Macro and micro prudential policies: sweet and lowdown in a credit network agent based model

Ermanno Catullo* Federico Giri† Mauro Gallegati ‡

Abstract

The paper presents an agent-based model reproducing a stylized credit network that evolves endogenously through the individual choices of firms and banks. We introduce in this framework a financial stability authority in order to test the effects of different prudential policy measures designed to improve the resilience of the economic system. Simulations show that a combination of micro and macroprudential policies reduces systemic risk, but at the cost of increasing banks' capital volatility. Moreover, the agent-based methodology allows us to implement an alternative *meso* regulatory framework that takes into consideration the connections between firms and banks. This policy targets only the more connected banks, increasing their capital requirement in order to reduce the diffusion of local shocks. Our results support the idea that the meso prudential policy is able to reduce systemic risk without affecting the stability of banks' capital structure.

Keywords: Micro prudential policy; Macro prudential policy; Credit Network; Meso prudential policy; Agent based model;

JEL classification codes: E50; E58; G18; G28; C63.

1 Introduction

The aim of this paper is to provide some insights into the interrelation between micro and macroprudential policies, the potential conflicts among them and to propose an alternative regulatory framework based on the credit network topology, that we define as the meso prudential policy. For this purpose, we build an agent-based model including a credit network where banks and firms can have multiple lending relations. We use this model to answer two questions: First, are there any drawbacks when the financial stability authority uses a combination of micro and macroprudential

*Corresponding author: Department of Management, Universit Politecnica delle Marche, Piazzale Martelli 8, Ancona, Italy. E-mail: ermanno.catullo@gmail.com

†Department of Economics and Social Sciences, Universit Politecnica delle Marche, Piazzale Martelli 8, Ancona, Italy

‡Department of Management, Universit Politecnica delle Marche, Piazzale Martelli 8, Ancona, Italy.

policies to achieve its target? Second, does the *meso* prudential policy, which takes into account the credit network relationships, works better in terms of output and credit stabilization than the one based on the traditional micro/macro framework?

In this study, we address these research questions by building an agent-based model that includes a credit network among firms and banks, which evolves endogenously according to the individual supply and demand for loans. In the standard DSGE literature, many recent contributions try to shed light on the relation between macroprudential and monetary policy (see Angelini et al., 2014, Mendicino and Punzi, 2014, and Cesa-Bianchi and Rebucci, 2017). However, given the difficulties of DSGE models in taking into account both micro and macro levels, very few attention is devoted to understand the connections between macro and microprudential policies. On the contrary, agent-based models (henceforth ABM, see Delli Gatti et al., 2005a and Tesfatsion and Judd, 2006, for a detailed description) are particularly well suited for this purpose as they allow to describe in a unified framework individual agent behavior and macroeconomic patterns.[1]

After the 2007/2008 financial crisis, the design and enforcement of effective prudential policies aiming at preventing or reducing the effects of financial and credit crises became central in the economic and political debate. According to Hanson et al. (2011) and Galati and Moessner (2013), the micro and macro approaches to financial regulation differ in a fundamental way: micro policies aim at reducing the riskiness of a single financial institution, whereas macroprudential policies are focused on mitigating the systemic effects of individual imbalances. While microprudential policy has a long tradition and has been extensively analyzed for the last decades (see Gorton and Winton, 2003, for a review), it was only in the aftermath of the financial crisis that macroprudential policy captured the attention of economists. It could be mentioned, as concluded by Galati and Moessner (2018), that at the current point there is no general consensus about the effectiveness of macroprudential policy as an instrument to reduce systemic risk.

A relative unexplored topic in the blooming literature on the macroprudential policy is related to its interaction with the microprudential measures. This topic is especially important, given that different circumstances, micro and macroprudential policy objectives may diverge (Angelini et al., 2012, Alessandri and Panetta, 2015, and Osinski et al., 2013). For instance, during downturns, macroprudential policies may be oriented at softening banks' capital requirement in order to avoid a credit crunch. On the contrary, microprudential policy may aim at consolidating the financial position of banks by tightening the capital requirements. We address this conflictive dichotomy in our research setting up a policy experiment in which micro and macro policies interact inside an ABM framework.

Our work is related to several recent studies that apply the ABM methodology to investigate financial stability. Cincotti et al. (2012) use an ABM model to show that the dynamic adjustment of capital requirements helps in output stabilization. Likewise, Baptista et al. (2016) explore the

[1]For a detailed description of the differences between macro policy analysis in DSGE and ABM framework see Fagiolo and Roventini (2017).

effects of a loan-to-income policy and finds that this policy is successful in smoothing house price fluctuation. Assenza et al. (2018) compare different macroprudential policies to show that the adjustment of capital requirements is more effective than constraining liquidity ratios in reducing the probability of a crisis. Popoyan et al. (2017) also build an ABM model with heterogeneous banks and firms in order to test the effectiveness of different macroprudential policies. Their main finding is that imposing a minimum capital requirement and introducing counter-cyclical capital buffer is the policy that best resembles the Basel III regulatory framework in a much more simplified way. In a similar framework, Krug et al. (2014) find that the macroprudential policy overlays impact with microprudential measures has a very limited impact on financial stability. Moreover, Riccetti et al. (2017) find that a tight regulation can generate a contraction of the credit supply whereas loose financial regulation can generate financial instability.[2] Secondly, our work is also related to the literature that investigates the role of financial networks, systemic risk and the implementation of prudential policy that may reduce financial instability (see Gai et al., 2011, Battiston et al., 2012 , Aldasoro et al., 2017 and van der Hoog and Dawid, 2019).

Our contribution is twofold: First, there exists a combination of micro and macroprudential policy that reduces macroeconomic volatility and the probability of an economic crisis in comparison to the scenario with the microprudential policy only. The side effect of this policy is that it leads to higher volatility of banks' equity. Second, we show that *meso* prudential policy is an effective tool in reducing systemic risk through tightening the capital requirements of more connected banks only. Exploiting network topology, we show that it is possible to better coordinate micro and macroprudential policy in order to increase the resilience of the economic system without impacting on the performance of the banking system.

The paper is organized as follow: Section 2 presents the model; Section 3 describes the micro/macro prudential policy experiments; Section 4 introduces the meso prudential policy experiment. Finally, Section 5 concludes.

