Systemic Risk and Macro-prudential policies: a credit network-based approach

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Abstract

Assessing systemic risk and defining macro-prudential policies aiming at reducing economic system vulnerability have been at the center of the economic debate of the last years. Credit networks play a crucial role in diffusing and amplifying local shocks, following the network-based financial accelerator approach (Delli Gatti et al., 2010; Battiston et al., 2012), we constructed an agent based model reproducing an artificial credit network populated by heterogeneous firms and banks. Calibrating the model on a sample of firms and banks quoted on Japanese stock-exchange markets from 1980 to 2012, we try to define both early warning indicators of crises and policy precautionary measures based on the analysis of the endogenous dynamics of credit network connectivity.

Keywords: economic crisis, credit network, leverage, heterogeneity, agent based model.
JEL classification codes: C63, E32, E52, G01.

1 Introduction

The 2007 global crisis restated the importance of dealing with the intrinsic vulnerability of economic systems (Minsky, 1975, 1982, 1986). Indeed, assessing systemic risk and defining macro-prudential policies aiming at reducing economic system vulnerability have been at the center of the economic debate of the last years (Basel Committee, 2011; Yellen, 2011; Angelini et al., 2012; Boissay et al., 2013). Credit networks play a crucial role in diffusing and amplifying local shocks, thus we try to define both early warning indicators of crises and policy precautionary measures based on the analysis of the dynamics of credit network connectivity.

Following the network-based financial accelerator approach (Delli Gatti et al., 2005, 2010; Battiston et al., 2012), we constructed an agent based model reproducing an artificial credit network populated by heterogeneous firms and banks. Firms fund their production process through their internal resources or borrowing money from the banks, hence the credit network is composed of the credit

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agreements established among firms and banks. Production results are influenced by idiosyncratic demand shocks, therefore if a firm increases its leverage, its expected production and profits augment but, at the same time, firm exposure to negative shocks rises, thus, incrementing failure probability. Moreover, higher levels of target leverage are associated with higher interest rates on loans and higher probability of suffering credit rationing; increasing the number of lending banks may reduce credit rationing but it augments total firms transaction costs. Similarly, higher levels of leverage increase profits for banks but raise their exposure, indeed when a firm fails, it does not repay its loans causing losses for the lending banks that may even lead to their failure. Therefore, firms and banks have to deal with the trade-off between increasing their leverage to augment expected profit and reducing exposure to contain failure probability, credit costs and rationing risk. Thus, in the attempt of gaining satisficing levels of realized profits, firms and banks choose their target level of leverage through a simple reinforcement learning procedure (Tesfatsion, 2005; Riccetti et al., 2013; Catullo et al., 2015). Consequently, agents' choices about their target leverage determine the evolution of the credit network, influencing aggregate output dynamics.

We calibrated the model on a sample of firms and banks quoted on Japanese stock-exchange markets from 1980 to 2012 (Marotta et al., 2013). In simulated data, we reproduce the levels of leverage, connectivity and output volatility observed in the Japanese dataset. The model simulations generate endogenous pro-cyclical fluctuations of credit and connectivity. Indeed, during the first periods of expansions, banks are able to increase their net-worth, because they lend to relatively robust firms and, then, they do not suffer from firm failures. Consequently, bank supply of loans may augment, leading to an increase of leverage and connectivity. However, high leverage raises firm default risk and high connectivity may diffuse easily the negative effects of firm and bank failures amplifying the effects of local shocks. In effect, aggregate credit leverage and connectivity are positively correlated with the number of firms failures. Therefore, during expansionary phases aggregate credit, leverage and connectivity augment, creating the conditions for future recessions and increasing the probability of huge output slowdowns.

Indeed, according to the methodology developed by Schularick and Taylor (2012), we found that both credit and connectivity growth rates are positively correlated with crisis probability and their combination represents an effective early warning measure in both empirical and simulated data. Therefore, we use credit and connectivity variations to assess systemic risk in order to define the timing and the target of loan-to-value macro-prudential interventions.

Simulation experiments show that when systemic risk increases beyond a certain threshold, forcing banks to avoid lending to more indebted firms may decrease output volatility without causing consistent credit and, thus, output contractions. While, reducing permanently the possibility of offering loans to riskier firms decreases output volatility and, hence, systemic risk, but at the price of a lower average output level.

We tested also permanent loan-to-value restrictions targeted only to more connected banks. When interventions focus on banks that are relatively central in the credit network, economic system vulnerability may be substantially reduced without affecting aggregate credit supply and output. As above the larger the set of banks that are targeted by the policy maker the lower is the resulting probability of crisis but, at the same time, credit supply may be excessively restrained reducing the average output level.

Concluding, the analysis of credit network connectivity may be useful for assessing system risk both through time, considering aggregate time series, and cross-sectionally, focusing on the role that central agents or institutions play in diffusing and amplifying negative shocks. Moreover, agent based models which endogenize credit and connectivity dynamics may be helpful for testing the effectiveness of early warning indicators and the results of macro-prudential policies.

The paper is structured as follows. The next section describes the agent based model: agents behavioral assumptions, matching among banks and firms and leverage decisions. The third section illustrates simulation results. In first instance, we focus on the patterns of calibrated simulation. After we apply the Schularick and Taylor (2012) approach to isolate early warning indicators. Moreover, we use simulation to test a simple macro-prudential loan-to-value policy. The last section concludes.

2 The Model

Our artificial economy is populated by M banks and N heterogeneous firms producing an homogeneous good using capital as the only input. Firms produce goods by means of capital funded by their internal resources and by bank loans. Both banks and firms are profit seeking and choose their target leverage through a *reinforcement learning mechanism* extending the framework proposed in Tesfatsion (2005). Credit agreements last for two periods and the credit network is endogenous.

2.1 Firms

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

$$Y_{it} = \rho K_{it}^{\beta} \tag{1}$$

The firm's balance sheet is:

$$K_{it} = L_{it} + \phi L_{it-1} + E_{it} \tag{2}$$

Capital is equal to the sum of equities (E_{it}) and loans. Loans are given by loans assumed in time t (L_{it}) and by the part of the loans borrowed at time $t-1$ that is repaid at time t (ϕL_{it-1}). 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 z lending banks:

$$L_{it} = \sum_{z} L_{izt} \tag{3}$$

In each period firms fix a target leverage level (λ_{it}), defined as the ratio between firm's loans and equities (E_{it}). Loans are given by the demand for loans (L_{it}^{d}) and past period loans (ϕL_{it-1}).

$$\lambda_{it} = E_{it}/(E_{it} + {L_{it}}^{d} + \phi L_{it-1}) \tag{4}$$

Thus, loans demand ($L_{it}{}^d$ which is always not negative) derives from the target leverage chosen:

$$L_{it}{}^d = \left(\frac{1}{\lambda_{it}} - 1\right) E_{it} - \phi L_{it-1}$$

The lower the target leverage the higher the level of indebtedness of the agent, leverage can not be equal to zero because in this case all the capital is financed from external sources, consequently the firm net worth is equal to zero and the firm fails. If $\lambda_{it} = 1$ the capital is financed completely by internal sources. Agents choose between a discreet set of leverage choices H

Each period, target leverage (λ_{it}) is chosen following the reinforcement learning algorithm described in section 2.4. Firms can choose their leverage strategy (λ_{it}) among a given finite countable set of strategies Λ, with $0 < \lambda_{it} \leq 1$.

