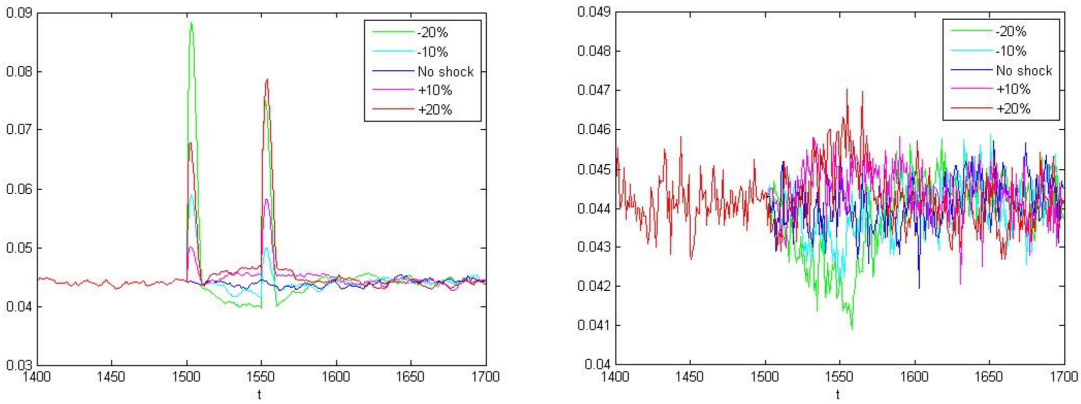

Figure 7: *Impact of the interest rate shock on the coefficient of variation of the loan interest rates considering all loans (left) and only new loans (right). The computation considers 2,500 values (50 banks times 50 simulations) in each period. Shocks last for 50 periods.*

Figure 8 displays the impact of the base interest rate shocks on the density. A positive interest rate shock decreases the density of the network, while a negative shock has the opposite effect. In the case of a permanent shock, this initial impact dissipates slowly, mainly for negative shocks. As expected, an increase (decrease) in the base interest rate decrease (increase) the leverage of both firms and banks (Figure 9). Hence, an increase in the flow of credit between banks and firms resulting from a fall in the base interest rate results in the creation of new links. Alternatively, a decrease in the flow of credit results in the destruction of links.

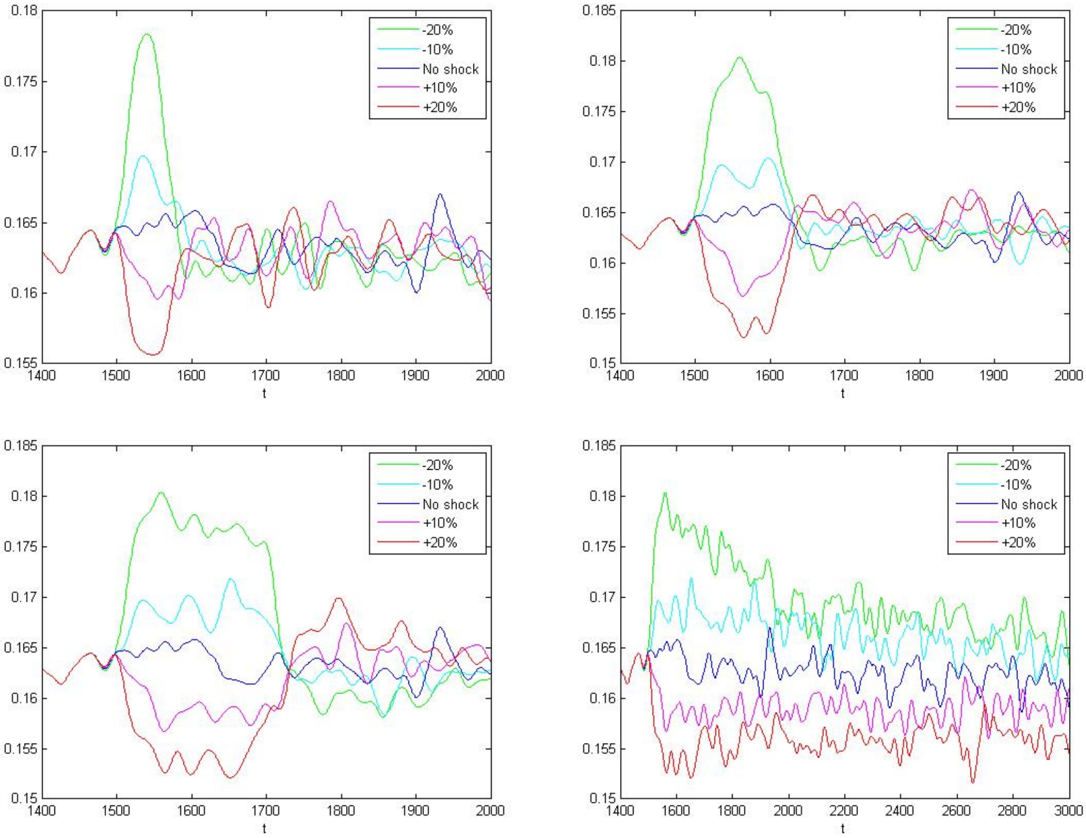

Figure 8: *Impact of the interest rate shock on the financial network density. Average of 50 simulations. Shocks last for 50 (top, left), 100 (top, right), 200 (bottom, left), and 1,500 (bottom right) periods. For the sake of a better visualization of the trend component, the series were smoothed using the HP filter.*

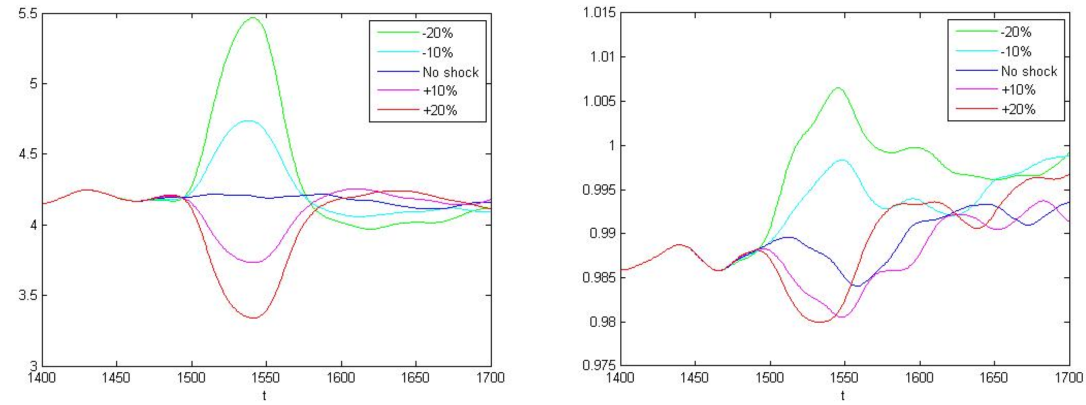

Figure 9: *Impact of the interest rate shock on the leverage of banks (left) and firms (right). Average of 50 simulations. Shocks start at period t=1500 and last for 50 periods. For the sake of a better visualization of the trend component, the series were smoothed applying the HP filter.*

Another interesting effect that can be observed is overshooting, mainly in the case of shocks of higher magnitude. For instance, a positive shock of 20% with duration equal to 200 periods causes a decrease in the density. When the shock ceases – that is, when the base interest rate comes back to its original value – at period 1700, the density starts to increase again. However, before returning to a value close to that of the no shock case, it reaches a value well above this one (approximately at period 1800) and then begins to move down again.