2 The Model

Our model reproduces a simplified credit network with M banks and N heterogeneous firms that evolves endogenously. Credit agreement stands for one period and they are repaid at the end of it. In line with Riccetti et al. (2013), Catullo et al. (2015), Catullo et al. (2018), the dynamics of the credit network emerges from a preferential attachment mechanism that allows banks, that offer better credit conditions in terms of interest rate, to increase the amount of loans granted to firms.

However, in our model, the preferential attachment mechanism also depends on the supply of credit that each bank is able to provide. Moreover, firms maximize profits under bounded rational

[2]However, in an ABM framework, Mazzocchetti et al. (2018) show that banks can avoid macroprudential regulation through the securitization process.

conditions, since they solve a static optimization problem that determines their desired level of capital at time t. Thus, firms choose loan demand and, consequently, their desired level of capital.

At the same time, banks follow heuristic rules to determine the amount of loans offered and the interest rates. They modify their credit supply according to firms demand and to the capital requirement fixed by the regulatory authority. Banks set interest rate in two steps. First, banks fix an internal component of the interest rate as a function of their own leverage. Every time the capital/asset ratio is below the threshold set by the prudential authority, the bank has to increase the interest rate on credit. Second, banks compute a firm-specific component of the interest rate charged on credit that depends on firms' leverage.

2.1 Banks

In each period t, each bank b determines its credit supply and the interest rate on loans. It does it by gradually adjusting credit supply with respect to the loan demand received in the previous period ($L^D_{b,t-1}$), taking into account the capital requirement set by the financial stability authority (ν_t). The associated maximum loan supply is:

$$L^{\nu}_{bt} = E_{bt}/\nu_t \tag{1}$$

where E_{bt} is bank b net-worth.

Therefore, bank's desired loan supply (L^O_{bt}) is equal to the minimum between loan previously demanded ($L^D_{b,t-1}$) and the maximum loan supply authorized by the financial stability authority (L^{ν}_{bt}):

$$L^O_{bt} = min(L^D_{b,t-1}, L^{\nu}_{bt}). \tag{2}$$

We assume that banks adapt gradually their credit supply (L^S_{bt}) to the desired offer (L^O_{bt}):

$$L^S_{bt} = \begin{cases} L^S_{b,t-1}(1-\delta) & \text{if } L^O_{b,t} < L^S_{b,t-1}(1-\delta) \\ L^O_{bt} & \text{if } L^S_{b,t-1}(1-\delta) \leq L^O_{b,t} \leq L^S_{b,t-1}(1+\delta) \\ L^S_{b,t-1}(1+\delta) & \text{if } L^O_{b,t} > L^S_{b,t-1}(1+\delta). \end{cases} \tag{3}$$

Equation 3 introduces stickiness in the credit creation process.[3] Banks can expand (reduce) their credit supply up to a maximum (minimum) given by a fraction δ of the previous period credit supply (maximum upper bound $L^S_{b,t-1}(1+\delta)$, minimum lower bound $L^S_{b,t-1}(1-\delta)$). If the desired offer is in between the upper and lower bounds, credit supply is equal to the desired one.[4]

[3]The myopic behavior of both firms and banks assumed in the model leads to stickiness in credit supply and demand. This mechanism allows us to capture in a very simple way the persistence of the credit cycle which is in line with recent empirical evidence (see Aikman et al., 2015 and Gelain et al., 2017).

[4]In the simulation exercise, the value of the parameter δ is common among firms and banks.

Moreover, banks may provide a maximum amount of their supply to a single firm i (L_{ibt}^{SM}):

$$L_{ibt}^{SM} = \zeta L_{bt}^{S}, \tag{4}$$

where ζ is the maximum share of credit allocated to each firms.

Deposits are computed residually as difference between loan supply and bank net-worth:

$$D_{bt} = L_{bt}^{S} - E_{bt}, \tag{5}$$

The interest rate is computed in two steps. Firstly, similar in spirit to Gerali et al. (2010), banks set interest rates according to their own leverage following a non-linear heuristic rule.

$$R_{bt} = \begin{cases} \eta r_t^d - k\left(E_{bt}/L_{bt}^S - \nu_t\right)\left(E_{bt}/L_{bt}^S\right)^2 & \text{if } E_{bt}/L_{bt}^S < \nu_t \\ \eta r_t^d & \text{if } E_{bt}/L_{bt}^S \geq \nu_t, \end{cases} \tag{6}$$

where η and k are the bank margin on the discount rate and the parameter governing the effect of leverage on the interest rate, respectively. According to Equation 6, a capital to asset ratio below the level set by the regulatory authority ($E_{bt}/L_{bt}^S < \nu_t$) is charged directly on credit interest rates (R_{bt}).[5] Moreover, as in Gerali et al. (2010), banks enjoy to have some kind of market power when they set interest rates. The parameter η is the bank margin that each financial intermediaries charges on the final interest rate on loan, indipendently from the capital position. Furthermore, similar to the financial accelerator of Bernanke et al. (1999), banks fix a firm specific interest rate premium that depends on firm's leverage (K_{it}^D/E_{it}), where K_{it}^D and E_{it} are the capital demanded by firms and their net-worth, respectively.

$$r_{ibt} = \bar{r}\left(\frac{K_{it}^D}{E_{it}}\right) + R_{bt}. \tag{7}$$

where $\bar{r}$ in Equation 7 is the risk free rate.

Banks compute profits (π_{bt}) as:

$$\pi_{bt} = \sum_{i}^{I} r_{ibt} L_{ibt} - \sum_{i}^{ID} BD_{ibt} - r_d D_{bt} - F. \tag{8}$$

Banks calculate revenues as the sum of debt service on loans allocated to firms J. Costs are given by the sum of bad debt (BD_{bt}), fixed cost (F) and interest on deposits ($r_d D_{bt}$). Bad debt is defined as the sum of credit that defaulting firms (ID) are not able to pay back to bank b. F is a small fixed cost that can be interpreted as an operating cost. [6]

Only a fraction of profits are accumulated by banks, increasing their net worth ($E_{b,t+1}$), indeed in line with the gradual adjusting processes that characterized the model we assume that the larger is profit the higher are dividends, thus the net profit π_{bt}^N is equal to $min(\pi_{bt}, |\pi_{bt}|^\gamma)$.

[5] This mechanism mimics the fact that any downward adjustment of the capital to asset ratio can be potentially costly forcing banks to increase their capital holding.

[6] In the simulation exercise, the value of F is common among firms and banks. For sake of simplicity, the two operating costs have the same notation in our model.

