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

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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 combining micro and macro prudential policies reduces systemic risk, but at the cost of increasing bank capital volatility. Moreover, agent based methodology allows us to implement an alternative *meso* regulatory framework that take 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 interrelations between micro and macro prudential policies, the potential conflicts among them and to propose an alternative regulation 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 relation lending. We use this model to answer two different questions: a) are there any drawbacks when the financial stability authority uses a combination of micro and macro prudential policies to achieve its target? b) Does a prudential policy that takes into account also

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the credit network relationships works better in terms of output and credit stabilization than the one based on traditional micro/macro framework?

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 aims at reducing the riskiness of single financial institution, on the other hand macro prudential policies are focused on mitigating the systemic effects of individual imbalances. While micro prudential policy has a long tradition and has been extensively analyzed during the decades (see Gorton and Winton, 2003, for a review), it was only in the aftermath of the Great Recession that macro prudential policy captured the attention of economists. Despite the progress, Galati and Moessner (2017) concludes that there is no general consensus about the effectiveness of macro prudential policy as an instrument to reduce systemic risk.

A natural step forward in this research agenda would be the investigation of the combine effect of micro and macro prudential measures. In fact, in different circumstances, micro and macro prudential policy objectives may diverge (Angelini et al., 2012, Alessandri and Panetta, 2015, and Osinski et al., 2013). For instance, during downturns, macro prudential policies may be oriented at softening banks patrimonial requirement in order to avoid a credit crunch. On the contrary, micro prudential policy may aim at consolidating the financial position of banks enhancing the capital requirements. This conflictive dichotomy is the subject of our research.

In order to answer our research questions, we build an agent based model that includes a simplified credit network among firms and banks evolving endogenously according to the individual supply and demand of loans. Agent based models (henceforth ABM, see Delli Gatti et al., 2005 and Tesfatsion and Judd, 2006, for a detailed description) have became popular among economists as an alternative tool with respect to standard DSGE models. In the context of micro/macro prudential policy interaction, the choice of setting up an ABM is motivated by the fact that such kind of models are particularly suited to describe, in a unified framework, individual agent behavior and macroeconomic patterns.

Several recent contributions tried to investigate financial instability in a macro ABM model. Cincotti et al. (2012) finds that the dynamic adjustment of capital requirements performs better in terms of output stabilization with respect to fixed ones. Likewise, Baptista et al. (2016) explores the effects of a loan-to-income policy finding that such policy may successfully smooth the house price cycle. Assenza et al. (2017) compares two different macroprudential policies, capital requirement and liquidity constraints, analyzing the differences on the dynamic of the system. The adjustment of the capital requirement results to be more effective than liquidity ratios to reduce the probability of a crisis. Popoyan et al. (2017) builds an ABM model with heterogeneous banks and firms in order to test the effectiveness of different macro prudential policies finding that imposing a minimum capital requirement and counter-cyclical capital buffer is the policy that best resemble the Basel III regulatory framework in a much more simplified way. However, in a similar set up, Krug et al. (2014) finds that the macro prudential policy overlays impact with micro prudential measures has a very limited impact on financial stability. Moreover, Riccetti et al. (2017) finds that a tight regulation can generate a contraction of the credit supply whereas loose financial regulation can generate financial instability.

The following results emerge from our investigation: *a*) the combination of micro and macro prudential policy reduces instability and the probability of an economic crisis with respect to the scenario that implements the micro prudential policy only, *b*) However, such instability does not disappear but it is transmitted to the banking system through the higher volatility of banks' equity. *c*) The implementation of a meso prudential policy is effective in reducing systemic risk through tightening the capital requirements of more connected banks only. Exploiting network topology, it is possible to better coordinate micro and macro prudential 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 the meso prudential policy experiment. Finally, Section 5 concludes.

2 The Model

Our model economy reproduces a simplified credit network that evolves endogenously (Riccetti et al., 2013, Catullo et al., 2015, Catullo et al., 2017). The credit market is populated by M banks and N heterogeneous firms. Banks provide credit to firms that produce an homogeneous final good. Both firms and banks are bounded rational agents and they are profit maximizers choosing their desired level of leverage. The size of their balance sheet determines their expected profits and the related default risk they have to bear. Indeed, bank credit supply and firm demand derive from the leverage choices of the agents that, consequently, shape the evolution of the credit network.

2.1 Banks

In every period, banks determine their credit supply and the interest rate on loans. Each bank b gradually adjusts credit supply with respect to the loan demand received in the previous period ($L^D_{b,t-1}$). Moreover, banks have to comply with the capital requirement fixed by the financial stability authority (ν_t). The associated maximum loan supply would be equal to ($L^{\nu}_{bt} = E_{bt}/\nu$). Therefore, bank's desired loan supply is equal to the minimum between loan previously demand ($L^D_{b,t-1}$) and the maximum loan supply authorized by the financial stability authority (L^{ν}_{bt}):

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

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

$$L^S_{bt} = \begin{cases} L^O_{bt} \text{ if } L^S_{b,t-1}(1-\delta) \leq L^O_{b,t-1} \leq L^S_{b,t-1}(1+\delta) \\ L^S_{bt}(1-\delta) \text{ if } L^O_{b,t-1} < L^S_{b,t-1}(1-\delta) \\ L^S_{bt}(1+\delta) \text{ if } L^O_{b,t-1} > L^S_{b,t-1}(1-\delta). \end{cases} \quad (2)$$

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

$$L^{SM}_{ibt} = \zeta L^S_{bt}. \quad (3)$$

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

$$D_{bt} = L^S_{b,t} - E_{bt}, \quad (4)$$

assuming that the minimum loan supplied is equal to the bank net-worth.