The interest rate associated (r_{it}) to each loan is a function of the firm target leverage and the interest rate (r) payed by banks on deposits (the latter for simplicity corresponds to the interest rate payed by banks and firms on their equities). The α parameter is a measure of the sensitivity of banks to borrower leverage, with $\alpha \in R^+$, it influences the strength of the cost channel in the network-based financial accelerator mechanism.

$$r_{it} = \alpha \frac{1}{\lambda_{it}} + r \tag{5}$$

Profits are given by the difference between revenues ($u_{it}Y_{it}$) and total costs, equal to financing costs, the fixed cost associated to each lending agreement of the firm (the number of agreements, n_z, times the fixed cost per agreement, F_a) and a term, F, capturing fixed cost components of each firm. Internal financial cost corresponds to the remuneration of the net worth (rE_{it}). The external financing cost is given by the interests on loans.

$$\pi_{it} = u_{it}Y_{it} - rE_{it} - r_{it}L_{it} - \phi r_{it-1}L_{it-1} - n_z F_a - F \tag{6}$$

Net revenues ($u_{it}Y_{it}$) depend on u_{it}, taking into account the presence of idiosyncratic shocks on firms revenues (ϵ_{it}), which represent the uncertainty events that firms face and that are not explicitly modeled, following Greenwald and Stiglitz (1993); Riccetti et al. (2013)) :

$$u_{it} = m + \epsilon_{it} \tag{7}$$

$$\epsilon_{it} \sim N(0, \sigma) \tag{8}$$

Thus, net revenues depend on both a fixed component (m) and a stochastic one that represent demand fluctuations not predictable by firms (ϵ_{it}). Because the expected value of ϵ_{it} is zero, the expected marginal net revenue is equal to parameter m.

Assuming that part of the profits are not accumulated ($\tau\pi_{it}$, $0 < \tau < 1$) equities evolve according to:

$$\begin{cases} E_{it} = E_{it-1} + (1-\tau)\pi_{it} & \pi_{it} > 0 \\ E_{it} = E_{it-1} + \pi_{it} & \pi_{it} \leq 0 \end{cases} \tag{9}$$

2.2 Banks

Banks supply loans (L_{zt}) through their net-worth (E_{zt}) and deposits (D_{zt}): the banks' balance sheet is given by $L_{zt} = D_{zt} + E_{zt}$. Banks establish the level of credit supply following the same reinforcement learning algorithm used by firms, choosing a level of target leverage λ_{zt}, from a discreet set of values in the set Λ, with $0 < \lambda_{zt} \leq 1$. Deposits (D_{zt}) are computed as residual between loans (L_{zt}) and equities (E_{zt}). The amount of bank potential credit is reduced by the sum of the loans to firms i ($i \in I_{zt-1}$) that are not already matured

$$L_{zt}{}^{s} = \left(\frac{1}{\lambda_{zt}} - 1 \right) E_{zt} - \sum_{I_{zt-1}} \phi L_{izt-1} \tag{10}$$

Thus, as for firms, riskier leverage strategies correspond to lower levels of λ_{zt}. Indeed, the lower is λ_{zt}, the higher is the supply of loans that is not covered by bank equities (E_{zt}) but relies on external financial sources, in our case deposits (D_{zt}). Consequently, lower λ_{zt} values increase bank leverage and, thus, its riskiness. Banks have a maximum level of target leverage deriving from prudential reasons and in conformity with international credit agreements (Basilea agreements). Moreover, for prudential reasons, a bank can provide to a single firm only a fraction of its supplied loans according to the parameter ζ: $\zeta L_{zt}{}^{s}$.

Bank revenues are given by the interest payed on the loans by borrowers at time $t-1$, $i \in I_{zt-1}$ and borrowers at time t, $i \in I_{zt}$. Costs derive by bad debts (BD_{zt} and BD_{zt-1}), *i.e.* loans in time t or time $t-1$ that are not payed back because of the failure of the borrowing firms. Moreover, banks have to pay a given interest rate r to deposits and equities and a fixed cost (F).

$$\pi_{zt} = \sum_{I_{zt}} r_{izt} L_{izt} + \sum_{I_{zt-1}} r_{izt-1} L_{izt-1} - BD_{zt} - BD_{zt-1} - r(E_{zt} + D_{zt}) - F \tag{11}$$

Part of the banks' profits is not accumulated ($\tau \pi_{zt}$, $0 < \tau < 1$):

$$\begin{cases} E_{zt} = E_{zt-1} + (1-\tau)\pi_{zt} & \pi_{zt} > 0 \\ E_{zt} = E_{zt-1} + \pi_{zt} & \pi_{zt} \leq 0 \end{cases} \tag{12}$$

2.3 Matching among banks and firms with transaction costs

Banks and firms establish respectively their supply and demand of loans choosing their target leverage. Each bank offers loans to demanding firms until its supply is exhausted. On the other hand, firms may borrow credit from different banks until their loan demand is satisfied. Thus, firms can be linked with one or more banks each time. When a bank provides credit to a firm, a link between the bank and the firm is established.

Imperfect information and agents' bounded rationality imply the presence of transaction costs declined in the form of fixed cost (F_a) associated to each credit agreement (link) and charged to both firms and banks. Thus, the higher the number of credit agreements (links) the higher the transaction costs agents have to pay.

Each firm expresses its loan demand first of all to its linked banks. Firms face a trade off between increasing the number of credit agreements to reduce the possibility of suffering credit scarcity and decreasing the number of agreements to reduce transaction costs.