In order to further understand the relationship between the density of the network and the leverage measure, we decomposed the average leverage $l^M_{F,B}$ (where F and B stands, respectively, for firms and banks) into two components: the average degree $k^M_{F,B}$ – i.e., the average number of partners of the opposite type – multiplied by $(l^M_{F,B})/(k^M_{F,B})$, the average flow of credit (as a fraction of the net worth) granted to (in the case of banks) or received by (in the case of firms) each partner. Then, we evaluated how shocks on the base interest rate affect each element of that decomposition.

The results are presented in Figures 10 and 11. A positive (negative) interest rate shock decreases (increases) both the average degree (Figure 10, left) and the average leverage-to-degree ratio (Figure 11, left) for the set of banks. Thus, the resulting changes along the extensive margin (measured by the average degree) and along the intensive margin (measured by the average flow of credit) occur in the same direction. However, for the firms, a positive interest rate shock decreases the average degree (Figure 10, right), but increases the average leverage-to-degree ratio (Figure 11, right). Therefore, the reduction in the average number of partners (that is, the reduction along the extensive margin) is accompanied by an increase in the average flow of credit across the remaining partners (that is, an increase along the intensive margin). Meanwhile, with a negative interest rate shock the average degree increases but the average leverage-to-degree ratio decreases, so that the rise in the average number of partners is accompanied by a decrease in the average flow of credit across the remaining partners.

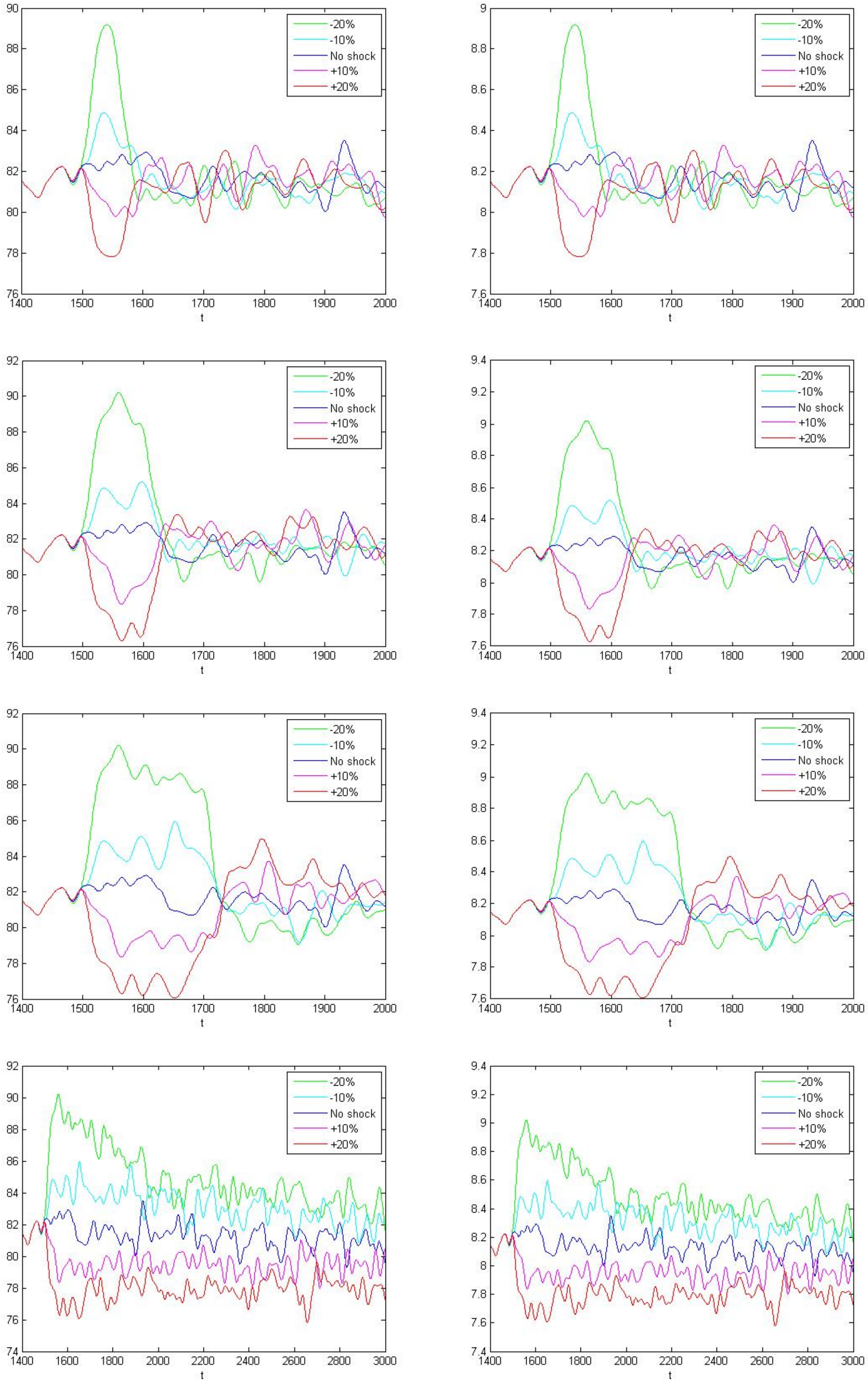

Figure 10: *Impact of the interest rate shock on the average degree of banks (left) and firms (right). Average of 50 simulations. Shocks last for 50 (top), 100 (2^{nd} row), 200 (3^{rd} row), and 1,500 (bottom) periods. For the sake of a better visualization of the trend component, the series were smoothed using the HP filter.*