Interest rate is computed in two steps. Firstly, following Gerali et al. (2010), banks maximize expected profits establishing a relation between interest rate and bank leverage. Since deviations from capital requirement are costly for the bank, they are charged directly on credit interest rates:

$$R_{bt} = \begin{cases} \eta r^d_t - k\left(E_{bt}/L^S_{bt} - \nu\right)\left(E_{bt}/L^S_{bt}\right)^2 \text{ if } E_{bt}/L^S_{bt} < \nu \\ \eta r^d_t \text{ if } E_{bt}/L^S_{bt} \geq \nu, \end{cases} \quad (5)$$

where the term $E_{bt}/L^S_{bt} < \nu$ captures the micro prudential policy intervention. Furthermore, similar in spirit to the financial accelerator mechanism of Bernanke et al. (1999), banks fix a firm specific interest rate premium (depending on firm's leverage (K^d_{it}/E_{it})) charging the following interest rate to firms:

$$r_{ibt} = \bar{r}\left(\frac{E_{it}}{K^d_{it}}\right)^{-\beta} + R_{bt}. \quad (6)$$

Therefore, bank's profit (π_{bt}), obtained from the interest charged on loans allocated to firms J after subtracting the bad debt (BD_{bt}) and capital costs, is:

$$\pi_{bt} = \sum_j^J r_{jbt}L_{jbt} - BD_{bt} - r_d D_{bt} - F. \quad (7)$$

Only a fraction of profits is accumulated by the 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^N_{bt} is equal to $min(\pi_{bt}, \pi^\gamma_{bt})$ with $0 < \gamma < 1$.

$$E_{b,t+1} = E_{bt} + \pi^N_{bt}. \quad (8)$$

2.2 Firms

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

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

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 contracted at time t (L_{it}). Firms can receive loans from more than one bank, thus the amount of loan borrowed by a firm is given by the sum of the loans received by the set of lending banks (Z):

$$L_{it} = \sum_{z \in Z} L_{izt}. \tag{11}$$

Profits derive from revenues ($p_{it}\phi K_{it}$) minus a variable cost on production (cK_{it}) interests on loans ($r_{it}L_{it}$) and a fixed cost (F), p_{it} is extracted from a uniform distribution ($p_{it} \sim U[0, 2]$)

$$\pi_{it} = p_{it}\phi K_{it} - r_{it}L_{it} - cK_{it} - F \tag{12}$$

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 $K_{it} > E_{it}$:

$$E(\pi_{it}) = E(p)\phi K_{it} - \left(\bar{r} \frac{K_{it}}{E_{it}}^{\beta} + E(R_{bt}) \right) (K_{it} - E_{it}) - cK_{it} - F, \tag{13}$$

assuming that $E(R_{bt}) = R_{b,t-1}$, thus maximizing expected profit for K_{it}, the first order condition is:

$$E(p)\phi - \ \bar{r}(\beta + 1)\frac{K^{\beta}_{it}}{E^{\beta}_{it}} + \bar{r} - R_{b,t-1} - c = 0. \tag{14}$$

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

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

However, firms may adapt only gradually to their optimum quantity (K^O_{it}), thus the productive quantity 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_{it}^{D}) is greater than the firm net-worth (E_{it}), loan demand is equal to:

$$L_{it}^{D} = min(K_{it}^{D}, K_{it}^{O}). \tag{17}$$

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

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

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

$$E_{i,t+1} = E_{it} + \pi_{it}^{N} \tag{19}$$

2.3 Credit Matching

In each period, firms can receive credit from different banks. The matching process between credit demand and supply follows three steps. 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 fulfill. Secondly, if firms do not receive enough credit, they ask for loans to banks that did not allocated all their supply in the previous step. Moreover, firms that did not receive credit in the previous period ask for loans to banks that still offer credit. In the third step, each firm that found lending banks in the previous periods may change the credit line in favor of an other bank that offers better credit conditions both in terms of the amount of loan provided and the interest rate.

Following Delli Gatti et al. (2010) and Riccetti et al. (2014), 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), that 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_{new}^{s} and L_{old}^{s}), with both of them not exceeding the loan demanded by the firm:

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

where $Ps(r)$ and $Ps(L)$ are given by:

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

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

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 ad Enter

Firms and bank with net-worth lower than zero exit from the economy and they are substituted by an equal number of agents, so the total number of agent is constant. The net-worth of the new enter 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 in steps:

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

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

3 Simulation Results: 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 calibrated the model parameters aiming at reproducing realistic values of the output standard deviation and of the aggregate credit over output value. For a detailed explanation of the calibration exercise see Appendix A.

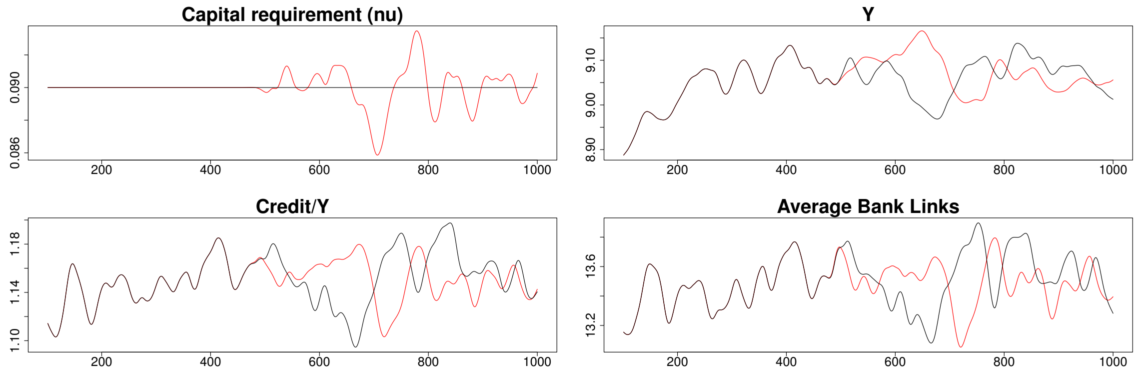

Figure 1: In black the baseline micro prudential scenario, in red the macro prudential scenario with $\chi = 0.8$. In all the figures. time on the x axis. In the top left figure, the capital requirement variation that are fixed in the baseline scenario while it fluctuate with the macro prudential policy. 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 money.