Therefore, we assume that only if in the previous period all the credit demand of firm i was satisfied ($L^d_{i,t-1} = L_{i,t-1}$), this firm may cut a single agreement with a certain probability p^θ ($0 \leq p^\theta \leq 1$), the link to cut is chosen according to a probability assigned to each bank j:

$$p^\Gamma_{ijt} = \frac{e^{(1-\frac{L_{ij,t-1}}{L_{i,t-1}})}}{\sum_z e^{(1-\frac{L_{iz,t-1}}{L_{i,t-1}})}}$$

where j is a specific bank and the sum over z is the sum over all the banks with which the firm is linked. The probability p^Γ_{ijt} increases the lower was the relative amount of credit received from bank j ($L_{ij,t-1}$) with respect to the total volume of credit ($L_{i,t-1}$). At every time t, for each bank z with which the firm remain in a credit agreement, the loan demanded is a fraction of the loan demanded by firm i in proportion to the weight of the credit that the bank z offered at time $t-1$.

$$L^d_{izt} = L^d_{it}\frac{L_{izt-1}}{L_{it-1}}$$

A bank can deny loans to riskier firms, the probability (p_R) that the demand for loans of firm i is not accepted increases in the firm target leverage (λ_{it}):

$$p_R = \iota(\lambda_{it})$$

If the bank loan supply is lower than the sum of the accepted demand of the linked firm, the bank assigns to each firm a part of the credit supply proportional to the loan provided in time $t-1$. Thus, the loan given to firm i, in the set of the j linked firms to which credit is provided (I_a), becomes:

$$L_{izt} = L^s_{zt}\frac{L_{izt-1}}{\sum_{I_a} L_{jzt-1}}$$

If the bank supply is higher than the accepted demand for loans, the bank may provide credit to other firms.

Therefore, the credit network evolves according to the individual demand and supply of loans. A new credit link is established when the demand of loans of a firm is accepted by a bank with which the firm was not previously linked, while the credit link between a bank and a firm is cut when:

1. The firm or the bank fails.
2. The firm or the bank does not ask/offer loans at time t.
3. The bank refuses to provide loans because the firm is considered too risky.
4. The firm breaks the credit agreement because it is considered as not convenient due to transaction costs.

2.4 Leverage choice

Agents, both banks and firms, in each period choose a target leverage (λ_{it}). The target leverage (λ_{it}) are chosen among a limited and countable set Λ. The choice mechanism is a simple generalization of the (Tesfatsion, 2005) reinforcement learning algorithm. In each period, firms and banks decide one of the possible leverage strategies. At the beginning of the next period, agents observe the result of their choices: *i.e.*, the profit (π_{it-1}) received. In this paragraph we denote the past profit π_{it-1} as π_{ist-1} to underline that it is the profit deriving from the choice of a particular leverage strategy, *i.e.* a particular value of λ_s at time $t-1$ for agent i. The profit received in the previous period, when was adopted the target leverage λ_s, is used to update $q(\lambda_s)_{it}$:

$$q(\lambda_s)_{it} = (1-\chi)q(\lambda_s)^F_{it-1} + \chi\pi_{ist-1} \tag{13}$$

The memory of the agent is given by the parameter χ which gives the weight of past values of the profit associated with a particular strategy compared to the profit receiving adopting this strategy. At the beginning of each period, the effectiveness of every leverage strategy $q(\lambda_s)_{t-1}$ is reduced by a small percentage (ξ): $q(\lambda_s)^F_{it-1} = (1-\xi)q(\lambda_s)_{it-1}$, where ξ represents the extent of 'forgetting processes'.

Agents may choose among the possible levels of leverage ($\Lambda_a \subseteq \Lambda$). In fact, because loans have a two-period maturity, agents have to consider also their past debts, which lead to a certain level of leverage inherited from past loans. Moreover, firms will not choose level of leverage which generates costs higher than the expected profits. Indeed, the production function is concave, thus the higher the level of capital used, funding it from both internal and external sources, the lower the marginal production and thus the marginal value of profit expected, while financial costs increase linearly with leverage. According to equations 1, 5 and 6 is convenient to take a certain level of leverage if the associated loan cost $r_{it}L^D_{it}$ is lower than production gains. $m\rho(K+L)^\beta - \rho(K)$. . Therefore, firms will choose among a reduced set of leverage target possibilities which may exclude higher level of λ because of the debt inherited from the past and, at the same time, lower level of λ because with lower levels of λ financial costs may overcome expected profits. While banks leverage set is reduced only by the previous debt inherited (in figure 1, in panel a the complete set of panel, while the reduced set illustrated in panel b).

Agents adjust only gradually their leverage, thus each period agents may choose among three strategies only: the leverage chosen in the past period and the two levels of leverage immediately higher or lower (for instance, in the figure 1 panel c, if the level of leverage in the past period was 0.5, the agent may choose among 0.4, 0.5 and 0.6), thus agent choices are restricted to the Λ_c set, with ($\Lambda_c \subseteq \Lambda_a \subseteq \Lambda$). If the past level of leverage is not into the available set of leverage, the agent will choose the nearest level of leverage allowed (in the figure 1 panel d, the level of leverage 0.5 is not allowed thus the agent will choose the nearest value allowed: 0.3). Moreover, in case no level of λ is allowed agents choose the one corresponding to the lowest level of leverage, thus the higher λ. In simulations the highest value of λ for firms is $\lambda = 1$, meaning that in this case a firm does not borrow money but use only its inner resources and previous loans to fund production. While the highest level of λ for banks is higher then one, otherwise with $\lambda = 1$ a bank will not offer any credit, thus, ceasing its activity.

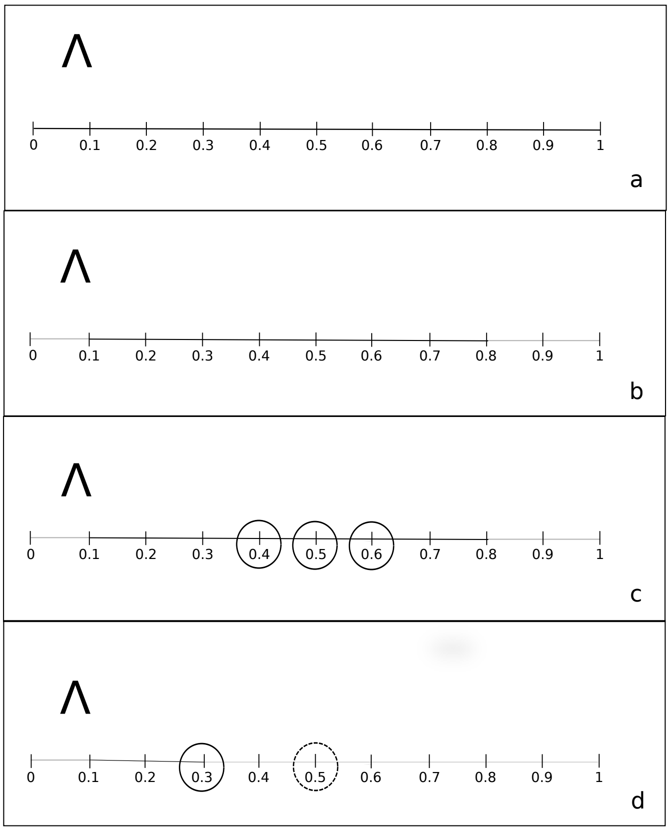

Figure 1: Target leverage choice

Once the effectiveness of each strategy is valued, agents associate to each strategy a certain probability that this strategy will be chosen in the following period. The probability of choosing a particular level of leverage (strategy λ_s) among the levels of leverage among which the firm may choose (Λ_c) is given by $p(\lambda_s)_{it}$, this probability is different for each agent according to its past profit results:

$$X_{ist} = \left(\frac{q(\lambda_s)_{it}}{c + v(\lambda_s)_{it}} \right)^{\nu} \tag{14}$$

$$p_(\lambda_s)_{it} = \frac{e^{X_{ist}}}{\sum\limits_{\Lambda c} e^{X_{ct}}} \tag{15}$$