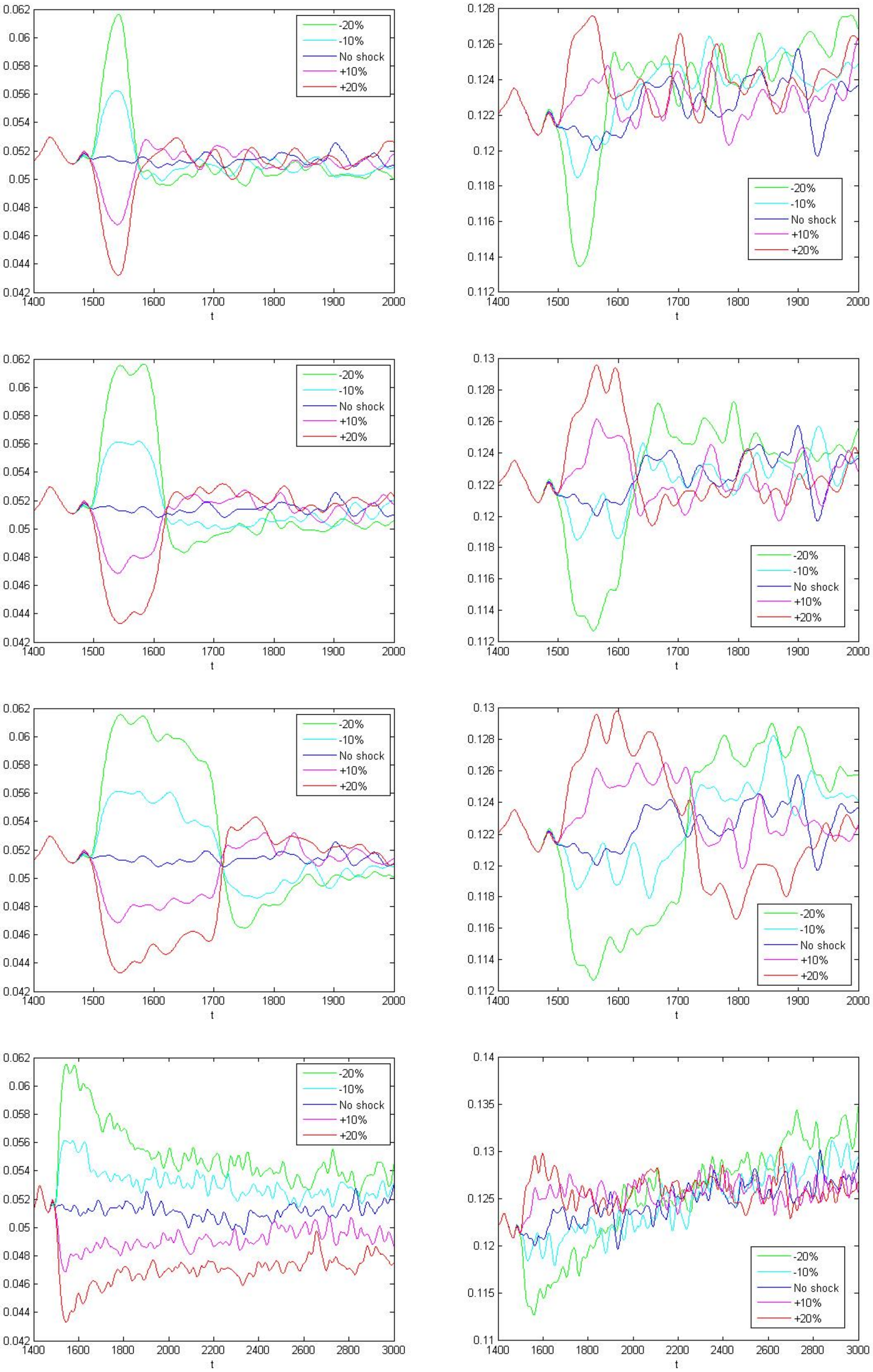

Figure 11: *: Impact of the interest rate shock on the average leverage-to-degree ratio of banks (left) and firms (right). Average of 50 simulations. Shocks last for 50 (top), 100 (2nd row), 200 (3rd row), and 1,500 (bottom) periods. For the sake of a better visualization of the trend component, the series were smoothed using the HP filter.*

Table 2 shows the difference between the average density when there is a shock in the base interest rate and when there is not. We computed this difference for two range of periods: during the duration of the shock and between periods 2500-3000, in order to observe any long-run effect. Non-negligeable long-run effects are caused only by permanent shocks. However, the impact of a permanent interest rate shock on the financial network density seems to feature a decreasing trend over time. After some time, the density seems to start to come back to its original value. Consider, for instance, the impact of a permanent negative shock of 20% starting at period $t = 1500$. Between periods 1500 and 1600, the average density is 7% above its original value. However, between periods 2500 and 3000, this value drops to less than half (3.2%).

Table 2: *Difference between the average density when there is an interest rate shock and when there is not (in %). Period P corresponds to that in which the shock starts, thus P=1500. *: significant at the 10% level. **: significant at the 5% level. ***: significant at the 1% level.*

s	D=50		D=100		D=200		D=1500
	P+1-P+D	2500-3000	P+1-P+D	2500-3000	P+1-P+D	2500-3000	2500-3000
-0.2	5.78***	-0.01	6.99***	-0.41***	7.61***	-0.33***	3.15***
-0.1	1.88***	0.22**	2.01***	0.09	2.81***	0.04	1.70***
0.1	-1.67***	-0.33	-3.00***	-0.09	-2.84***	-0.02	-1.78***
0.2	-4.00***	0.42***	-5.53***	0.25***	-5.48***	0.25***	-3.59***

In Table 3, we present the elasticity of density with respect to the base interest rate. For a shock of size s, we computed the elasticity as follows:

$$\xi = \frac{dens^M_{1501-1500+D} - dens^M_{1000-1500}}{s.dens^M_{1000-1500}}, \tag{19}$$

where $dens^M_{a-b}$ is the average density between periods a and b (recalling that D is the duration of the shock). One can observe that density is inelastic to the base interest rate, i.e., a 1% variation in the base interest rate leads to an absolute variation of the density smaller than 1%. The elasticity is not uniform and depends on both s and D. The absolute elasticity increases with D. For negative shocks, the highest absolute elasticity is observed at the highest absolute value of s; for positive shocks, the opposite happens (except for $D = 200$). As also observed in Table 2, the effect of positive and negative shocks of the same magnitude is asymmetric. In general, the absolute elasticity is higher for negative shocks.

Table 3: *Elasticity of the density of the financial network with respect to the base interest rate.*

s	D=50	D=100	D=200
-0.2	-0.3199	-0.3868	-0.3893
-0.1	-0.2474	-0.2724	-0.2974
0.1	-0.1101	-0.2317	-0.2678
0.2	-0.1721	-0.2433	-0.2661

In Figures 12 and 13, we present the impact of shocks to the base interest rate on the assortativity of banks and firms, respectively. It can be seen that the shocks are positively correlated to the assortativity in both cases. As the average assortativity is negative, a positive (negative) shock decreases (increases) its absolute value. The links created by negative shocks are mostly between highly-connected agents and poorly-connected agents of the oppositive type, making the network more disassortative. Similarly, positive shocks to the base interest rate tend to decrease the disassortativity of the financial network, mostly destroying the links between highly-connected agents and those with less connections of the opposite type.