2.2 Firms

Firms use capital (K_{it}) to produce output using a linear production function:

$$Y_{it} = \phi K_{it}, \tag{9}$$

where ϕ is firms' productivity. The firm's balance sheet is:

$$K_{it} = L_{it} + E_{it}. \tag{10}$$

Capital is given by the sum of the net worth (E_{it}) and loans obtained at time t (L_{it}). Firms can borrow from more than one bank, thus the total amount of credit received by a single firm is given by the sum of loans obtained by the set of lending banks (B):

$$L_{it} = \sum_{b \in B} L_{ibt}. \tag{11}$$

Profits derive from revenues ($p_{it}Y_{it}$) minus a variable cost on production (cK_{it}, see Delli Gatti et al., 2005b) interests on loans ($r_{it}L_{it}$) and a fixed cost (F) where c is positive coefficient determining the user cost of physical capital. p_{it} is extracted from a uniform distribution ($p_{it} \sim U[0, 2]$) and it can be interpreted as an idiosyncratic stochastic demand shock (see Greenwald and Stiglitz, 1993 and Delli Gatti et al., 2005b):

$$\pi_{it} = p_{it}Y_{it} - r_{it}L_{it} - cK_{it} - F. \tag{12}$$

Firms choose the desired level of production assuming that they would ask for loans only if they do not have sufficient internal resources. Loan demanded (L^d_{it}) is equal to desired level of capital (K_{it}) minus firm's net-worth $L^d_{it} = K_{it} - E_{it}$. Thus, if $K_{it} > E_{it}$:

$$E(\pi_{it}) = E(p)\phi K_{it} - \left[\bar{r}\left(\frac{K_{it}}{E_{it}}\right) + E(R_{Bi,t})\right](K_{it} - E_{it}) - cK_{it} - F, \tag{13}$$

Where $\bar{r}(K_{it}/E_{it})$ is the firm-specific component of the interest rate and $E(R_{Bi,t})$ is the bank-specific one. In particular, $E(R_{Bi,t})$ is the expected average of the banks B that will provide credit to firms i weighted by the amount of credit that each bank will provide. For simplicity we assume that $E(R_{Bi,t})$ is equal to its average past value $R_{Bi,t-1}$. We make this assumption because firms have to compute their loan demand before the matching with banks. In case a firm has not any previous connection, $E(R_{Bi,t})$ is assumed to be equal to the average of all the banks interest rate component.

Thus maximizing expected profit with respect to K_{it}, the first order condition is:

$$E(p)\phi - 2\bar{r}\frac{K_{it}}{E_{it}} + \bar{r} - R_{Bi,t-1} - c = 0. \tag{14}$$

If $K_{it} > E_{it}$ and $E(p)\phi - c - R_{Bi,t-1} + \bar{r} > 0$ the optimum capital level (K^O_{it}) is equal to:

$$K^O_{it} = \begin{cases} \frac{(E(p)\phi - c - R_{Bi,t-1} + \bar{r})E_{it}}{2\bar{r}} & \text{if } K_{it} > E_{it} \\ E_{it} & \text{if } K_{it} \leq E_{it}. \end{cases} \tag{15}$$

Similarly to the banking system, firms may adapt only gradually to their optimum quantity (K^O_{it}), thus the productive amount of capital (K^D_{it}) is computed as:

$$K^D_{it} = \begin{cases} max[K^O_{it}, K^D_{i,t-1}(1-\delta)] & \text{if } K^D_{i,t-1} > K^O_{it} \\ min[K^O_{it}, K^D_{i,t-1}(1+\delta)] & \text{if } K^D_{i,t-1} \leq K^O_{it}. \end{cases} \tag{16}$$

Therefore, if the capital desired (K^D_{it}) and the optimum level of capital (K^O_{it}) are greater than the firm net-worth (E_{it}), loan demand is equal to:

$$L^D_{it} = min(K^D_{it} - E_{it}, K^O_{it} - E_{it}). \tag{17}$$

In general, firms accept credit if the charged interest rate is lower than the expected incremental gains from loan ($r_{ibt} < \phi - c$).

The quantity of capital effectively used in production depends on the quantity of loan effectively received L_{it} and thus is equal to:

$$K^E_{it} = L_{it} + E_{it}. \tag{18}$$

Similarly to the banking sector, only a fraction of the profits is accumulated by firms. Thus the net profit π^N_{it} is equal to $min(\pi_{it}, |\pi_{it}|^{\gamma})$ with $0 < \gamma < 1$.

$$E_{i,t+1} = E_{it} + \pi^N_{it} \tag{19}$$

2.3 Credit Matching

In each period, firms receive credit from different banks. The matching process between credit demand and supply follows three stages. Firstly, firms, in a random order, apply for a loan to banks that provided credit to them in the previous period until their demand is fulfilled.

Secondly, if firms do not receive enough credit, they ask for loans to banks that did not allocate all their supply in the previous stage. Moreover, firms that did not receive credit in the previous period ask for loans to banks that still offer credit.

In the third stage, each firm that was linked with a bank in the previous period may switch a credit line in favor of another bank that offers better credit conditions. Following Delli Gatti et al. (2010) and Riccetti et al. (2015), each firm can change a randomly chosen linked bank with a new randomly chosen bank that has an excess of credit supply. Firms choose to remain linked with the previous bank or to shift to the new bank with a probability (Ps), which depends on the interest rate charged by the old and the new bank (respectively r_{new} and r_{old}) and the quantity of credit supplied to the firm (respectively L^s_{new} and L^s_{old}).[7]

$$Ps = max[Ps(r), Ps(L)], \tag{20}$$

[7] In general, the firm-bank links are quite sticky over time (Bernardo et al., 2019)

where $Ps(r)$ and $Ps(L)$ are respectively:

$$Ps(r) = \begin{cases} 1 - e^{(r_{new} - r_{old})/r_{new}} \text{ if } r_{new} < r_{old} \\ \\ 0 \text{ othewise }, \end{cases} \tag{21}$$

$$Ps(L) = \begin{cases} 1 - e^{(L^s_{old} - L^s_{new})/L^s_{new}} \text{ if } L^s_{new} > L^s_{old} \\ \\ 0 \text{ otherwise }. \end{cases} \tag{22}$$

Thus, if the new bank offers lower interest rate and a larger amount of credit the probability that the firm will substitute the old bank with the new one increases.