Where X_{ist} is the strength associated by firm i to a strategy at time t, which depends on its effectiveness. The exponential values of the strength (X_{ist}) of each strategy is used to compute the probability of choosing it $p(\lambda_s)_{it}$. Taking the exponential, strategies that are more efficient have a more than proportional probability to be chosen, moreover we avoid to associate negative values to the strength of the strategies. The probability of choosing a strategy s is computed as the exponential value of its strength divided by the sum of the exponential value of all the strategies among which the agent may choose.

In general, choosing higher levels of leverage may lead to higher profits. However, higher leverage implies higher risks for both firms and banks. Moreover, firms with higher target leverage levels pay higher interest rates and they have a higher probability of not being accepted as borrowers. Besides, banks with higher target leverage have to pay a higher volume of interest to deposits, and they may not be able to lend all the credit they supply in case of credit demand scarcity.

To allow a continuous exploration of the action space, there is a relatively little probability (μ) that in each period agents may choose their leverage strategy randomly without considering their respective effectiveness. The parameter ξ indicates that there is a certain degree of 'forgetting' of past experience, while parameter μ indicates that there is a certain 'error probability' in making choices. Forgetting and the error probability allow agents to explore their strategy space avoiding the possibility of being trapped in sub-optimal solutions or in strategies that are not more effective in a continuously evolving economic environment.

3 Simulation results

Simulated data are calibrated on a sample of firms and banks quoted on the Japanese stock exchange markets including 33 yearly data from 1980 to 2012. On average each year the dataset includes 2218.152 firms and 226.181 banks[1]. In simulations, we fix a ratio of 10 firms to each bank that is not significantly different from the empirical one (according to t-test). We assume that each simulated period corresponds to a quarter of year. We run simulations for 500 periods, but we consider as a transition time the first 368 periods. We use this long transition period to be sure that simulation reach a certain degree of stability in all the parameter specification we tested. From the 368th period to the 500th one we have 132 quarters that correspond to 33 years, the same time span of empirical data. We run 35 Monte Carlo simulations. We calibrate the model to obtain the same level of leverage, connectivity and output volatility observed in the empirical data [2].

Analyzing quarterly simulated data it is possible to have some insight into the relation between macro-variables, considering the cross correlation of their cyclical component[3]. Unfortunately it is not possible to implement the same analysis on empirical data because, the data-set includes only annual data for just 33 years, while in simulations we have quarterly data, thus 132 quarters for each simulation, moreover on several Monte Carlo simulations.

From figure 2 it is possible to notice that output is strongly positively correlated with leverage and credit, thus high levels of output are associated with higher level of credit and leverage, this last measured as the aggregate debt of firms divided by their aggregate equities. Even connectivity, defined as the average normalized degree, is positively correlated with output. Moreover, connectivity seems to negatively anticipate output and credit: high levels of output lead to high levels of connectivity in the following period, but conversely high levels of connectivity lead to low levels of both output and credit. Thus, output growth increases credit network connectivity, but specularly high levels of connection may conduce to output slowdowns.

In the simulated model crises are triggered by the failure of firms. Indeed when a firm fails, it does not repay its debts to lending bank, thus in turn some bank may fail, reducing the supply of loans to whole the economy and, consequently, output may fall down. From figure 3 we see that failures are significantly correlated with the four macro variable we considered above: output, credit, leverage and connectivity. Indeed, when leverage is high also the probability that agent fail increases and as we have seen above output, credit and connectivity are all positively correlated with leverage. Moreover, these four macro variables seems to anticipates firm failures, thus when their value increase also the number of firm failures tend to augment in the next periods. Consequently, in the following sections, we are going to test the effectiveness of these macro variables in anticipating crisis, thus, their use as early warning indicators.

[1]We consider only banks and firms with strictly positive equity, asset and liability values, in order to clear the dataset from uncertain values

[2]Simulated average firm level, as liability over equity, is equal to 2.724 and is not significantly different from the Japanese one 2.799, according to t-test. Simulated normalized degree is 0.093 not significantly different from 0.089 of the Japanese dataset. Besides, Japanese output volatility is 0.069 not significantly different from the simulated one 0.068

[3]Simulated data are de-trended through HP filter calibrated on quarterly data

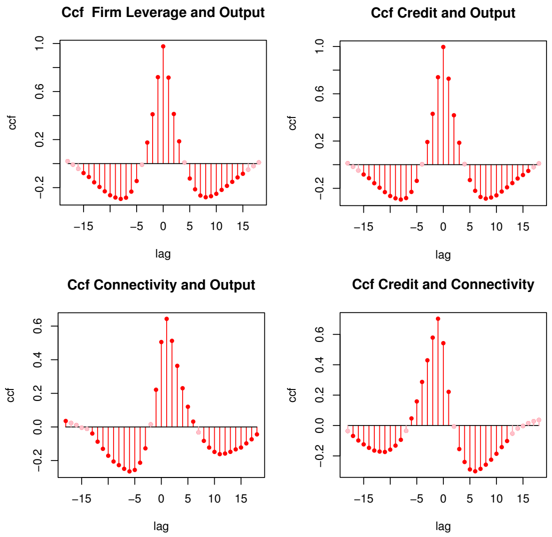

Figure 2: Cross Correlation among output and other macro-variable: leverage, credit, connectivity

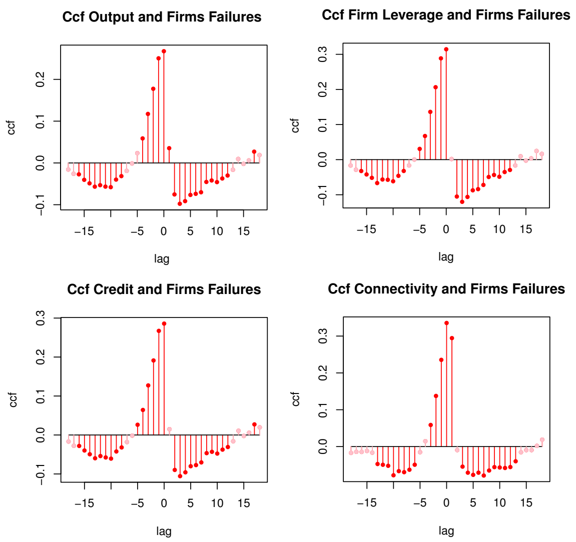

Figure 3: Cross Correlation among number of firm failures and selected macro-variable: output, leverage, credit and connectivity