In the baseline scenario, we only implement a micro prudential framework: according to Equation (1) and (4) each bank have to adjust its leverage in order to satisfy the capital requirement (ν). Equation (1) governs the leverage dynamics, whereas Equation (4) drives the spread between the interest rates on deposits and wholesale credit. We compare the baseline micro prudential framework 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):

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

The parameter χ represents the strength of the macro prudential policy intervention. Assuming $\chi > 0$, the macro prudential authority behaves countercyclically, increasing ν_t when the aggregate amount of credit allocated in the economy (L_t) grows, and viceversa when credit decreases. When χ is negative the macro prudential policy is procyclical.

We apply the macro prudential policy after the period 500. Figure 1 shows that after the period 500 ν_t starts to change and this implies that the macro and micro dynamics of the model are affected by the intervention of the financial stability authority. We report the time series of output, credit over output and the average number of credit agreements of each bank, these last intended as links of the credit network.

Since results crucially depend on the value of χ, we perform a sensitivity analysis varying this parameter, considering 100 Monte Carlo simulations for each specification. We focused on the variations of the standard deviation of both credit and output, which give us a measure of the volatility of the system, and the crisis probability of credit and output provide a synthetic indicator of the vulnerability of the economy, this last measured as the frequency of a reduction lower than the -0.02 per cent.

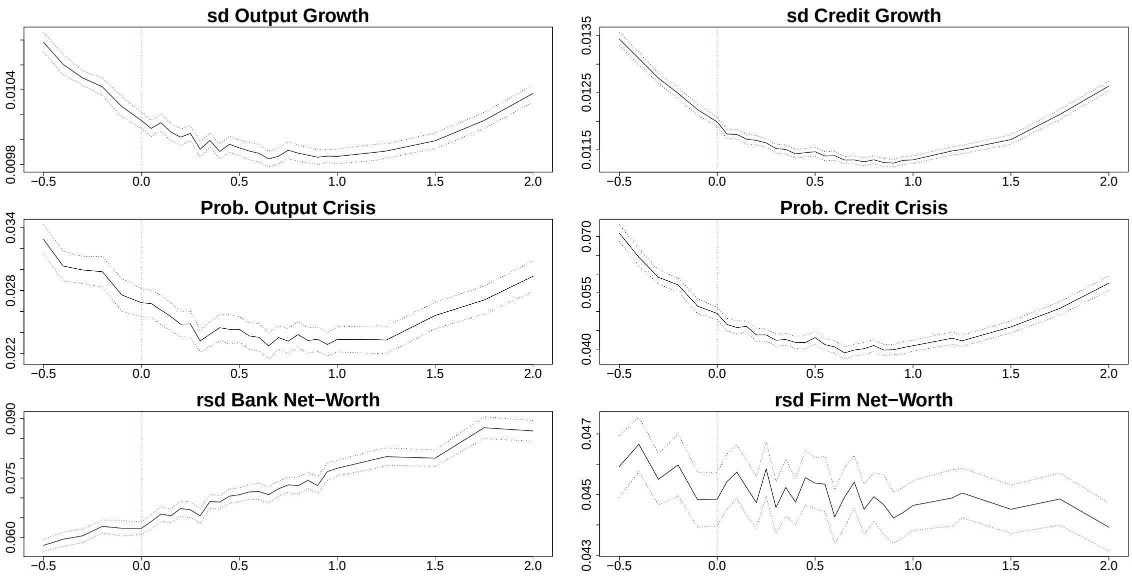

Figure 2: On the x-axis the values of the χ parameter, the solid line reports the average of one-hundred simulations and in dashed line the confidence interval of 95%. The dotted red line in correspondence with $\chi = 0$ where 'de facto' is applied the micro policy only. In the top left figure, the 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, measured as the aggregate standard deviation of equity divided by the average value. In the bottom right panel, the standard deviation of firm net-worth, measured as the aggregate standard deviation of equity divided by the average value.

Figure 2 shows that varying this sensitivity parameter (χ) has a U-shaped effect on the standard deviation of output and credit and on the probability of output and credit crisis. When χ is equal to zero the macro prudential policy is inactive reproducing 'de facto' the micro prudential policy. Until $\chi = 0.8$, increasing χ reduces the volatility. Instead, for values above about 0.8, the volatility of output and credit increases.

However, the macro prudential policy seems to have an hidden side effect. Figure 2 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 impacts consistently on bank leverage and thus on bank profit volatility. Figure 3 shows that when the capital requirement ν_t is below the average bank leverage increases, because banks may offer a larger amount of credit at a lower interest rate (Equation 5), while the opposite occurs when ν_t is under the average level $\bar{\nu}$. In particular, with χ greater than zero, profits increase when the capital requirement is under the average but at the cost of higher profit volatility, due to the increased risk associated with higher leverage. On the other hand, when ν_t is over the average both the profit rate and its standard deviation decrease. 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, augmenting financial instability. Therefore, a well calibrated macro prudential policy reduces the vulnerability of the economic systemic risk but at the potential cost of a more