2.4 Exit and Entry

Firms and banks with net-worth lower than zero exit from the economy and they are replaced by an equal number of agents. When a firm default, the previous period credit obtained from banks is not repaid and it becomes bad debt (BD_{ibt}) for the counterpart bank. The net-worth of the new entering firm (E_{it}) is equal to

$$E_{it} = max[E^{med}_{Ft}, E^0_F], \tag{23}$$

where E^{med}_{Ft} is the median firm net-worth and E^0_F a given minimum firm net-worth level. Similarly, the net-worth of the new enter bank (E_{bt}) is equal to

$$E_{bt} = max[E^{med}_{Bt}, E^0_B], \tag{24}$$

where E^{med}_{Bt} is the median bank net-worth and E^0_B a given minimum bank net-worth level.

2.5 Simulation Time-Schedule

The simulation model follows a discrete agents' decision process divided into the following steps:

1. Banks offer credit
2. Firms determine loan demand
3. Credit matching among firms and banks
4. Idiosyncratic shock on firms
5. Firms and banks compute profit and net-worth
6. Failing firms and banks exit the market and new agents enter

when all these steps are implemented a new cycle of the computation starts again.

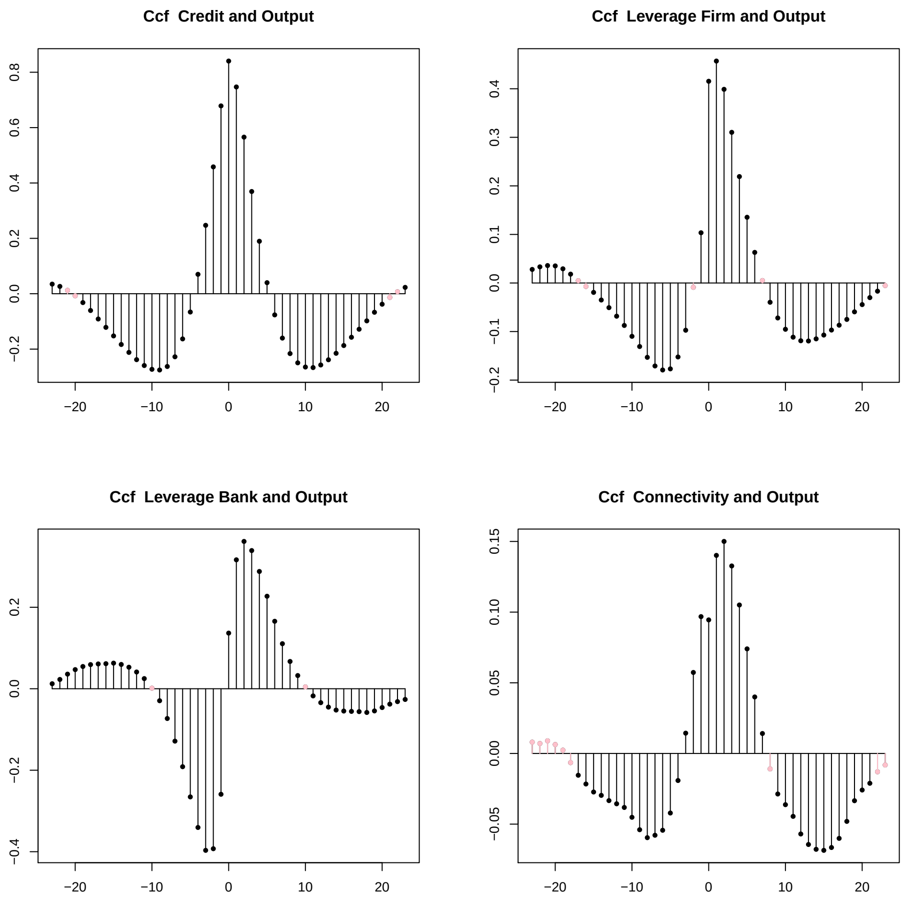

Figure 1: Cross-correlations of the baseline scenario. Pink bars are not statistically significant cross-correlations at 5 % confidence interval. Connectivity is defined as the average numbers of banks' links.

3 Micro and Macro Prudential Policies

The simulated economy is populated by 1000 firms and 100 banks, simulations last for 1000 periods, discarding the first 500 as transient. We calibrate the model so that it reproduces output standard deviation and the aggregate credit over output value. A detailed explanation of the calibration process is provided in the Online Appendix A.[8]

In order to have some insights on the behavior of the baseline model, Figure 1 presents the cross-correlation between four variables, credit, firms, and banks' leverage and connectivity, with respect to total output. The upper left panel of Figure 1 shows that credit is positively correlated with output. Also, firms and banks leverage are positively correlated with output but they anticipate it with a negative sign suggesting the existence of a Minskyan credit cycle (Minsky, 1986). In fact, when leverage increases it also causes a contemporaneous rise of output, however, growing

[8]In the Online Appendix B, we provide several sensitivity analysis with respect to different combination of the parameters in the model. The results of the baseline model are robust to different calibration of the parameters.

leverage leads to a contraction of output in the following periods because of the surge of financial instability. Finally, connectivity, intended as the number of credit linkages between firms and banks, is positively correlated with the business cycle. Since credit plays a crucial role in determining business cycle fluctuations, any regulatory intervention that affects the behavior of credit can be potentially effective in order to achieve financial stability.

In this framework we implement our prudential policy experiment acting on the variable ν_t. According to Equations 2 and 6, each bank has to adjust its leverage in order to satisfy the capital requirement (ν_t). Equation 2 governs the leverage dynamics, whereas Equation 6 drives the spread between the interest rates on deposits and wholesale credit. In the baseline scenario, we only implement a microprudential framework fixing $\bar{\nu} = 9\%$. We compare the baseline micro prudential simulations with a scenario where, in addition, a macro prudential policy is implemented as a time-varying capital requirement mechanism, similar in spirit to the one proposed by Angelini et al. (2014):

$$\nu_t = (1 - \rho)\bar{\nu} + \chi(1 - \rho)\Delta L_t / L_{t-1} + \rho\nu_{t-1}. \tag{25}$$

The parameter χ represents the strength of the macroprudential policy intervention. Assuming $\chi > 0$, the macroprudential authority behaves countercyclically, increasing ν_t when the aggregate amount of credit allocated in the economy (L_t) grows, and vice-versa when credit decreases. When χ is negative the macroprudential policy is procyclical. The parameter ρ captures the persistence of capital requirement adjustment over time.

We introduce the macroprudential policy to the system after period 500. The left upper panel of Figure 2 shows that after this moment ν_t starts to fluctuate. This leads to changes in the dynamics of output (upper left panel), credit (lower right panel) and the average number of links between banks and firms in the credit network (lower right panel).