3.1 Empirical and Simulated relation between credit network dynamics and crises

We follow the methodology adopted by Schularick and Taylor (2012) to test the relation between credit dynamics and crisis. We apply the same Logit model implemented by Schularick and Taylor (2012) on simulated data referring to several Monte Carlo runs (100):

$$logit(p_{it}) = \beta_{0i} + \beta_1(L)\Delta logCREDIT_{it} + \beta_2(L)\mathbf{X}_{it} + \epsilon_{it} \tag{16}$$

Where (p_{it}) is the crisis probability, $(L)\Delta logCREDIT_{it}$ are lagged credit logarithmic variations and $\mathbf{X}_{it}$ are control variables. The predicted probabilities of the Logit regressions are used as early warning indices: the higher the predicted values the higher the probability of a crisis. Thus, Roc analysis is used to test the effectiveness of credit variations as early warning measures. Roc methodology is based on computing the extent of the trade-off between false alarm and hit ratio of early warning indicators. Indeed an early warning indicator may be conceived as source of signal of different intensity. Over a certain threshold the signal may alerts policy makers because the stronger the signal, the higher the probability of having a crisis. Thus, if the policy maker intervenes only when the intensity of signal is strong, false alarm probability is reduced. Conversely, an alert threshold that is too high may discourage policy intervention even when in reality a crisis is approaching, hence it reduces the hit ratio of the indicator. Therefore, early warning indicators may be valued by their capacity of reducing the trade of between false alarm and hit ratio. A basic measure of this trade-off is the Auroc, which is the area below the Roc curve, the largest this area the higher the effectiveness of the indicator as an early warning measure.

Schularick and Taylor (2012) found that credit growth rates have a significant impact on crisis probability and they represent an effective early warning measure, thus they underline the importance of endogenous credit cycles in determining the conditions which may lead to crises.

We implemented Logit regressions on the Japanese data set. We divided the data set in 35 sub-samples which corresponds to the Japanese prefectures where firms are located. The dataset includes 33 yearly data. Similarly we considered only 35 simulation runs of 33 years each.

In both empirical and simulated data (tab. 4), credit variations are correlated with crisis probability. We define a crisis as a consistent output slow down, considering both output reduction lower than -5% and lower than -10%.[4].

As in Schularick and Taylor (2012), in Japanese data lags of credit growth rate are correlated with crisis probability, defined as an output reduction of 5%. The first lag of credit variation is negatively correlated, while the other lags are positively correlated with crisis probability. Controlling for other possible predictors, as the lagged values of output and credit over output, credit variations remain significant. Moreover, adding to the regression variations of the

[4]In empirical data the probability of an output slowdown of -5% is equal to 0.218, while the probability of a slow down of -10% is 0.127. In simulated data the probability of an output slowdown of -5% is equal to 0.171, while the probability of a slow down of -10% is 0.065, thus the probability of having a crisis is relatively lower with respect to empirical data, probability a result of the slightly lower volatility of simulated data with respect to empirical ones

average normalize degree leads to a significant increase of the predictive efficiency of the regression measured by the Auroc (Fig. 1), indeed connectivity is positively correlated with crisis probability. While considering only huge output reduction, lower than minus 10%, credit variations loss part of their predictive capacity while connectivity variations remain strongly positively correlated with crisis probability (Fig. 2). In effect, increasing connectivity may augment crisis probability, because more connected network may allow a larger diffusion of the effects of negative shocks.

The importance of both credit and connectivity variations is shown by comparing regressions on both empirical and simulated data. From a quantitative point of view regressions on simulated data produce similar results with respect to empirical ones, especially considering crises as output reduction lower than 5% (Fig. 1). Both empirical and simulated regressions show negative values for the first lag of the credit growth rate and positive correlation for the other lags. Moreover, the first lag of connectivity variations is positively correlated with crisis probability. In simulated data, the importance of credit and connectivity remain strong even focusing only huge output reductions (lower than -10%), but credit variations are not significant in empirical data. Moreover, in both crisis specifications, the marginal effects of credit and degree variation are more marked in simulated data.

The role played by connectivity in augmenting crisis probability is underlined by the ROC curves (fig. 4). Indeed, in the specifications which include variations of the normalized degree the Auroc show a significant increase. Thus, in both the empirical and simulated data, combining credit and connectivity variations increases the effectiveness of both these measures as early warning indicators.

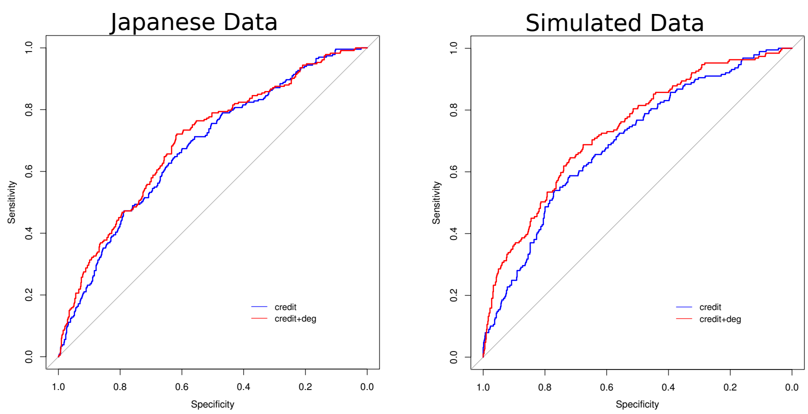

Figure 4: Roc curves of EWI specification with (credit+deg) and without connectivity (credit)

	credit	credit+ y	credit + credit/out	credit + deg
L1 Δ log(credit)	-1.398**	-1.985**	-1.409**	-1.265**
	(0.478)	(0.563)	(0.480)	(0.486)
L2 Δ log(credit)	1.050**	0.571	1.033**	0.997**
	(0.429)	(0.530)	(0.429)	(0.446)
L3 Δ log(credit)	0.783*	1.021**	0.770*	0.689
	(0.435)	(0.517)	(0.436)	(0.443)
L4 Δ log(credit)	0.943**	0.634	0.945**	1.016**
	(0.426)	(0.533)	(0.427)	(0.446)
L5 Δ log(credit)	0.213	0.092	0.209	0.162
	(0.428)	(0.523)	(0.431)	(0.444)
L1 Δ log(y)		1.119*		
		(0.606)		
L2 Δ log(y)		0.978*		
		(0.591)		
L3 Δ log(y)		-0.485		
		(0.564)		
L4 Δ log(y)		0.905		
		(0.601)		
L5 Δ log(y)		0.362		
		(0.574)		
L1 Δ log(credit/y)			-0.112	
			(0.170)	
L1 Δ log(deg)				2.885**
				(0.893)
L2 Δ log(deg)				1.115
				(0.881)
L3 Δ log(deg)				-0.647
				(0.861)
L4 Δ log(deg)				0.658
				(0.872)
L5 Δ log(deg)				-0.313
				(0.866)
Observation	1,155	1,155	1,155	1,155
Groups	35	35	35	35
Pseudo R^2	0.065	0.075	0.066	0.120
AUROC	0.676**	0.689**	0.676**	0.734**
Standard error	(0.019)	(0.019)	(0.020)	(0.020)