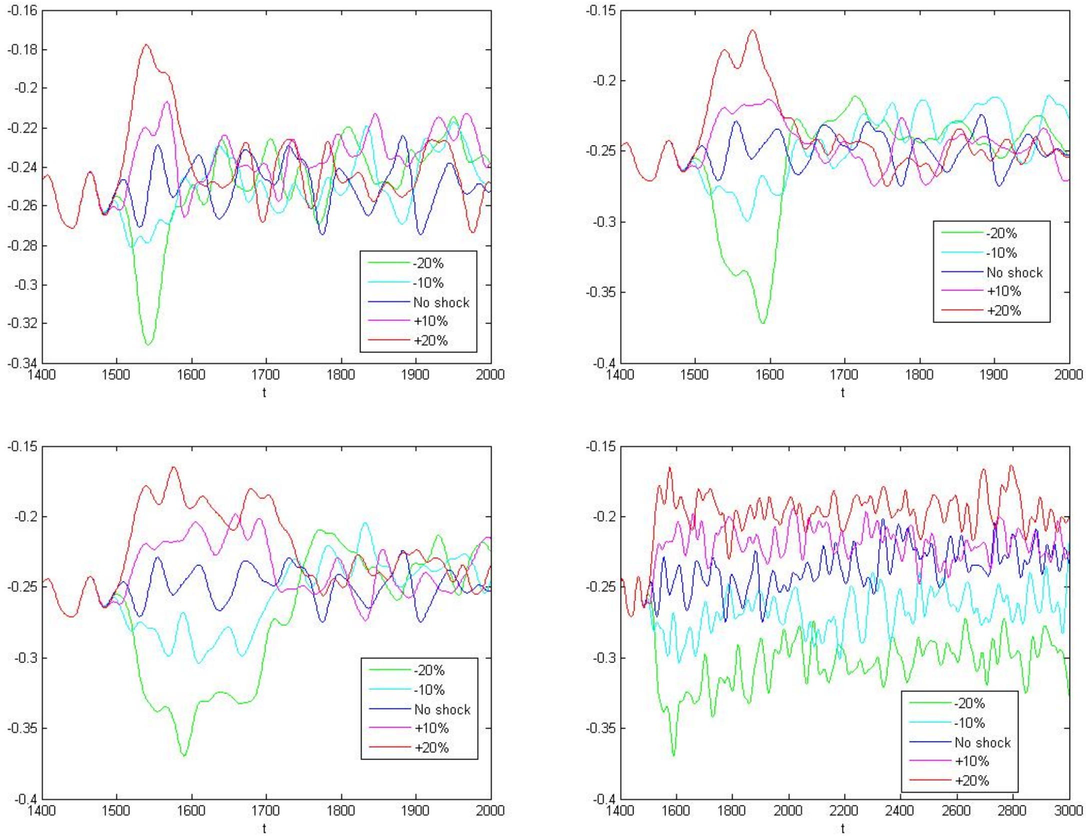

Figure 12: *Impact of the interest rate shock on the banks' assortativity. Average of 50 simulations. Shocks last for 50 (top, left), 100 (top, right), 200 (bottom, left), and 1,500 (bottom right) periods. For the sake of a better visualization of the trend component, the series were smoothed using the HP filter.*

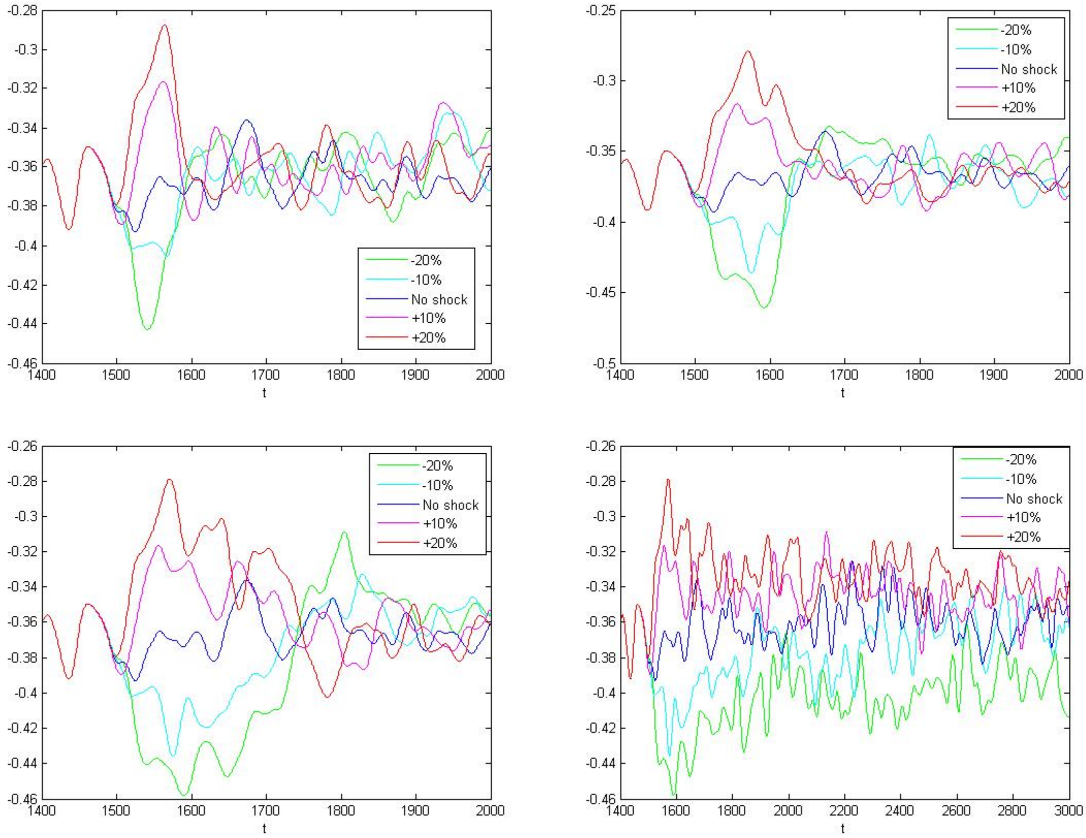

Figure 13: *Impact of the interest rate shock on the firms' assortativity. Average of 50 simulations. Shocks last for 50 (top, left), 100 (top, right), 200 (bottom, left), and 1,500 (bottom right) periods. For the sake of a better visualization of the trend component, the series were smoothed using the HP filter.*

Tables 4 and 5 corroborate the results presented in Figures 12 and 13. Positive shocks to the base interest rate decrease the absolute value of assortativity and negative shocks have the opposite effect. In general, the impact of base interest rate shocks is higher in banks' assortativity than in firms' assortativity. In some cases, there are significant long-run effects of temporary shocks (e.g., the long-run impact of a shock of magnitude -0.2 and duration 200 on banks' assortativity) and non-decreasing effects of permanent shocks (e.g., the impact of permanent negative shocks on banks' assortativity). The higher impact of shocks to the base interest rate on banks' assortativity is confirmed through the computation of the respective elasticities (Tables 6 and 7).