Since the impact of macroprudential policy crucially depends on χ, we explore the responses of the system to different values of this parameter running 100 Monte Carlo simulations in the interval $[-0.5, 2]$ (see Angelini et al., 2014). Across different simulations, we focused on the standard deviation of both credit and output, which give us a measure of the volatility of the system, and the probability of credit and output crises as synthetic indicators of the vulnerability of the economy. The probability of crises is measured as the percentage of credit and output contractions lower than -2%.

Figure 3 shows that varying parameter χ, we might significantly change the economic outcome. In fact, the relationship between χ and volatility and vulnerability take a U-shaped form. When χ is equal to zero the macro prudential policy is inactive reproducing 'de facto' the micro prudential policy. Starting from $\chi = 0$, and increasing it until 1.0, this leads to a contraction of both output and credit volatility and vulnerability. On the contrary, when the level of χ is too greater than 1.0 the augmenting fluctuation of the capital requirement produces a destabilizing effect. Similarly,

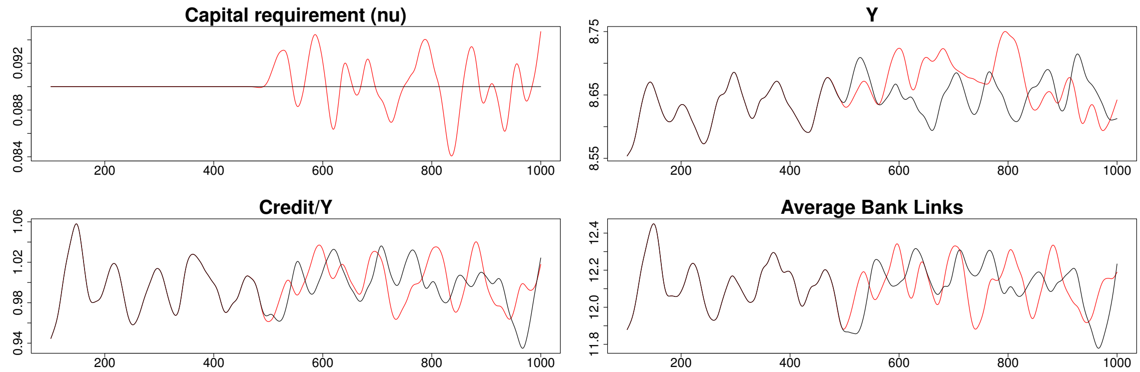

Figure 2: In black the baseline microprudential scenario, in red the macro-prudential scenario with $\chi = 1.0$ (The value that minimizes output and credit volatility, see Figure 3). In all figures, time is on the x axis. In the top left figure, the capital requirement variation that is fixed in the baseline scenario while it fluctuates with the macroprudential policy. In the top right figure, the output time series. In the bottom left figure, aggregate credit over output variations. In the bottom right, the average number of firms at which each bank lend credit. The series are obtained using the same seed for both these experiments.

when the macroprudential policy behaves pro-cyclically ($-0.5 \leq \chi \leq 0$), we have the same increase of financial instability.

However, the macroprudential policy seems to have a hidden side effect. The lower left panel of Figure 3 shows that with higher values of χ, the standard deviation of the bank net-worth increases, while the volatility of firm net worth does not change. Thus, the macro policy seems to shift part of the systemic risk to the banking sector. This is due to the fact that a fluctuating capital requirement is consistently reflected in bank leverage and, thus, in bank profit volatility. Figure 4 reports three bank specific variables: leverage, profits rate and its standard deviation. Since the value of ν_t fluctuates when macroprudential policy is active, we separate periods in which the capital requirement is below its average ($\nu_t < \bar{\nu}$, left column of Figure 4) from periods in which it is above ($\nu_t > \bar{\nu}$, right column of Figure 4). When macroprudential policy is counter-cyclical ($\chi > 0$), the left upper panel of Figure 4 shows that when the capital requirement ν_t is below its average, bank leverage increases, because banks may offer a larger amount of credit (see Equation 2) at a lower interest rates (see Equation 6), while the opposite occurs when $\nu_t > \bar{\nu}$ (right upper panel of Figure 4). In particular when $\nu_t < \bar{\nu}$, profits increase but at the cost of higher profit volatility (central left panel of Figure 4), due to the increased risk associated with higher leverage (lower left panel of Figure 4). On the contrary, when ν_t is above its average, both the profit rate and its standard deviation decrease (central and lower left panel of Figure 4, respectively). To sum up, when $\nu_t > \bar{\nu}$, a more restrictive macroprudential policy reduce profit rate standard deviation. On the contrary, when $\nu_t < \bar{\nu}$, a less stringent macroprudential policy leads to an increase of profit rate standard deviation. According to Albertazzi and Gambacorta (2009) and De Haan and Poghosyan (2012), this excess of earnings volatility tends to lead to an unstable capital structure, leading to financial instability. Therefore, a well calibrated macroprudential policy reduces the