Table 1: Relation between crisis and macrovariables variations in Japanese data, crisis defined as -5% output variation

	credit	credit+ y	credit + credit/out	credit + deg
L1 Δ log(credit)	-0.879*	-1.794**	-0.882*	-0.785
	(0.482)	(0.622)	(0.483)	(0.496)
L2 Δ log(credit)	0.676	0.612	0.667	0.582
	(0.458)	(0.584)	(0.458)	(0.472)
L3 Δ log(credit)	0.702	1.013 *	0.695	0.702
	(0.471)	(0.570)	(0.473)	(0.480)
L4 Δ log(credit)	0.500	0.440	0.502	0.542
	(0.456)	(0.599)	(0.458)	(0.473)
L5 Δ log(credit)	0.229	0.165	0.227	0.181
	(0.483)	(0.591)	(0.486)	(0.491)
L1 Δ log(y)		1.662**		
		(0.710)		
L2 Δ log(y)		0.059		
		(0.653)		
L3 Δ log(y)		-0.541		
		(0.646)		
L4 Δ log(y)		0.376		
		(0.690)		
L5 Δ log(y)		0.136		
		(0.664)		
L1 Δ log(credit/y)			-0.087	
			(0.202)	
L1 Δ log(deg)				2.634**
				(1.013)
L2 Δ log(deg)				-0.026
				(1.017)
L3 Δ log(deg)				-0.089
				(0.861)
L4 Δ log(deg)				0.828
				(1.026)
L5 Δ log(deg)				0.375
				(1.002)
Observation	1,155	1,155	1,155	1,155
Groups	35	35	35	35
Pseudo R^2	0.065	0.069	0.061	0.071
AUROC	0.676**	0.686**	0.677**	0.684**
Standard error	(0.023)	(0.023)	(0.023)	(0.024)

Table 2: Relation between crisis and macro-variables variations in Japanese data, crisis defined as -10% output variation

	Japanese data credit	Simulated data credit	Japanese data credit + deg	Simulated data credit + deg
L1 Δ log(credit)	-1.398**	-0.202	-1.265**	-3.328**
	(0.478)	(0.691)	(0.486)	(1.080)
L2 Δ log(credit)	1.050**	3.331**	0.997**	2.819**
	(0.429)	(0.740)	(0.446)	(1.244)
L3 Δ log(credit)	0.783*	1.492**	0.689	0.627
	(0.435)	(0.713)	(0.443)	(1.180)
L4 Δ log(credit)	0.943**	0.762	1.016**	-0.862
	(0.426)	(0.672)	(0.446)	(1.148)
L5 Δ log(credit)	0.213	0.695	0.162	-1.046
	(0.428)	(0.682)	(0.444)	(1.001)
L1 Δ log(deg)			2.885**	6.322**
			(0.893)	(1.608)
L2 Δ log(deg)			1.115	-1.223
			(0.881)	(1.612)
L3 Δ log(deg)			-0.647	2.523
			(0.861)	(1.624)
L4 Δ log(deg)			0.658	2.449
			(0.872)	(1.593)
L5 Δ log(deg)			-0.313	1.865
			(0.866)	(1.457)
Observation	1,155	1,155	1,155	1,155
Groups	35	35	35	35
Pseudo R^2	0.065	0.072	0.079	0.100
AUROC	0.676**	0.691**	0.695**	0.718**
Standard error	(0.019)	(0.020)	(0.019)	(0.020)

Table 3: Credit and network variations in empirical and simulated data, crisis defined as -5% output variation

	Japanese data credit	Simulated data credit	Japanese data credit + deg	Simulated data credit + deg
L1 Δ log(credit)	-0.879*	0.741	-0.785	-4.649**
	(0.482)	(1.000)	(0.496)	(1.641)
L2 Δ log(credit)	0.676	2.759**	0.582	2.217
	(0.458)	(1.051)	(0.472)	(1.889)
L3 Δ log(credit)	0.702	1.936*	0.702	1.082
	(0.471)	(1.023)	(0.480)	(1.738)
L4 Δ log(credit)	0.500	0.026	0.542	-1.855
	(0.456)	(0.943)	(0.473)	(1.732)
L5 Δ log(credit)	0.229	-0.375	0.181	-3.964**
	(0.483)	(0.952)	(0.491)	(1.520)
L1 Δ log(deg)			2.634**	11.053**
			(1.013)	(2.537)
L2 Δ log(deg)			-0.026	-2.898
			(1.017)	(2.416)
L3 Δ log(deg)			-0.089	3.550
			(0.861)	(2.518)
L4 Δ log(deg)			0.828	3.376
			(1.026)	(2.440)
L5 Δ log(deg)			0.375	5.254**
			(1.002)	(2.276)
Observation	1,155	1,155	1,155	1,155
Groups	35	35	35	35
Pseudo R^2	0.065	0.101	0.071	0.173
AUROC	0.676**	0.730**	0.684**	0.806**
Standard error	(0.023)	(0.026)	(0.024)	(0.024)

Table 4: Relation between crisis and macro-variables variations in Japanese data, crisis defined as -10% output variation

3.2 Precautionary macro policy experiments

Early warning indicators may the timing of precautionary policies aimed at reducing the occurrence and the deepness of crises (Nier, 2009; IMF, 2010, 2011; Drehmann and Juselius, 2013).

We tested a simple loan-to-value policy measure: when a bank is targeted by the policy intervention, this bank will not provide credit to riskier firms, the ones with high levels of leverage. We explore different basic declinations of the loan-to-value measure. In first instance we apply this policy to all the banks permanently. After we implement temporary the policy only when credit or connectivity growth a overcome certain threshold. Finally we focus the policy only to the more connected or bigger banks. We tested these three scenarios running, as above, 35 simulations lasting for 33 years, we apply the policy measures to the last 17 year[5].