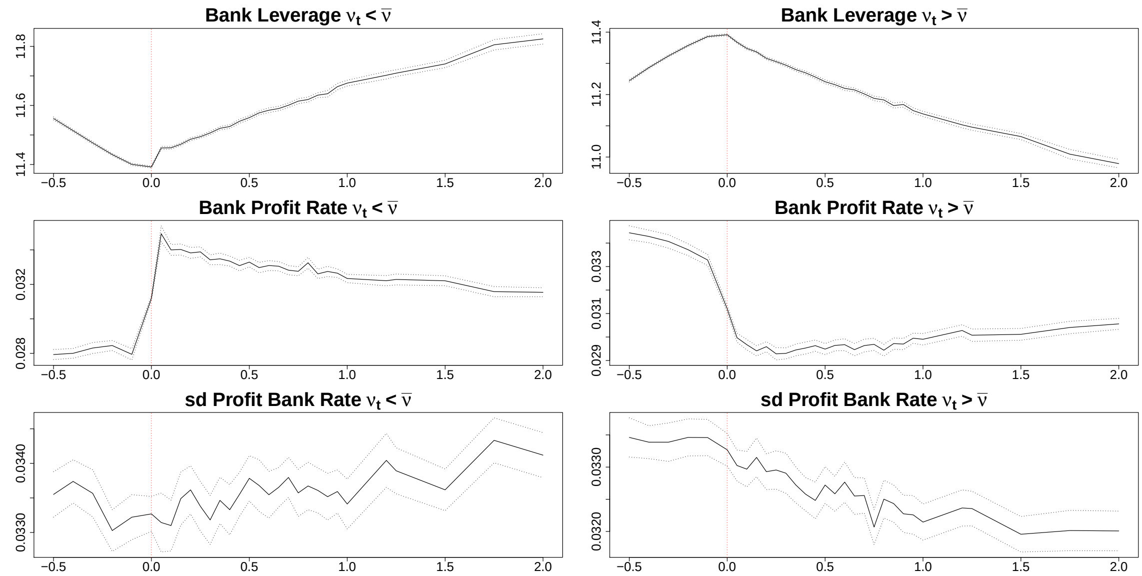

Figure 3: On the x-axis the values of the χ parameter, the solid line reports the average of one-hundred simulations and in dashed line the confidence interval of 95% The dotted red line in correspondence with $\chi = 0$ where 'de facto' is applied the micro policy only. In the top left panel, the bank 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 ($\nu_t > \nu$).

fragile banking system.

4 Simulation Results: 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.

Results show that a basic prudential policy that target 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 allowed us to isolate an efficient prudential policy. The number connections of a bank b (NC_{bt}) is given by the sum of the number of banks connected with the firms that received loans from the b bank. Thus, if NF_{bt} is the number of firms j connected with the bank b at time t and NB_{jt} is the number of banks that provide credit to a firm j at time t:

$$NC_{bt} = \sum_{j}^{NF_{bt}} NB_{jt}. \tag{26}$$

This measure tries to take into account both the direct links of a bank and the indirect connections between banks. Indeed, if a bank b provides credit to NF_{bt} firms and, in turn, these firms have not any other lender NB_{jt} is equal to one for each firm and $NC_{bt} = NF_{bt}$, thus NC_{bt} is equal to the number of direct links; while if these firms receive credit from other banks NB_{jt} 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 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 4 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, 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 the eighty per cent of the banks of the model. The remaining panels of Figure 4 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

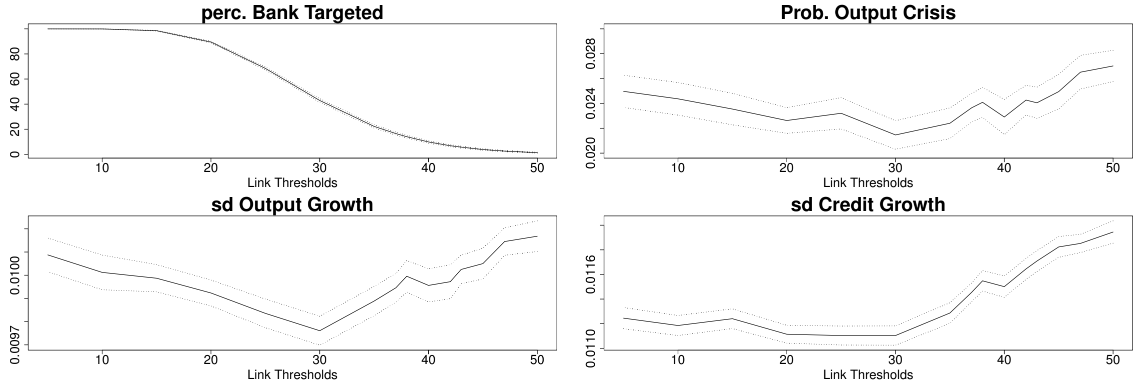

Figure 4: On the x-axis the values of the threshold level of connectivity. In the top left panel, the average number of bank targeted. In the top right, the output crisis probability. The bottom left, the output growth standard deviation. In the bottom right, the credit growth standard deviation.

reduction of the instability of the system with respect to the baseline scenario when only the micro prudential 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 5 shows that bank connectivity distribution 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 justify the implementation of a meso prudential policy that target only the more connected ones, that potentially can diffuse local shocks across the entire network. However, also bank size presents a fat tail distribution (see the right panel of Figure 5).