Table 4: *Difference between the average banks' assortativity when there is an interest rate shock and when there is not (in %). Period P corresponds to that in which the shock starts, thus P=1500. *: significant at the 10% level. **: significant at the 5% level. ***: significant at the 1% level.*

s	D=50		D=100		D=200		D=1500
	P+1-P+D	2500-3000	P+1-P+D	2500-3000	P+1-P+D	2500-3000	2500-3000
-0.2	14.8***	-0.39	29.1***	-3.71***	30.8***	4.42***	29.4***
-0.1	7.68***	-0.97	11.7***	-4.14***	14.5***	0.52	13.6***
0.1	-6.98***	-3.81***	-8.89***	2.68***	-11.8***	-1.13	-3.03***
0.2	-20.4***	-0.68	-22.6***	0.30	-21.9***	0.67	-15.1***

*Table 5: Difference between the average firms' assortativity when there is an interest rate shock and when there is not (in %). Period P corresponds to that in which the shock starts, thus P=1500. *: significant at the 10% level. **: significant at the 5% level. ***: significant at the 1% level.*

s	D=50		D=100		D=200		D=1500
	P+1-P+D	2500-3000	P+1-P+D	2500-3000	P+1-P+D	2500-3000	2500-3000
-0.2	7.92***	-3.01***	14.46***	-0.97**	16.9***	-1.44***	8.53***
-0.1	3.04***	-1.47***	7.46***	-1.45***	10.1***	-1.78***	-0.07
0.1	-5.99***	-1.66***	-9.17***	-0.98**	-6.98***	-1.01**	-4.20***
0.2	-12.5***	1.32***	-15.7***	-1.76***	-13.4***	-0.55	-6.57***

Table 6: Elasticity of the banks' assortativity with respect to the base interest rate.

s	D=50	D=100	D=200
-0.2	-0.7106	-1.2551	-1.2954
-0.1	-0.7086	-0.8253	-1.0210
0.1	-0.7492	-1.1687	-1.5124
0.2	-1.0394	-1.2471	-1.2404

Table 7: Elasticity of the firms' assortativity with respect to the base interest rate.

s	D=50	D=100	D=200
-0.2	-0.5794	-0.8101	-0.8006
-0.1	-0.6550	-0.9096	-0.9302
0.1	-0.2795	-0.7787	-0.7655
0.2	-0.4785	-0.7227	-0.7017

The resilience of the financial network, as measured by its largest component, is negatively related to the magnitude of the interest rate shock (Figure 14). A positive interest rate shock destroys some links, creating more isolated components in the financial network. However, this impact is very small (Table 8). The elasticity is always smaller than 3% and larger for smaller changes in absolute value, probably because in this case the denominator is smaller (Table 9). It is worth noting that a permanent interest rate shock seems to have an increasing impact on the largest component. Consider, for instance, the impact of a permanent interest rate shock of –20% on the largest component. Between periods 1501 and 1550, the average largest component will be 0.21% above the value of the no interest rate shock case. This value increases through the length of time of the simulation, reaching 1.06% between periods 2500-3000.

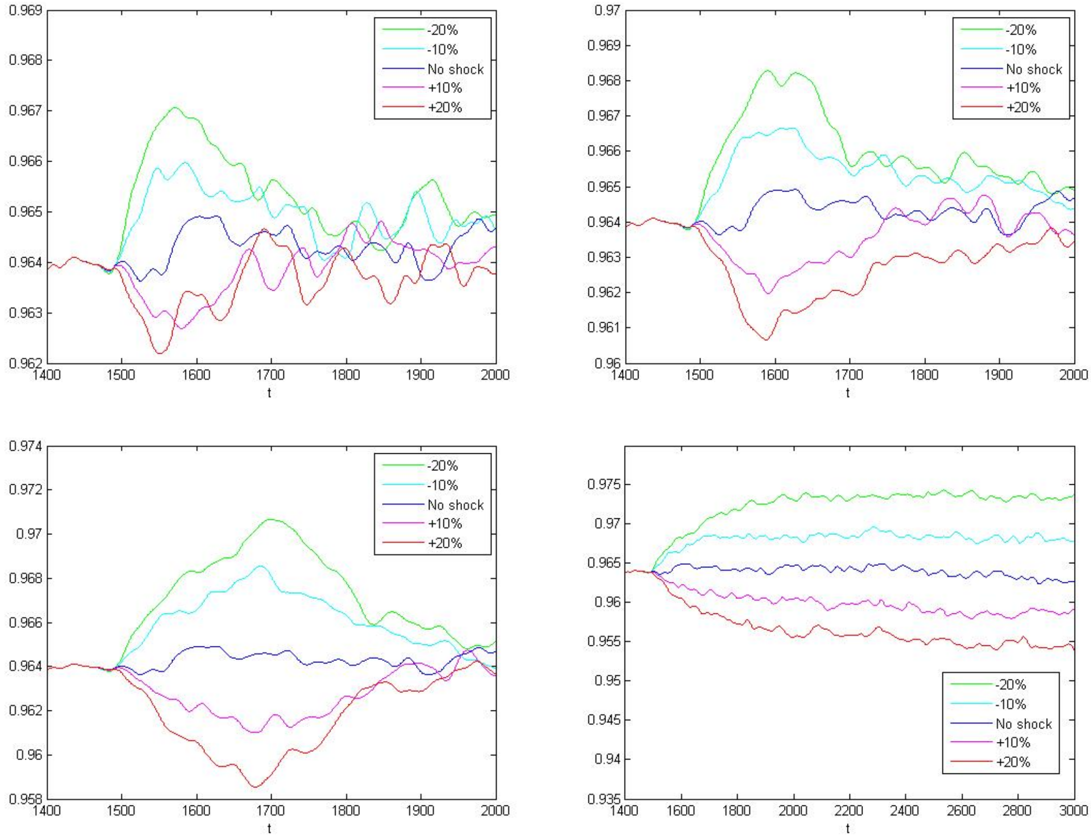

Figure 14: *Impact of the interest rate shock on the largest component. Average of 50 simulations. Shocks last for 50 (top, left), 100 (top, right), 200 (bottom, left), and 1,500 (bottom right) periods. For the sake of a better visualization of the trend component, the series were smoothed applying the HP filter.*

Table 8: *Difference between the average largest component when there is an interest rate shock and when there is not (in %). Period P corresponds to that in which the shock starts, thus P=1500. *: significant at the 10% level. **: significant at the 5% level. ***: significant at the 1% level.*

s	D=50		D=100		D=200		D=1500
	P+1-P+D	2500-3000	P+1-P+D	2500-3000	P+1-P+D	2500-3000	2500-3000
-0.2	0.21***	0.01**	0.28***	0.01	0.38***	0.02***	1.06***
-0.1	0.13***	0.00	0.17***	0.01**	0.25***	0.05***	0.51***
0.1	-0.06***	-0.01**	-0.13***	-0.01	-0.22***	0.02**	-0.48***
0.2	-0.11***	0.02***	-0.23***	-0.02***	-0.39***	-0.01	-0.89***