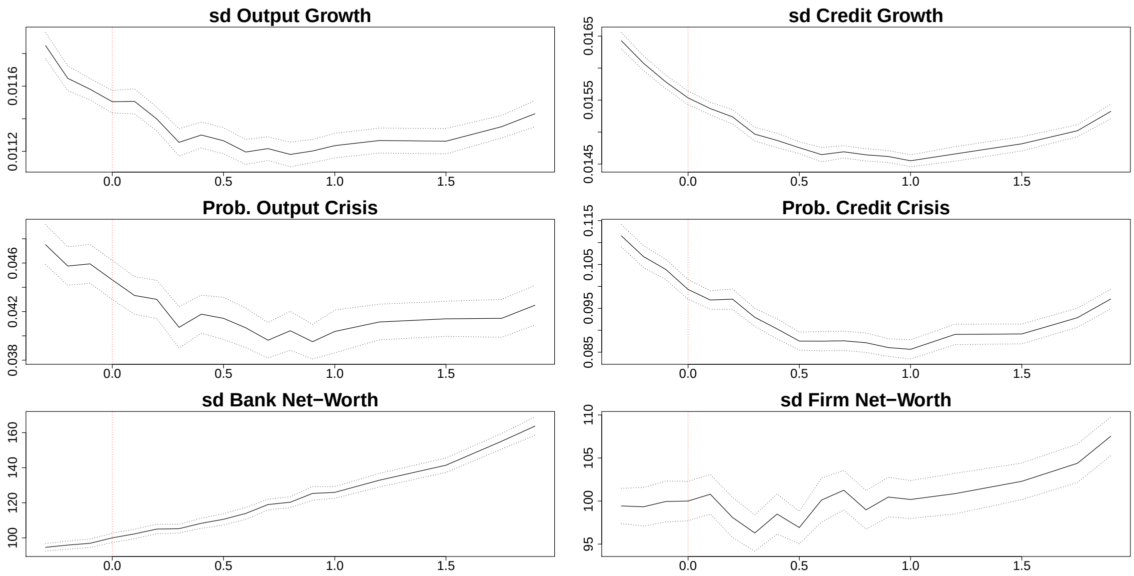

Figure 3: On the x-axis the values of the χ parameter, the solid line reports the average of one-hundred simulations and in dashed line the confidence interval of 95%. The dotted red line in correspondence with $\chi = 0$ where 'de facto' is applied to the micro policy only. In the top left figure, the standard deviation of output growth rate. In the top right, the standard deviation of credit growth rate. In the center left panel, the output crisis probability. In the center right, the credit crisis probability. In the bottom left panel, the standard deviation of bank net-worth. In the bottom right panel, the standard deviation of firm net-worth.

vulnerability of the economic systemic but at the potential cost of a more volatile banking sector.

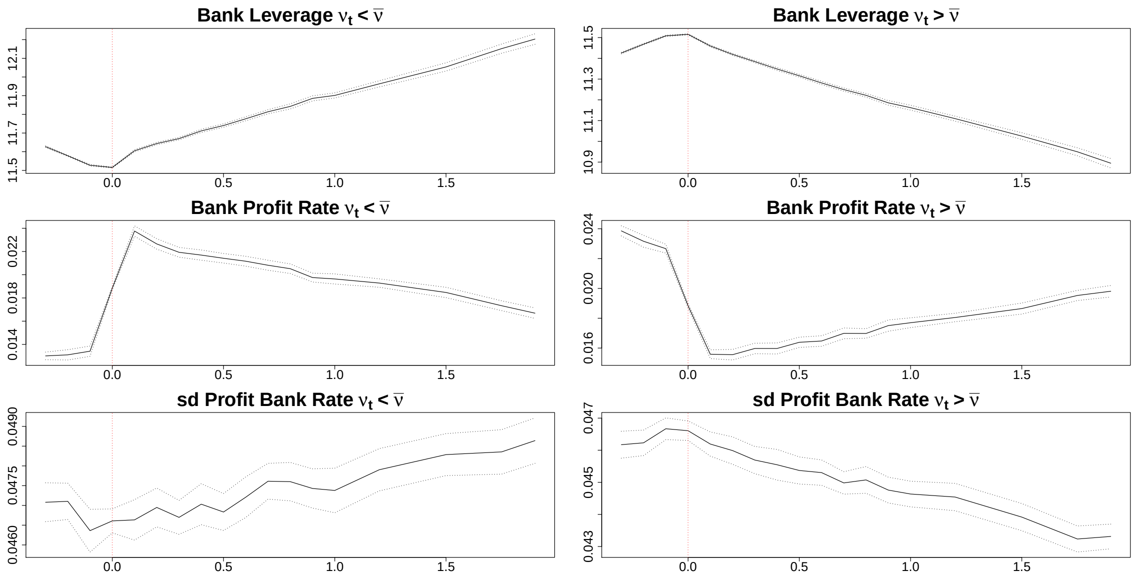

Figure 4: On the x-axis the values of the χ parameter, the solid line reports the average of one-hundred simulations and in dashed line the confidence interval of 95% The dotted red line in correspondence with $\chi = 0$ where 'de facto' is applied to the micro policy only. In the top left panel, the bank sector leverage, measured as aggregate credit divided by bank net-worth computed when the capital requirement is under the average ($\nu_t < \nu$). In the top right, the bank sector leverage computed when the capital requirement is over the average ($\nu_t > \nu$). In the center left, the profit rate when the capital requirement is under the average ($\nu_t < \nu$). In the center right, the profit rate when the capital requirement is over the average ($\nu_t > \nu$). In the bottom left, the standard deviation of the profit rate when the capital requirement is under the average ($\nu_t < \nu$). In the bottom right, the standard deviation of the profit rate when the capital requirement is over the average ($\nu_t > \nu$).

4 Meso Prudential Policy

In this section, we provide an alternative prudential scheme in which, in addition to the micro policy, the regulatory authority takes into account the number of banks-firms connections. We call this framework the meso prudential policy set-up because the evolving configuration of the connections on the credit market triggers the response of the financial stability authority. Our meso prudential measure is in line with new directives proposed by the Basel III agreement (see BIS, 2011) regarding the importance of controlling interconnectedness among global systemically important banks as an instrument to tame financial instability. While BIS's directives focus on the money market, we propose a measure of connection that takes into account the number of firms-banks linkages. As suggested by Lux (2016), default contagion through loans to firms is much stronger than the effect that boils down from the interbank market.

Results show that a basic prudential policy that targets just the more connected banks is able to reduce the vulnerability of the system without affecting negatively the banking sector as a whole. Indeed, increasing the capital requirement of the more connected bank reduces the possibility of diffusing local shocks, improving the resilience of the system.

In order to carry on our policy experiment, we define a simple measure of bank connectivity that allow us to isolate an efficient prudential policy. The number of connections of bank b (NC_{bt}) is given by the sum of the number of banks connected with the firms that received loans from bank b. Thus, if NF_{bt} is the number of firms i connected with bank b at time t and NB_{it} is the number of banks that provide credit to a firm i at time t:

$$NC_{bt} = \sum_{i}^{NF_{bt}} NB_{it}. \tag{26}$$

This measure tries to take into account both the direct links of a bank and the indirect connections between banks. Indeed, if bank b provides credit to NF_{bt} firms and, in turn, these firms have not any other lender, NB_{it} is equal to one for each firm and thus $NC_{bt} = NF_{bt}$. In this case, NC_{bt} is equal to the number of direct links only. On the contrary, if these firms receive credit from other banks, NB_{it} becomes greater than one for each firm and NC_{bt} increases ($NC_{bt} > NF_{bt}$).