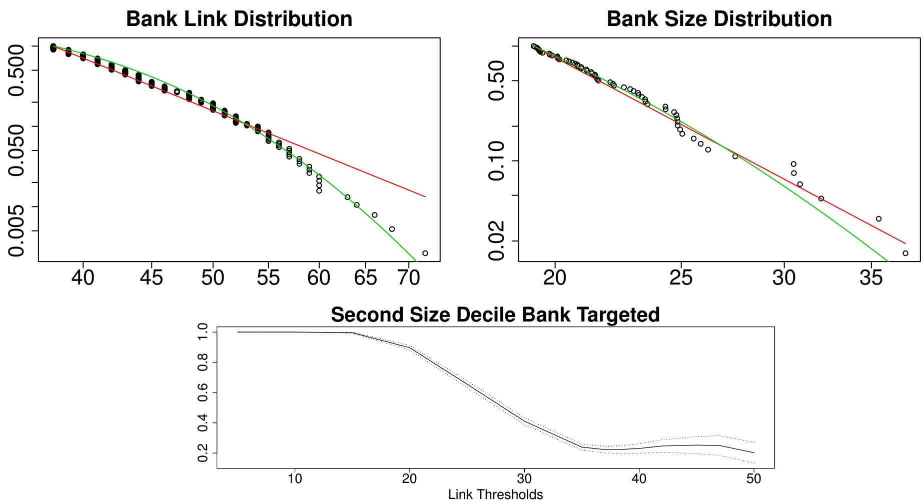

Figure 5: In the top left panel, the distribution of the connectivity measure used for the meso prudential policy. In the top right panel, the distribution of bank size, measured as the bank net-worth.In blue log normal distribution, in red Pareto distribution estimates.In the bottom panel,the percentage of banks belonging to the 20% of the larger ones that are targeted by the meso policy.

In fact, one of the possible critique to our experiment is that bigger banks in terms of size could be also the most connected banks of the credit network.[1] Nevertheless, according to our

[1]The relationship between bank size ans systemic risk is widely studied in the literature. See for instance Laeven

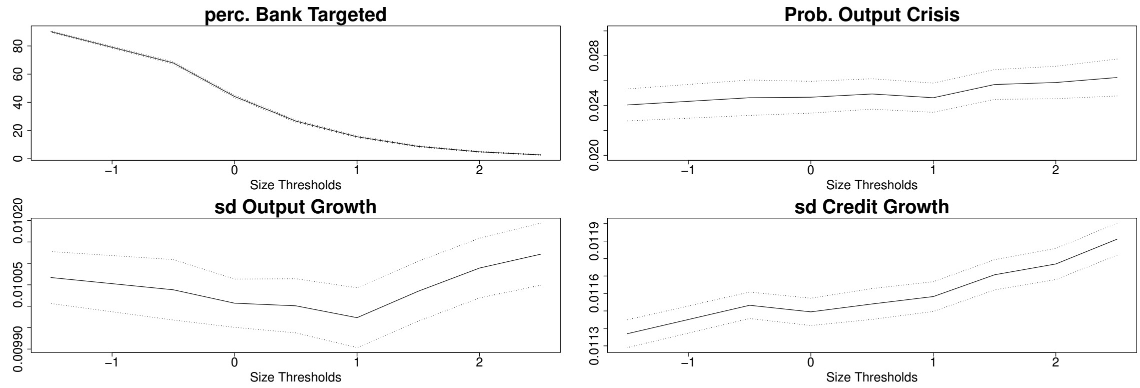

Figure 6: On the x-axis the values of the threshold level of size reported in standard deviations from the average. In the top left panel, the average number of bank targeted. In the top right, the output crisis probability. In the bottom left, the output growth standard deviation. In the bottom right, the credit growth standard deviation.

connectivity measure (Eq 26), the bottom panel of Figure 5 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 output and credit standard deviations (Figure 6).

Moreover, we 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 and at the same time targeting the more connected bank. 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 7, with respect to the baseline micro scenario, the combination of macro and meso policies has the better performance in reducing the volatility of the system. However, as for the macro policy scenario, it causes an increase of 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. On the other hand, the meso prudential policy does not have a negative impact on bank capital volatility. In terms of policy recommendation the meso prudential policy seems to be a good compromise between the soundness of the banking system and a stable real economy.

et al. (2016, 2014).