Table 9: *Elasticity of the largest component with respect to the base interest rate.*

s	D=50	D=100	D=200
-0.2	-0.0071	-0.0120	-0.0185
-0.1	-0.0063	-0.0130	-0.0233
0.1	-0.0125	-0.0175	-0.0238
0.2	-0.0088	-0.0135	-0.0202

Concerning the impacts of shocks to the base interest rate on the kurtosis of the degree distribution (Tables 10 and 11), some suggestive conclusions can be drawn from our results: i) while the short-term effects of temporary shocks are ambiguous, they have a clear long-term impact, which is a decrease (in most of the cases) in the kurtosis of the degree distribution of both banks and firms. This suggests that the impact of negative and positive shocks is asymmetric; ii) while permanent negative (positive) shocks decrease (increase) the kurtosis of banks' degree distribution, this relationship is the opposite in the case of the firms. This effect is asymmetric, in the sense that it is stronger for firms and in the case of negative shocks. The rationale behind these results seems to be the following: a higher supply of credit, brought by a negative interest rate shock, take the form of more banks supplying credit to the more credit-demanding firms. Therefore, there are new links being created between isolated banks and these firms (i.e., an increase along the extensive margin); iii) lasting positive shocks (100 periods or more) also decrease significantly the kurtosis of the firms' degree distribution.

Table 10: *Difference between the average kurtosis within the mentioned period interval of banks' degree distribution when there is an interest rate shock and when there is not (in %). The computation considers 2,500 values (50 banks times 50 simulations). Period P corresponds to that in which the shock starts, thus P=1500.*

s	D=50		D=100		D=200		D=1500
	P+1-P+D	2500-3000	P+1-P+D	2500-3000	P+1-P+D	2500-3000	2500-3000
-0.2	-0.0009	-1.7939	-0.5619	-0.2524	-0.8008	-1.0273	-3.7803
-0.1	0.4126	-0.9312	1.3628	-1.2479	1.6223	-1.9575	-3.6683
0.1	0.4707	-1.3735	0.0767	-0.9854	1.0659	-1.5866	0.1786
0.2	-0.2820	-0.9564	-0.2964	-1.7028	1.1315	-1.2400	1.7987

Table 11: *Difference between the average kurtosis within the mentioned period interval of firms' degree distribution when there is an interest rate shock and when there is not (in %). The computation considers 25,000 values (500 firms times 50 simulations). Period P corresponds to that in which the shock starts, thus P=1500.*

s	D=50		D=100		D=200		D=1500
	P+1-P+D	2500-3000	P+1-P+D	2500-3000	P+1-P+D	2500-3000	2500-3000
-0.2	4.1026	-0.5896	-1.2149	-9.9445	0.6089	9.1163	24.2379
-0.1	0.4113	-3.0865	-1.3341	-10.2206	1.1731	-0.1723	16.6770
0.1	-4.2716	-10.8553	-2.1998	3.7021	-0.9814	-10.7725	-1.7572
0.2	-0.6702	-10.2046	-3.9324	-2.1713	-8.8474	-3.9199	-13.2025

5 Concluding remarks

An important question raised by many studies on financial networks is how the propagation of shocks through the financial network is driven by its topological features. In this paper, we address a different but related and equally relevant question bearing important theoretical and policy implications. More precisely, we assess how shocks to the policy interest rate affect some key topological measures of a bank-firm credit network.

In order to perform this task, we develop an ABM in which banks extend loans to consumption-good firms. The bank-firm credit network is topologically structured according to plausible behavioral assumptions, in the sense that both firms and banks are always willing (but not always able) to close a credit deal with the network partner perceived to be less risky. After assessing some artificial time series generated by the model (output, banks' and firms' leverage, non-performing loans etc.), we then show that our model is able to reproduce several key stylized facts of bank-firm credit networks documented in the literature: for example, i) the degree distributions are fat-tailed; ii) the bipartite bank-firm credit network is characterized by a disassortative behavior; and iii) the correlation between the size of the node and its degree is positive.

As elaborated and documented in literature, the propagation of shocks through a financial network depends mainly on three key topological features: degree distribution, assortativity, and density. We then assessed how positive and negative shocks to the base interest rate that vary in terms of magnitude and duration affect these topological features. Moreover, we included in our analysis the largest component, which can be reasonably seen as a determinant of the financial network resilience.

We have found that the density of the financial network decreases with positive interest rate shock and increases with negative ones. Therefore, the increase in the flow of credit between banks and firms, as a result of a negative interest rate shock, results in the creation of new links. Similarly, when the flow of credit decreases in face of a positive interest rate shock, some links of the financial network are destroyed. Assessing the relationship between the density of the network and the leverage of banks and firms, we observed that, in the case of the banks, changes along the extensive margin (number of partners) and intensive margin (average flow of credit per partner) occur in the same direction. However, in the case of firms, changes along the extensive and intensive margin occur in opposite directions: an increase (decrease) in the average number of partners is accompanied by a decrease (increase) in the average flow of credit (as a fraction of the firms' net worth) granted by each partner.

Another interesting result is that negative shocks to the base interest rate make the financial network formed by banks and firms more disassortative (i.e., the absolute value of the negative assortativity increases), while positive shocks generate the opposite effect. This implies that the links created by negative shocks are mostly between highly-connected agents and poorly-connected agents of the opposite type. On the other hand, the links destroyed by positive interest rate shocks are mostly those between highly-connected agents and that of the opposite type with less connections.

Finally, we have found that shocks to the base interest rate have a long-term impact on the kurtosis of the degree distribution of both banks and firms. The type of impact depends on the duration of the shock. Usually, temporary shocks lead to a decrease in the kurtosis of the degree distribution. This suggests an asymmetry in the impact of negative and positive shocks. Meanwhile, permanent negative (positive) shocks decrease (increase) the kurtosis of banks' degree distribution. In the case of the firms, the considered relationship is the opposite one. A possible explanation for these results is that a higher supply of credit, caused by a negative interest rate shock, takes the form of more banks supplying credit to the more credit-demanding firms – that is, an increase in the flow of credit along the extensive margin.

Our results have important implications with respect to the role played by financial networks in driving economic outcomes. It is widely recognized that the effect of some processes in the economic system depends on the topological structure of the financial networks embedded in such a system. For instance, in network models of systemic risk, the considered effect is computed as the potential loss of economic value generated by an exogenous shock. In these models, the topology of the financial network is typically assumed to remain fixed and exogenous. However, our simulation study robustly suggests that the topology of a financial network both affects and is affected by shock propagation in a complex coevolutionary way. Therefore, understanding how the topology of a financial network coevolves with a given shock propagation is crucial to more properly and precisely computing the impact of the considered shock, and our study sheds some suggestive light on such a key issue.