In this experiment, the meso prudential policy targets only banks that overcome a certain threshold level of connectivity (TC) increasing the capital requirement of a fraction (δ_v) only for the more connected ones ($\nu_{bt} = \nu(1 + \delta_\nu)$), thus:

$$\nu_b = \begin{cases} \nu(1 + \delta_\nu) \text{ if} & NC_{bt} > TC \\ \nu \text{ if} & NC_{bt} \leq TC. \end{cases} \tag{27}$$

The top left panel of Figure 5 shows that increasing the link threshold (TC) reduces the number of banks targeted by the meso policy. The number of banks subject to the meso prudential regulation approaches to zero when the number of connections (NC_{bt}) is above 50. On the contrary,

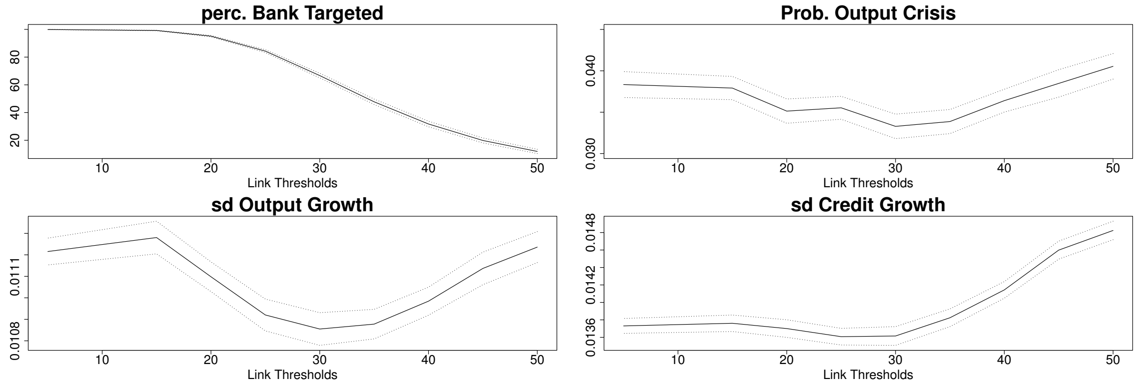

Figure 5: On the x-axis the values of the threshold level of connectivity. In the top left panel, the average number of bank targeted. In the top right, the output crisis probability. The bottom left, the output growth standard deviation. In the bottom right, the credit growth standard deviation.

when the number of connections is too low, the sample of banks that should be monitored becomes high. For instance, when TC is equal to ten, the financial stability authority should monitor more than eighty percent of banks. The remaining panels of Figure 5 show that there is an intermediate interval of meso prudential intervention thresholds (TC) that stabilizes the economy in terms of probability of output crisis, output, and credit growth volatility. For instance, if the threshold is 40, even if the number of targeted banks is below 20% we observe a significant reduction of the instability of the system with respect to the baseline scenario when only the microprudential policy is applied.

The effectiveness of the meso prudential policy is related to the emerging topology of the credit network: the left panel of Figure 6 shows that bank connectivity presents a fat tail log-normal distribution. As a consequence, just few banks can have a huge impact on the dynamics of the system and this justifies the implementation of a meso prudential policy that targets only the more connected ones. Potentially, these banks can diffuse local shocks across the entire network. However, also bank size presents a fat tail distribution (see the right panel of Figure 6).

In fact, one of the possible critique to our experiment is that bigger banks in terms of size could be also the most connected ones.[9] Nevertheless, according to our connectivity measure (see Equation 26), the bottom panel of Figure 6 shows that more connected banks do not coincide with bigger ones. For instance, taking 40 as the meso policy threshold ($NC = 40$) and the second decile of the bank size distribution (thus bigger banks), only about the 20% of the banks belonging to this second decile are also the more connected ones.

Moreover, applying the same policy but using a threshold size instead of a measure of connectivity (increasing the capital requirement of the larger banks according to a given size threshold), we do not observe a significant impact on crisis probability even if volatility decreases in terms of

[9] The relationship between bank size and systemic risk is widely studied in the literature. See for instance Laeven et al. (2016, 2014).

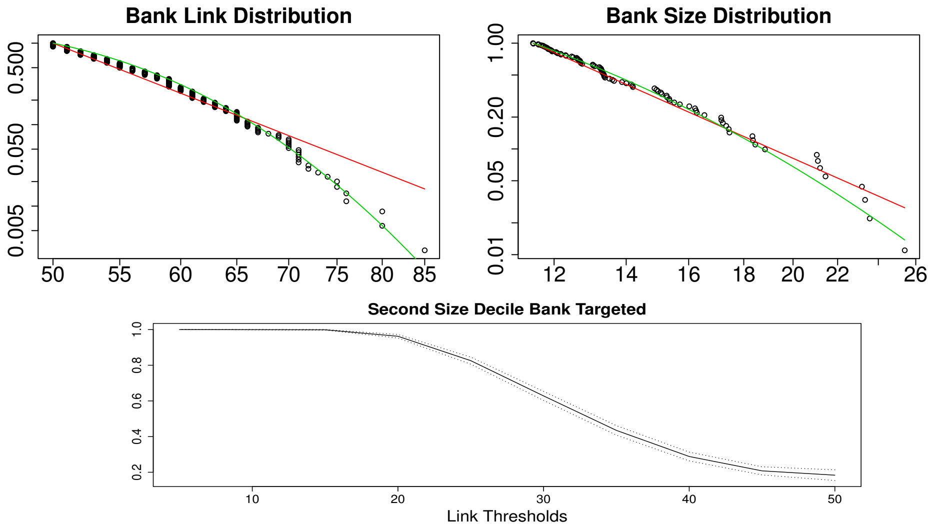

Figure 6: In the top left panel, the distribution of the connectivity measure used for the meso prudential policy. In the top right panel, the distribution of bank size, measured as the bank net-worth.In green log normal distribution, in red Pareto distribution estimates.In the bottom panel,the percentage of banks belonging to the 20% of the larger ones that are targeted by the meso policy.

output and credit standard deviations (Figure 7).

We also tested the effect of a combination of the meso prudential policy with the macro policy, thus letting change the capital requirement according to the credit cycle (see Equation 25) and at the same time targeting the more connected bank. [10] ν_{bt} becomes:

$$\nu_{bt} = \begin{cases} \nu_t(1+\delta_\nu) & \text{if } NC_{bt} > TC \\ \nu_t & \text{if } NC_{bt} \leq TC. \end{cases} \tag{28}$$

As shown in Figure 8, with respect to the baseline micro scenario, the combination of macro and meso policies has a better performance in reducing the volatility. However, as for the macro policy scenario, it leads to an increase in bank capital volatility. The meso policy stabilizes the economy, achieving comparable results in terms of output and credit volatility with respect to the macro policy. However, on the other hand, the meso prudential policy does not have a negative impact on bank capital volatility. In terms of policy recommendations, the meso prudential policy seems to be a good compromise between the soundness of the banking system and a stable real economy.