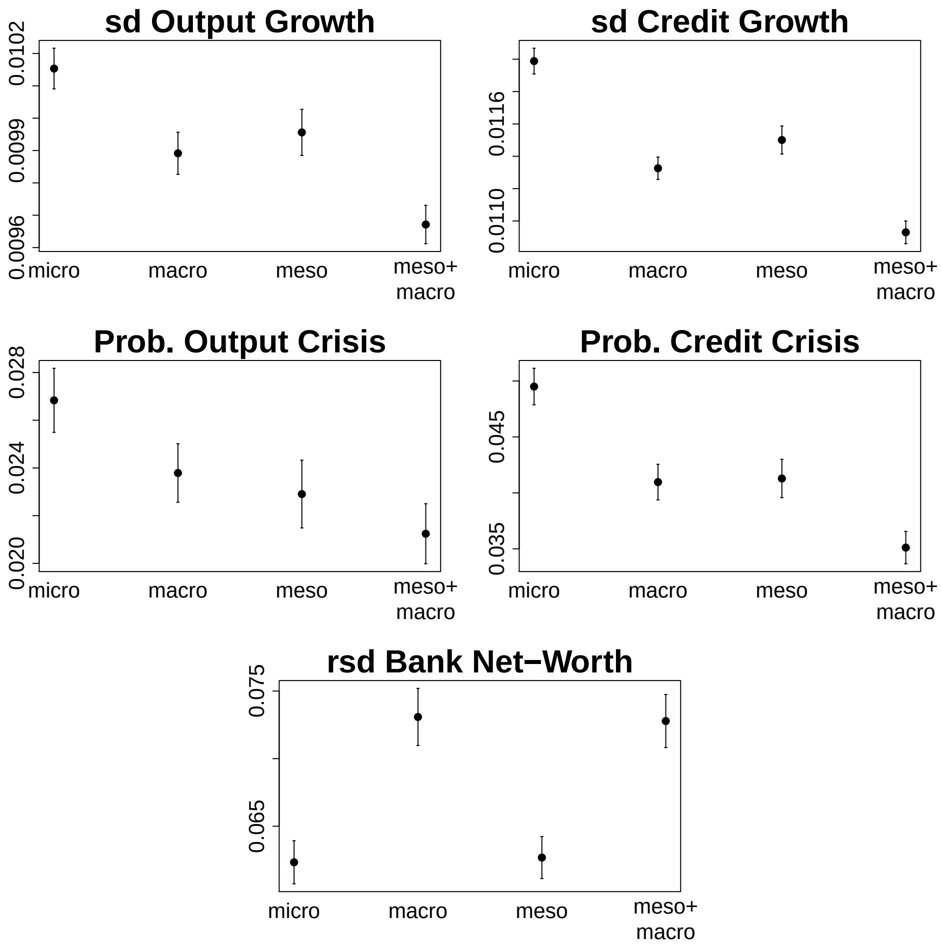

Figure 7: In the top left panel, the output growth standard deviation. In the top right, the credit growth standard deviation. In the center left, the output crisis probability. In the center right, the credit crisis probability. In the bottom, the standard deviation of bank net-worth.

5 Conclusions

The 2007/2008 crisis highlights the importance of regulation as a tool that may contribute to improve the resilience of the economy. Our contribution tries to feed the literature that focus on the interrelation between micro and macro prudential policy and the possible conflicts that may arise among them. We also explore alternative regulatory frameworks.

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

Simulation results show that combining micro and countercyclical macro prudential policy reduces the volatility of the economic system. However, the dark side of this policy mix is an increasing instability of the banking sector capital structure, in line with recent contributions by Albertazzi and Gambacorta (2009) and De Haan and Poghosyan (2012).

Moreover, we propose 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 implement a combined micro and meso prudential policy that leads to higher capital requirements only for more connected banks. In this way we reduce the diffusion of local shocks to the whole economy without affecting the banking system. Our results show that a combination of micro and meso prudential policy achieves the best compromise between banking sector and real economy 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, and Bongini et al., 2015).

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Appendix A: Calibration

Table 1: Calibrated parameters

parameters	Description	Value
M	Number of banks	100
N	Number of firms	1000
E_B^0	Initial Bank net-worth	1
E_F^0	Initial Firm net-worth	1
ϕ	Firm productivity	0.5
c	Firm variable cost	0.45
F	Firm fixed cost	0.01
r_d	Discount Rate	0.001
ζ	Bank maximum credit share	0.1
γ	Firms and banks dividend policy	0.5
$\bar{v}$	Capital requirement	0.09
ρ	Persistence of capital requirement adjustment	0.9
δ_ν	Meso policy capital requirement variation	0.15
δ	Capital and credit adjustment	0.1
κ	Capital requirement adjustment cost	10
β	Risk premium coefficient	1.25
$\bar{r}$	Risk free rate	0.005
η	Bank margin on the discount rate	10

We calibrated the model in order to reproduce realistic level of output volatility and aggregate leverage, which are the crucial variables of our analysis. Considering the results of one-hundred simulation of the baseline specification the output standard deviation is in line with data provide by Uribe and Schmitt-Grohé (2017): data show that 1.12% is the word quarterly standard deviation of output growth rates, while in simulation this value is close to 1.01%. Moreover, the credit over output ratio is equal to 1.15, in line with the Euro area average between 2006 and 2015 that is 1.05. As expected credit volatility is higher than output volatility.

The number of agents depends on the necessity of a numerous population for producing robust results during the simulation, the ratio between banks and firms follow Catullo et al. (2015) and Catullo et al. (2017). The initial level of net-worth of firms and bank (E_b^0 and E_f^0) are fixed equal to one for simplicity. The productivity of capital (ϕ) and the variable cost of capital (c) are fixed in order to have a difference between productivity, thus expected revenues given $E(p) = 1$, and variable costs that allow firms to borrow money until the quarterly interest rate is lower of 5%. F is intended as little fixed cost that eliminates agents that are too small to impact on the credit network, allowing new agent to enter. r_d is fixed to 0.001 for simplicity. ζ is 0.1 to avoid excessive exposure of banks and, thus, an excessive failure rate of banks. γ is fixed to 0.5 for simplicity, value of γ that are near to zero do not allow accumulation of firms and banks, on the other side value of γ near to 1.0 lead to high levels of capital accumulation of firms, which generates an excessive reduction of their leverage.

In the baseline scenario we keep the capital requirement fixed ($\nu = 0.09$ in line with Basel's Agreements, see Gerali et al., 2010), thus in this specification a basic micro prudential policy is implemented: banks have to align to the capital requirement in order to reduce their riskiness. Indeed, bank leverage is slightly above the maximum leverage possible for the banks given $\nu = 0.09$ (Table 2) and the number of firms that receive loans is 13.51 a value larger than the ratio between the number of firms and banks. In this simple credit model the dynamic of credit and, thus, the probability of crisis occurrence depends on negative shocks affecting the economy through bad debts: debts that are not payed back by failing firms. The percentage of bad debt on credit is 1.9% with a low standard deviation, meaning that on average bad debt is quite stable through different simulations. Similarly $\bar{v} = 0.15$ allow an effective Meso policy. The remaining parameters are fixed in order to permit a good calibration of the model with respect to output standard deviation and aggregate leverage. In Appendix B, we report sensitivity experiments on the adjustment parameters δ and the parameters that are associated with the financial accelerator mechanism of banks (κ, β,$\bar{r}$,η) running one-hundred simulation for each specification. The sensitivity experiments are also implemented in the macro and meso scenarios.

Table 2 shows the emergent aggregate variable results in the micro baseline simulation.