In first instance, we apply the loan-to-value measure permanently to all the banks and we consider different levels of firm riskiness allowed. Fig. 5 shows that starting from no intervention ('no') and we gradually reduce the maximum level of firm leverage allowed. Initially output slightly increases and the crisis probability decreases. However, after a certain leverage level the supply of credit suffers an excessive compression that leads to output reduction.

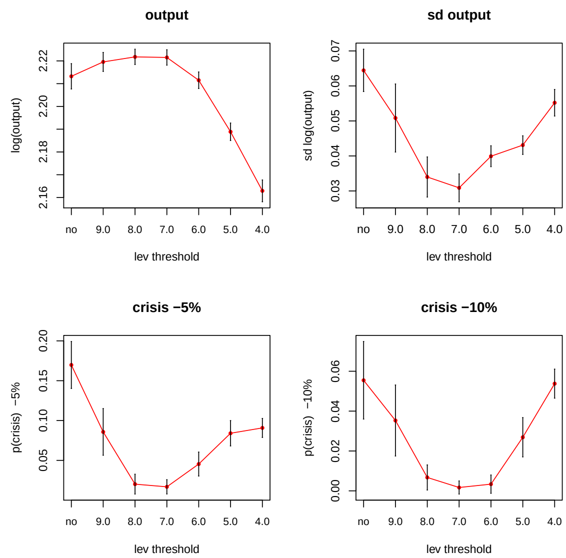

Figure 5: Strength of the prudential intervention. In the left panel above, the output logarithmic level. In the right panel above output standard deviation. In the left panel below, crisis probability, defining crisis as an output slowdown lower than 5%. In the right panel below, crisis probability, defining crisis as an output slowdown lower than 10%

Permanent credit restrictive measures may meet some resistance in their

[5]We used the same simulation seeds for the different policy scenarios in order to reproduce the same conditions when policies start.

implementation or may suffer of high monitoring costs. Therefore, we test temporary measures associating policy interventions to early warning signals. From the previous analysis, we know that credit and connectivity variations are correlated with crisis probability, thus, when credit or degree growth rate overcome a certain threshold the loan-to-value measure is activated. We fixed the level of leverage accepted at a relatively low value in order to give strength to these temporary policies, nevertheless leverage allowed is higher then the average value observed in simulations. [6] Table 5 shows the effects of the policy adopting several threshold of credit and connectivity variations. We observe that using early warning measures to activate loan-to-value policies may effectively reduce crisis probability with lower impact on output, at the same time adopting temporary measures the invasiveness and the potentially distortive effects of these policies may be contrasted.

For instance, in the case we use both credit and degree variations as EWI and we fix the activation threshold to 12.5% (thus if credit and the normalized degree grow more than this threshold the policy is activated), crisis probability (p(crisis) -5% and p(crisis) -10%) and output standard deviation (sd(growth)) show a significant decrease. While output level (log(output)) does not change with respect to the standard case without policy intervention (no). Given this threshold, the probability of intervention for each period of the simulation (quarter) computed ex-post is equal to 16.5%.

policy	threshold	log(output)	sd(growth)	p(int)	p(crisis) -5%	p(crisis) -10%
no policy		2.213	0.064		0.169	0.055
permanent		2.188**	0.043**	1.0	0.084**	0.026**
degree	0.05	2.218	0.051**	0.287	0.100**	0.021**
degree	0.075	2.216	0.059	0.106	0.132**	0.038**
degree	0.1	2.213	0.065	0.009	0.166	0.062
degree	0.125	2.213	0.064	0.001	0.168	0.055
credit	0.05	2.213	0.034**	0.437	0.055**	0.006**
credit	0.075	2.214	0.034**	0.411	0.048**	0.008**
credit	0.1	2.214	0.037**	0.343	0.048**	0.016**
credit	0.125	2.215	0.052**	0.168	0.102**	0.034**
credit+degree	0.05	2.212	0.049**	0.521	0.112**	0.020**
credit+degree	0.075	2.213	0.036**	0.445	0.049**	0.013**
credit+degree	0.1	2.213	0.038**	0.346	0.057**	0.018**
credit+degree	0.125	2.214	0.051**	0.164	0.100**	0.030**

Table 5: Intervention and connectivity and credit variations as EWI. Standard simulation defined as no policy. The effect of a permanent policy of loan to value restriction in the permanent row. Using connectivity (degree), credit or both (credit+degree in the other row). Value significantly lower than the no policy specification are reported using asterisks **.

Figure 6 shows the effects of this policy intervention specification (thus, considering both credit and connectivity as EWI with a 12.5% of variation threshold) referred as EWP with respect to the result of the calibrated model, thus without policy intervention (N). Moreover, we consider the same policy

[6] The maximum level of leverage of firm is equal to a ratio of debt over equity of 5, that is significantly larger than the average of firm leverage in both empirical and simulated data.

of credit control but implemented randomly during simulation (R) with the same probability of intervention measured in the EWP case ex-post. Besides, we show the case of a permanent application of this loan-to-value policy (P). From the bottom panels of Figure 6 we see that this EWP policy reduces crisis probability with respect to the no policy case (N), while in the random policy implementation scenario (R) crisis probability does not change significantly. The permanent intervention policy (P) results in a consistent reduction of crisis probability but at the same time causes a large contraction of the output level due to the reduction of lending possibility. Thus, the R and P case underline the importance of correct policy timing to reduce crisis probability without affecting excessively output level.

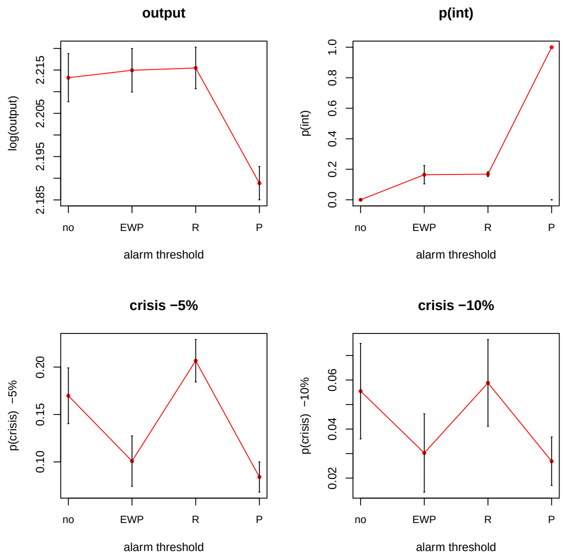

Figure 6: A specific EWI policy effectiveness. In the left panel above, probability of intervention. In the right panel above output standard deviation. In the left panel below, crisis probability, defining crisis as an output slowdown lower than 5%. In the right panel below, crisis probability, defining crisis as an output slowdown lower than 10%

Moreover, we test the effects of this loan-to-value policy to the more important banks in the credit network, thus targeting the banks that offer a larger amount of loans and that are more connected. Indeed, when the credit restriction is applied only to banks that control a larger share of the total volume of loans, the system becomes more stable without presenting output losses (Fig. 7). For instance if the policy is applied to banks that control more than the 10% of loans, crisis probability is reduced, while the number of banks involved in this measure is very limited (considering p(int) as the probability that each period a bank is involved in the intervention).