References

Acemoglu, D., Ozdaglar, A., and Tahbaz-Salehi, A. (2015). Systemic risk and stability in financial networks. *American Economic Review*, 105(2):564–608.

Acharya, V. V. (2009). A theory of systemic risk and design of prudential bank regulation. *Journal of Financial Stability*, 5(3):224–255.

Albert, R., Jeong, H., and Barabási, A.-L. (2000). Error and attack tolerance of complex networks. *nature*, 406(6794):378–382.

Alexandre, M. and Lima, G. T. (2017). Combining monetary policy and prudential regulation: an agent-based modeling approach. *Journal of Economic Interaction and Coordination*, pages 1–27.

Allen, F. and Gale, D. (2000). Financial contagion. *Journal of Political Economy*, 108(1):1–33.

Altman, E. I. and Sabato, G. (2013). Modeling credit risk for smes: evidence from the us market. In Roggi, O. and Altman, E. I., editors, *Managing and Measuring Risk: Emerging Global Standards and Regulations After the Financial Crisis*, pages 251–279. World Scientific.

Amini, H., Cont, R., and Minca, A. (2016). Resilience to contagion in financial networks. *Mathematical Finance*, 26(2):329–365.

Assenza, T., Gatti, D. D., and Grazzini, J. (2015). Emergent dynamics of a macroeconomic agent based model with capital and credit. *Journal of Economic Dynamics and Control*, 50:5–28.

Attanasio, O., Kovacs, A., and Moran, P. (2020). Temptation and commitment: Understanding hand-to-mouth behavior. Technical report, National Bureau of Economic Research.

Banerjee, R. N., Gambacorta, L., and Sette, E. (2021). The real effects of relationship lending. *Journal of Financial Intermediation*, 48:100923.

Battiston, S., Caldarelli, G., and D'Errico, M. (2016). The financial system as a nexus of interconnected networks. In *Interconnected networks*, pages 195–229. Springer.

Battiston, S., Puliga, M., Kaushik, R., Tasca, P., and Caldarelli, G. (2012). Debtrank: Too Central to Fail? Financial Networks, the FED and Systemic Risk. *Scientific Reports*, 2:541.

BCBS (2014). Supervisory framework for measuring and controlling large exposures. *Bank for International Settlements*.

Bech, M. L. and Garratt, R. J. (2012). Illiquidity in the interbank payment system following wide-scale disruptions. *Journal of Money, Credit and Banking*, 44(5):903–929.

Berger, A. N. and Udell, G. F. (2002). Small business credit availability and relationship lending: The importance of bank organisational structure. *The Economic Journal*, 112(477):32–53.

Bluhm, M., Faia, E., and Krahnen, J. P. (2014). Monetary policy implementation in an interbank network: Effects on systemic risk. *SAFE Working Paper Series No. 46*.

Bottazzi, G., De Sanctis, A., and Vanni, F. (2020). Non-performing loans and systemic risk in financial networks. *Available at SSRN 3539741*.

Brusco, S. and Castiglionesi, F. (2007). Liquidity coinsurance, moral hazard, and financial contagion. *The Journal of Finance*, 62(5):2275–2302.

Caccioli, F., Catanach, T. A., and Farmer, J. D. (2012). Heterogeneity, correlations and financial contagion. *Advances in Complex Systems*, 15(supp02):1250058.

Chinazzi, M. and Fagiolo, G. (2015). Systemic risk, contagion, and financial networks: A survey. *Institute of Economics, Scuola Superiore Sant'Anna, Laboratory of Economics and Management (LEM) Working Paper Series*, (2013/08).

Collard, F. (1998). Spectral and persistence properties of cyclical growth. *Journal of Economic Dynamics and Control*, 23(3):463–488.

Cottarelli, C. and Kourelis, A. (1994). Financial structure, bank lending rates, and the transmission mechanism of monetary policy. *Staff Papers*, 41(4):587–623.

D'Agostino, G., Scala, A., Zlatić, V., and Caldarelli, G. (2012). Robustness and assortativity for diffusion-like processes in scale-free networks. *EPL (Europhysics Letters)*, 97(6):68006.

De Bondt, G. (2002). Retail bank interest rate pass-through: new evidence at the euro area level. *Available at SSRN 357380*.

De Masi, G., Fujiwara, Y., Gallegati, M., Greenwald, B., and Stiglitz, J. E. (2011). An analysis of the japanese credit network. *Evolutionary and Institutional Economics Review*, 7(2):209–232.

De Masi, G. and Gallegati, M. (2012). Bank–firms topology in italy. *Empirical Economics*, 43(2):851–866.

Dosi, G., Fagiolo, G., Napoletano, M., and Roventini, A. (2013). Income distribution, credit and fiscal policies in an agent-based keynesian model. *Journal of Economic Dynamics and Control*, 37(8):1598–1625.

Elliott, M., Golub, B., and Jackson, M. O. (2014). Financial networks and contagion. *American Economic Review*, 104(10):3115–53.

Elsas, R. and Krahnen, J. P. (1998). Is relationship lending special? Evidence from credit-file data in Germany. *Journal of Banking & Finance*, 22(10-11):1283–1316.

Freixas, X., Parigi, B. M., and Rochet, J.-C. (2000). Systemic risk, interbank relations, and liquidity provision by the central bank. *Journal of Money, Credit & Banking*, 32(3):611.

Freund, C. (2017). Bipartite clustering in bank-firm networks. *Available at SSRN 2986341*.

Gai, P. and Kapadia, S. (2010). Contagion in financial networks. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 466(2120):2401–2423.

Gatti, D. D., Di Guilmi, C., Gallegati, M., and Giulioni, G. (2007). Financial fragility, industrial dynamics, and business fluctuations in an agent-based model. *Macroeconomic Dynamics*, 11(S1):62–79.

Gatti, D. D., Gallegati, M., Greenwald, B., Russo, A., and Stiglitz, J. E. (2010). The financial accelerator in an evolving credit network. *Journal of Economic Dynamics and Control*, 34(9):1627–1650.

Georg, C.-P. (2013). The effect of the interbank network structure on contagion and common shocks. *Journal of Banking & Finance*, 37(7):2216–2228.

Giordani, P., Jacobson, T., Von Schedvin, E., and Villani, M. (2014). Taking the twists into account: Predicting firm bankruptcy risk with splines of financial ratios. *Journal of Financial and Quantitative Analysis*, 49(4):1071–1099.

Halaj, G. and Kok, C. (2015). Modelling the emergence of the interbank networks. *Quantitative Finance*, 15(4):653–671.