	Micro (Baseline)		
Sd Output Growth Rate	1.01%	Prob Output Crisis	2.68%
	(0.003%)		(0.0692%)
Sd Credit Growth Rate	1.19%	Prob Credit Crisis	4.95%
	(0.004%)		(0.0840%)
rsd Bank Net-Worth	6.23%	rsd Firm Net-Worth	4.48%
	(0.0813%)		(0.0446%)
Credit/Output	1.15	Bank Leverage	11.41
	(0.0005)		(0.0017)
Average Bank Links	13.51	Bad-Debt/Credit	1.9%
	(0.0043)		(0.0001%)

Table 2: Macro Variable Simulated Results. Bank Leverage is measured as aggregate credit over aggregate bank net-worth. Average Bank Links are the average number of firms that receive loans from a bank. Bad-Debt/Credit is the value of the debts that are not payed back by failing firms divided by the total amount of credit in the economy.

Appendix B: Sensitivity Analysis

As expected reducing the adjustment parameter δ decreases the volatility of the system, while the opposite happens when δ is increased. Also the parameters that impact on the financial accelerator mechanism has been calibrated to produce realistic levels of systemic volatility (κ, β,$\bar{r}$,η): values that are too distant from the baseline tent to increase volatility. Indeed, for instance decreasing or increasing too much the parameter β impacts in significant way on the system. When β is higher than the benchmark level interest rate may easily surges when firm leverage augment, this may increase rapidly firms's bad debt and, at the same time, may reduce the credit in the economy. On the other hand, lower levers of β may increase too much firm capacity of borrowing money and, thus leverage in the economy. Varying the other financial accelerator parameters produces similar effects Moreover, the adjustment parameter (δ) and the parameters of the financial accelerator seem to impact on the simulated system following the same patterns in both the Macro prudential policy and the meso prudential policy specifications.

Table 3: Micro (Baseline) Configuration Sensitivity Analysis

variable	sd(Output)	sd(Credit)	prob(Crisis Output)	prob(Crisis Credit)	rsd(Bank net-worth)
Micro (Baseline)					
	1.015	1.199	2.682	4.95	6
	(0.032)	(0.0405)	(0.6829)	(0.8333)	(0.8113)
δ					
0	0.897	0.316	1.14	0.042	15
	(0.0265)	(0.1143)	(0.3913)	(0.0955)	(6.2339)
0.05	0.776	0.603	0.54	0.06	5
	(0.0241)	(0.0251)	(0.3222)	(0.1119)	(0.6075)
0.15	1.374	1.888	7.568	14.58	8
	(0.0516)	(0.0789)	(0.9393)	(1.4286)	(1.1505)
0.2	1.747	2.635	12.742	21.94	9
	(0.062)	(0.094)	(1.233)	(1.3477)	(1.3007)
β					
0.75	1.203	3.149	5.028	26.336	25
	(0.0356)	(0.1241)	(0.7995)	(1.4113)	(1.3228)
1	1.345	2.521	7.108	20.088	14
	(0.0497)	(0.1196)	(1.02)	(1.4231)	(2.1747)
1.5	1.713	1.705	12.206	12.08	20
	(0.0559)	(0.0571)	(1.2165)	(1.2355)	(1.0843)
1.75	1.607	1.672	10.604	11.502	20
	(0.0502)	(0.0499)	(1.1364)	(1.2538)	(0.2484)
κ					
0	1.121	1.553	3.966	10.02	10
	(0.0391)	(0.0702)	(0.7702)	(1.3826)	(1.4704)
5	1.049	1.343	3.114	6.986	8
	(0.0399)	(0.051)	(0.8146)	(1.0595)	(1.1516)
15	1.377	1.88	7.672	14.092	5
	(0.044)	(0.065)	(0.9183)	(1.1835)	(0.7352)
20	1.986	3.109	15.312	24.398	5
	(0.0742)	(0.1226)	(1.3545)	(1.3383)	(0.6968)
$\bar{r}$					
0.003	1.316	2.931	6.758	23.704	17
	(0.0448)	(0.1317)	(0.9906)	(1.553)	(1.5681)
0.004	1.192	1.734	4.924	12.374	9
	(0.0384)	(0.0682)	(0.7805)	(1.3966)	(1.5062)
0.006	1.772	1.757	13.014	12.822	5
	(0.056)	(0.0571)	(1.2303)	(1.2335)	(1.5292)
0.007	1.705	1.707	12.04	12.098	20
	(0.0544)	(0.0531)	(1.1976)	(1.1287)	(0.4019)
η					
5	1.18	1.718	4.896	12.278	10
	(0.0385)	(0.0713)	(0.8187)	(1.2713)	(1.6626)
7.5	1.102	1.425	3.788	8.016	8
	(0.0364)	(0.0464)	(0.9038)	(1.0248)	(0.826)
12.5	0.939	0.992	1.798	2.29	6
	(0.0336)	(0.0317)	(0.5857)	(0.6453)	(0.7992)
15	1.806	1.785	13.44	12.94	5
	(0.0631)	(0.0621)	(1.2905)	(1.3164)	(1.3424)