Finally, we targeted the previous loan-to-value policy only to the more connected banks. Figure 8 shows the effects of this policy targeted to different normalized degree thresholds (from zero, thus hitting all the banks to banks

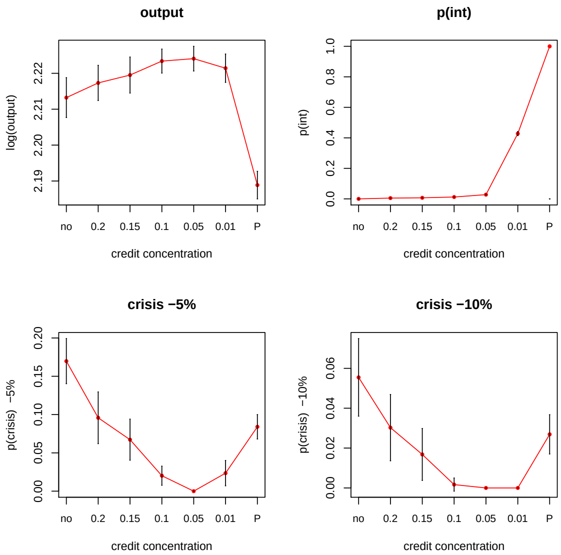

Figure 7: Targeting larger loan supplier banks. In the left panel above, number of banks affected by the policy. In the right panel above output standard deviation. In the left panel below, crisis probability, defining crisis as an output slowdown lower than 5%. In the right panel below, crisis probability, defining crisis as an output slowdown lower than 10%

with a normalized degree higher than 50%). Targeted policy have a significant impact on output fluctuations at least since the threshold is larger than 0.05 normalized degree, meaning that hit all the banks that are linked with more than the 5% of firms. Then, the number of crises may be significantly reduced targeting the more connected banks without decreasing output level. For instance, targeting only banks with a normalized degree higher than the 0.3% consistently reduces crisis probability. While the number of bank affected by this policy is extremely low (as shown in the p(int) panel).

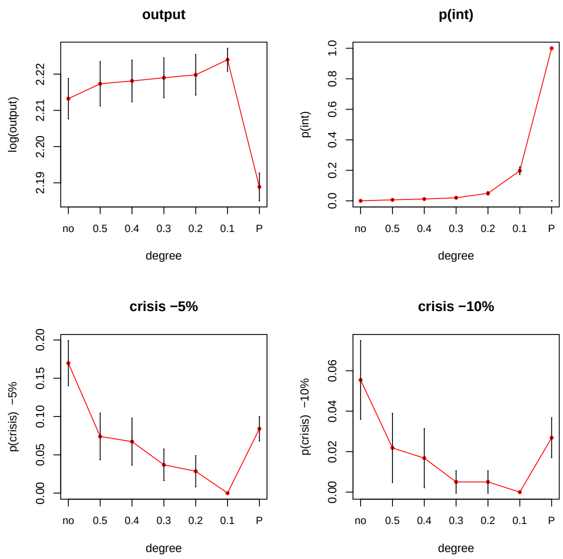

Figure 8: Targeting more connected banks. In the left panel above, number of banks affected by the policy. In the right panel above output standard deviation. In the left panel below, crisis probability, defining crisis as an output slowdown lower than 5%. In the right panel below, crisis probability, defining crisis as an output slowdown lower than 10%

Therefore, restricting loans to more exposed firm is an effective measure to reduce output volatility and, hence, crisis probability. However, massive loan-to-value policy interventions may cause a restriction of credit supply, thus, contracting average output level.

4 Conclusions

The analysis of credit network configurations may offer some insight into the dynamics of business cycles and, in particular, may be helpful to assessing systemic risk. Both our empirical and simulated data seem to show that credit and connectivity variations are effective early warning measures. Indeed, expansions lead to an increase of credit and connectivity which may create the conditions for the following slow-downs or even for crises.

Therefore, credit network connectivity may be used to define timing and targeting of macro-prudential policies. According to our simulated experiments loan-to-value restricting policies may be effective in reducing crisis probability. However, excessive loan-to-vale interventions may excessively reduce credit, then depressing the economy. While selective loan-to-value measures through time, that are activated only when credit or connectivity growth overcome certain threshold, or focusing only on larger or more connected banks may reduce systemic risk without affecting negatively credit access and output level.

The model described in this paper may be modified in different directions. Certainly, if it would be possible to access to other datasets, the analysis developed in this paper may be tested calibrating simulations to other samples of firms and banks. Moreover, the model could be extended to include different macro-prudential policies regarding, for instance, liquidity requirements or interbank transactions. Besides, using a more complex model, it might be interesting to test the relation between monetary and macro-prudential policies.

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Simulation Parameters

Simulations last 500 periods, there are 500 firms and 50 banks. The initial value of firms' equity is $E_i = 1$, that of bank's equity is $E_z = 5$. Firms and banks with non positive equity levels exit from the market and are substituted with firms and banks having a level of equity relatively lower than the one of incumbents; entering firms have $E_i = mf + U(-0.1, 0.1) * mf$ and entering banks have $E_z = mb + U(-0.1, 0.1) * mb$, with mf the average size of firms and mb the average size of banks. This entry condition assures that enters have a size that is in line with the one of other competitors.

The set of leverage value of firms is
$H_f = \{1.0, 1/1.5, 1/2.0, 1/1.25, 1/3.0, 1/3.5, 1/4.0, 1/4.5, 1/5.0, 1/5.5, 1/6.0, 1/6.5, 1/7.0, 1/7.5, 1/8.0, 1/8.5, 1/9.0, 1/9.5, 1/10.0\}$.

The set of leverage value of banks is
$H_b = \{1/10.0, 1/15.0, 1/20.0, 1/25.0, 1/30.0, 1/35.0, 1/40.0, 1/45.0, 1/50.0, 1/55.0, 1/60.0, 1/65.0, 1/70.0, 1/75.0, 1/80.0, 1/85.0, 1/90.0, 1/95.0, 1/100.0\}$.

agents		learning	
α	0.001	χ	0.4
ϕ	0.5	ν	0.5
ρ	0.5	c	0.1
τ	0.4	ξ	0.05
ζ	0.04	μ	0.05
F	0.001		
σ	0.209		
ι	0.001		
r	0.001		
p^θ	0.01		
m	0.04		
β	0.8		
F_a	0.001		