Haldane, A. G. and May, R. M. (2011). Systemic risk in banking ecosystems. *Nature*, 469(7330):351.

Hofmann, B. and Mizen, P. (2004). Interest rate pass-through and monetary transmission: Evidence from individual financial institutions' retail rates. *economica*, 71(281):99–123.

Hurd, T. R., Gleeson, J. P., and Melnik, S. (2017). A framework for analyzing contagion in assortative banking networks. *PloS one*, 12(2):e0170579.

Kaplan, G. and Violante, G. L. (2010). How much consumption insurance beyond self-insurance? *American Economic Journal: Macroeconomics*, 2(4):53–87.

Kaplan, G., Violante, G. L., and Weidner, J. (2014). The wealthy hand-to-mouth. Technical report, National Bureau of Economic Research.

Krause, S. M., Štefančić, H., Caldarelli, G., and Zlatić, V. (2021). Controlling systemic risk: Network structures that minimize it and node properties to calculate it. *Physical Review E*, 103(4):042304.

Loepfe, L., Cabrales, A., and Sánchez, A. (2013). Towards a proper assignment of systemic risk: The combined roles of network topology and shock characteristics. *PloS One*, 8(10):e77526.

López-Espinosa, G., Moreno, A., Rubia, A., and Valderrama, L. (2012). Short-term wholesale funding and systemic risk: A global covar approach. *Journal of Banking & Finance*, 36(12):3150–3162.

Lucas, R. E. (1976). Econometric policy evaluation: A critique. *Carnegie-Rochester Conference Series on Public Policy*, 1:19–46.

Luu, D. T. and Lux, T. (2019). Multilayer overlaps and correlations in the bank-firm credit network of spain. *Quantitative Finance*, 19(12):1953–1974.

Miranda, R. and Tabak, B. (2013). Contagion risk within firm-bank bivariate networks. *Central Bank of Brazil Working Paper Series No. 322*.

Nier, E., Yang, J., Yorulmazer, T., and Alentorn, A. (2007). Network models and financial stability. *Journal of Economic Dynamics and Control*, 31(6):2033–2060.

Poledna, S., Hinteregger, A., and Thurner, S. (2018). Identifying systemically important companies by using the credit network of an entire nation. *Entropy*, 20(10):792.

Ramadiah, A., Di Gangi, D., Sardo, D., Macchiati, V., Pham, M. T., Pinotti, F., Wiliński, M., Barucca, P., and Cimini, G. (2019). Network sensitivity of systemic risk. *Journal of Network Theory in Finance*, 5(3).

Riccetti, L. (2019). Systemic risk analysis and sifis detection: A proposal for a complete methodology. *Available at SSRN 3415730*.

Riccetti, L., Russo, A., and Gallegati, M. (2013). Leveraged network-based financial accelerator. *Journal of Economic Dynamics and Control*, 37(8):1626–1640.

Riccetti, L., Russo, A., and Gallegati, M. (2015). An agent based decentralized matching macroeconomic model. *Journal of Economic Interaction and Coordination*, 10(2):305–332.

Riccetti, L., Russo, A., and Gallegati, M. (2021). Firm–bank credit network, business cycle and macroprudential policy. *Journal of Economic Interaction and Coordination*, pages 1–25.

Roukny, T., Bersini, H., Pirotte, H., Caldarelli, G., and Battiston, S. (2013). Default cascades in complex networks: Topology and systemic risk. *Scientific Reports*, 3:2759.

Sette, E. and Gobbi, G. (2015). Relationship lending during a financial crisis. *Journal of the European Economic Association*, 13(3):453–481.

Silva, T. C., Guerra, S. M., Alexandre, M., and Tabak, B. M. (2020). Micro-level transmission of monetary policy shocks: The trading book channel. *Journal of Economic Behavior & Organization*, 179:279–298.

Stein, J. C. (2012). Monetary policy as financial stability regulation. *The Quarterly Journal of Economics*, 127(1):57–95.

Traczynski, J. (2017). Firm default prediction: A bayesian model-averaging approach. *Journal of Financial and Quantitative Analysis*, 52(3):1211–1245.

Upper, C. (2011). Simulation methods to assess the danger of contagion in interbank markets. *Journal of Financial Stability*, 7(3):111–125.

Weil, P. (1992). Hand-to-mouth consumers and asset prices. *European Economic Review*, 36(2-3):575–583.

A Parameters and initial conditions

Symbol	Meaning	Value
Parameters:		
N^F	Number of firms	500
η	Labor productivity parameter	3
ψ_w^{min}	Nominal wage adjustment parameter (Eq. 1)	0.5
ψ_w^{max}	Nominal wage adjustment parameter (Eq. 1)	1.1
ψ_l^{max}	Target leverage adjustment parameter (Eq. 3)	0.2
l^{max}	Firms' maximum leverage	5
l^{min}	Firms' minimum leverage	0.5
N^B	Number of banks	50
κ	Banks' maximum leverage ratio	0.04
α	Banks' capital buffer sensitivity to financial fragility (Eq. 4)	0.5
t_D	Duration of debt (in periods)	10
λ	Probability of choosing a bank at random	0.1
f^{min}	Minimum fraction of credit to be supplied in each credit deal	0.2
i^B	Base interest rate	0.02
β	Interest rate markup parameter (Eq. 5)	0.25
γ	Risk premium parameter (Eq. 5)	0.2
f_{RI}	Fraction of investment randomly shared among firms (Eq. 6)	0.1
ε	Investment distribution parameter (Eq. 6)	2
ϕ	Sensitivity of firms' markup to a change in market share (Eq. 9)	0.2
ψ_ρ	Propensity to consume parameter (Eq. 11)	0.02
f_{RD}	Fraction of the aggregate demand randomly distributed among firms (Eq. 12)	0.1
θ	Sensitivity of firms' market share to relative price (Eq. 14)	1
s^{max}	Maximum market share	0.04
δ	Proportion of profits distributed as dividends	0.15
τ	Tax rate	0.15
ψ_ζ	Sensitivity of government spending to the growth rate (Eq. 18)	0.05
ζ^{min}	Minimum fraction of government spending (Eq. 18)	0.02
$g*$	Growth rate target (Eq. 18)	0.03
Initial conditions:		
$NW_{i,0}$	Firms' initial net worth	$NW_{i,0} \sim N(10,2)$
$\mu_{i,0}$	Firms' initial markup	$\mu_{i,0} \sim N(0.15,0.03)$
$l^*_{i,0}$	Firms' initial target leverage	$l^*_{i,0} \sim U(1.5,2)$
$NW_{j,0}$	Banks' initial net worth	$NW_{j,0} \sim N(10,2)$
R_0^H	Households' initial cash	1,000
Γ_0	Government initial surplus	1,000
w_0	Initial nominal wage	1
ζ_0	Initial fraction of government spending (Eq. 18)	0.04