[10] Macroprudential policy parameters χ is fixed at 1.0, the specification in which the macroprudential policy is more effective.

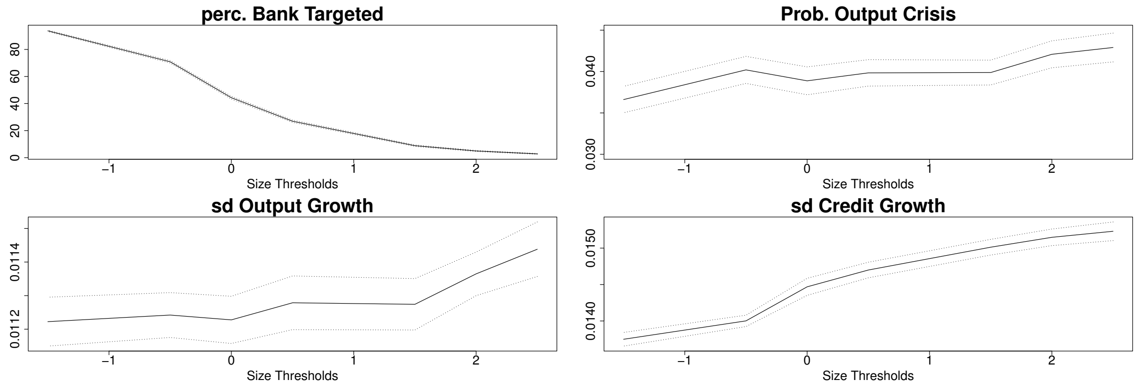

Figure 7: On the x-axis the values of the threshold level of size reported in standard deviations from the average. In the top left panel, the average number of bank targeted. In the top right, the output crisis probability. In the bottom left, the output growth standard deviation. In the bottom right, the credit growth standard deviation.

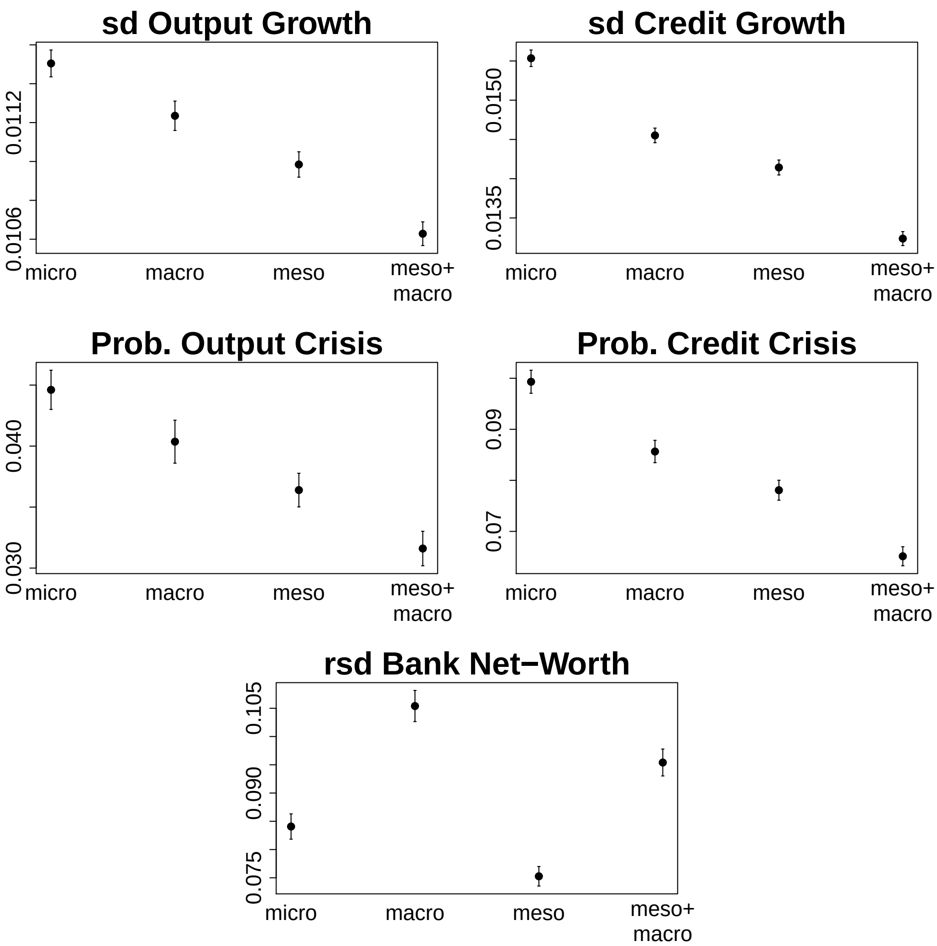

Figure 8: In the top left panel, the output growth standard deviation. In the top right, the credit growth standard deviation. In the center left, the output crisis probability. In the center right, the credit crisis probability. In the bottom, the standard deviation of bank net-worth. The parameter χ is fixed to 1.0 for the meso + macro experiment.

5 Conclusions

The 2007/2008 crisis highlighted the importance of regulation as a tool that may contribute to improve the resilience of the economy. Our contribution has tried to feed the literature that focuses on the interrelation between micro and macroprudential policy and the possible conflicts that may arise among them. We have also explored alternative regulatory frameworks.

In order to do that, we have built an agent-based credit network model. The ABM set-up has allowed us to design policy measures that may target specific agents according to the interaction structure of the economy, taking into account in a unified framework both individual behaviors and macroeconomic patterns.

Simulation results have shown that combining micro and countercyclical macro prudential policy reduces the volatility of the economy. However, the dark side of this policy mix is an increasing instability of the banking sector capital structure.

Moreover, we have proposed a meso prudential policy rule based on the topology of the credit network, in which the financial stability authority monitors the evolution of the connections among firms and banks. Thus, we have implemented a combined micro and meso prudential policy that leads to higher capital requirements only for more connected banks, reducing the diffusion of local shocks to the whole economy without affecting the banking system. Our results have shown that a combination of micro and meso prudential policy achieve the best compromise between banking sector and real economic stability, according to the idea that financial institutions might not only be "too big to fail", but they can also be "too interconnected or too systemic to fail" (see Markose et al., 2012, Kelly et al., 2016, Bongini et al., 2015, and Hser, 2015).

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