Table 4: Macro Configuration Sensitivity Analisis

variable	sd(Output)	sd(Credit)	prob(Crisis Output)	prob(Crisis Credit)	rsd(Bank net-worth)
Macro					
	0.989	1.132	2.378	4.098	7
	(0.0332)	(0.035)	(0.624)	(0.8028)	(1.0755)
δ					
0	0.895	0.316	1.096	0.036	13
	(0.0328)	(0.1215)	(0.4561)	(0.0772)	(5.8194)
0.05	0.764	0.567	0.58	0.086	6
	(0.026)	(0.0183)	(0.3321)	(0.1311)	(0.7924)
0.15	1.387	1.907	7.722	14.76	9
	(0.0534)	(0.0775)	(1.0552)	(1.4176)	(1.3145)
0.2	1.919	3.017	15.06	25.21	11
	(0.067)	(0.1266)	(1.2185)	(1.4423)	(1.6364)
β					
0.75	1.226	3.08	5.466	24.976	27
	(0.0442)	(0.1053)	(0.9543)	(1.3613)	(2.4675)
1	1.31	2.321	6.576	18.304	18
	(0.0484)	(0.0891)	(1.0388)	(1.5563)	(2.6735)
1.5	1.725	1.714	12.212	12.262	20
	(0.0578)	(0.0599)	(1.1423)	(1.2169)	(1.0691)
1.75	1.608	1.672	10.614	11.498	20
	(0.0504)	(0.0505)	(1.135)	(1.2619)	(0.2459)
κ					
0	1.079	1.417	3.542	8.264	11
	(0.0349)	(0.0515)	(0.7766)	(1.0205)	(1.6437)
5	1.021	1.26	2.828	5.866	9
	(0.0356)	(0.0412)	(0.7975)	(0.907)	(1.3323)
15	1.896	2.903	13.622	22.228	6
	(0.1107)	(0.1942)	(1.5157)	(1.8315)	(0.8351)
20	7.242	77.252	22.944	39.58	6
	(2.039)	(54.7402)	(7.9463)	(1.8896)	(2.0183)
$\bar{r}$					
0.003	1.291	2.692	6.532	21.92	20
	(0.0466)	(0.1043)	(0.9599)	(1.3862)	(2.4957)
0.004	1.163	1.622	4.544	10.726	12
	(0.037)	(0.0649)	(0.7811)	(1.26)	(1.7539)
0.006	1.781	1.763	13.064	12.632	6
	(0.0519)	(0.0515)	(1.1082)	(1.24)	(1.3808)
0.007	1.705	1.707	12.042	12.088	20
	(0.0538)	(0.0523)	(1.2431)	(1.1432)	(0.4099)
η					
5	1.154	1.618	4.49	10.852	12
	(0.039)	(0.0596)	(0.7875)	(1.2096)	(1.6655)
7.5	1.064	1.33	3.302	6.924	9
	(0.0362)	(0.043)	(0.8469)	(1.0397)	(1.1742)
12.5	0.911	0.937	1.658	1.786	6
	(0.0343)	(0.034)	(0.5645)	(0.568)	(0.9157)
15	1.813	1.791	13.504	13.156	5
	(0.0552)	(0.0556)	(1.1348)	(1.1643)	(1.3118)

Table 5: Meso Configuration Sensitivity Analysis

variable	sd(Output)	sd(Credit)	prob(Crisis Output)	prob(Crisis Credit)	rsd(Bank net-worth)
Meso					
	0.996	1.151	2.296	4.15	6
	(0.0365)	(0.0443)	(0.72)	(0.8726)	(0.792)
δ					
0	0.893	0.152	1.15	0.004	11
	(0.0344)	(0.1135)	(0.4959)	(0.0281)	(4.6958)
0.05	0.775	0.599	0.52	0.08	5
	(0.0233)	(0.0232)	(0.2814)	(0.1421)	(0.7199)
0.15	1.295	1.771	6.252	12.838	7
	(0.0349)	(0.0579)	(0.8573)	(1.2123)	(0.9714)
0.2	1.601	2.409	10.858	20.206	9
	(0.0491)	(0.0845)	(1.2431)	(1.2363)	(1.1169)
β					
0.75	1.392	3.366	7.748	27.488	18
	(0.0448)	(0.1068)	(1.0853)	(1.4189)	(1.5009)
1	1.255	1.91	5.552	13.59	12
	(0.0443)	(0.0884)	(0.9203)	(1.4271)	(1.7305)
1.5	1.713	1.705	12.206	12.08	20
	(0.0559)	(0.0571)	(1.2165)	(1.2355)	(1.0843)
1.75	1.607	1.672	10.604	11.502	20
	(0.0502)	(0.0499)	(1.1364)	(1.2538)	(0.2484)
κ					
0	1.088	1.509	3.502	9.262	10
	(0.0406)	(0.0679)	(0.7058)	(1.1833)	(1.41)
5	1.03	1.309	2.836	6.338	8
	(0.0355)	(0.0498)	(0.659)	(0.9784)	(1.0059)
15	1.383	1.913	7.722	14.372	5
	(0.0479)	(0.0743)	(1.03)	(1.2384)	(0.6419)
20	1.982	3.112	15.44	24.544	5
	(0.0748)	(0.1229)	(1.3421)	(1.4383)	(0.6439)
$\bar{r}$					
0.003	1.334	2.572	6.916	21.122	15
	(0.0471)	(0.1121)	(0.9901)	(1.36)	(2.2364)
0.004	1.133	1.558	4.008	9.636	9
	(0.0327)	(0.0559)	(0.7445)	(1.1358)	(1.1235)
0.006	1.776	1.76	12.888	12.626	6
	(0.0466)	(0.0479)	(1.1429)	(1.2009)	(1.6597)
0.007	1.705	1.707	12.04	12.098	20
	(0.0544)	(0.0531)	(1.1976)	(1.1287)	(0.4019)
η					
5	1.122	1.574	3.956	10.218	9
	(0.0362)	(0.0593)	(0.7689)	(1.2476)	(1.1604)
7.5	1.054	1.327	3.078	6.718	7
	(0.0352)	(0.0453)	(0.7269)	(1.0131)	(0.8711)
12.5	0.934	0.978	1.754	2.21	6
	(0.0317)	(0.0322)	(0.5825)	(0.5745)	(0.8278)
15	1.807	1.789	13.376	13.02	6
	(0.0639)	(0.0634)	(1.3476)	(1.3149)	(1.3103)