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Towards a credit network based early warning indicator for crises

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ABSTRACT

This paper presents an agent based model which underlines the importance of credit network and leverage dynamics in determining the resilience of the system, defining an *early warning indicator* for crises. The model reproduces macroeconomic dynamics emerging from the interactions of heterogeneous banks and firms in an endogenous credit network. Banks and firms are linked through multiple credit relations, which derive from individual target leverage choices: agents choose the more convenient leverage level, according to a basic reinforcement learning algorithm. Simulations are calibrated on balance sheet data of banks and firms quoted in the Japanese stock-exchange markets from 1980 to 2012.

1. Introduction

"Why did nobody notice it?", asked the Queen at the London School of Economics during a discussion on the 2008 financial crash. The crisis seems to prove what many economists already asserted: the Modigliani–Miller (Modigliani and Miller, 1958, 1963) theorem does not hold.[1] The financial condition of a firm may change its value producing real effects.

From one hand, economic theory recognizes the nonvalidity of the Modigliani–Miller theorem building models with asymmetric information in which firms' financial positions matter in determining real quantities. On the other, this kind of model was not able to generate (and so to forecast) crises of the order of magnitude we observed.

Economists, after some time, explained why no one foresaw the timing and severity of the crisis by laying responsibility on the "failure of the collective imagination of many bright people". But why was the imagination of so many economists so limited? According to this paper, it is not an "imagination failure": rather the failure of a paradigm (Lakatos, 1976) not able to explain and predict crises of these dimensions.

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[1] Actually, the first of the two.

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This paper aims to build an *early warning indicator* based on a network financial accelerator mechanism (Delli Gatti et al., 2010; Battiston et al., 2012) in which the amount of leverage is a strategic choice of the economic agents. Delli Gatti et al. (2010) show that the analysis of network interactions between heterogeneous agents is crucial in understanding the aggregate impact of the financial accelerator. In this paper, agents' leverage is the self-organizing source of the system and it is coupled with idiosyncratic demand shocks. The financial accelerator (Bernanke and Gertler, 1989, 1990; Bernanke et al., 1999) amplifies economic fluctuations, while interactions and heterogeneity generate complex patterns and dynamics, where even a small shock may lead to large business fluctuations.

This work follows the methodological approach defined in Delli Gatti et al. (2005, 2008). Business cycle dynamics are conceived as the emerging result of interactions of heterogeneous agents. In order to deal with the complex patterns which characterize the evolution of the credit network, we recur to agent based simulation modeling to analyze the relation between micro and macro configurations.

In part, the agent based simulation model presented in this paper extends the Riccetti et al. (2013) model, which analyzes leverage cycles in a credit network economy. The Riccetti et al. (2013) model assumes that the conditions holding the Modigliani–Miller theorem are not valid, thus external credit is more expensive than internal financial sources. Consequently, firms make their production decision following a target leverage approach: they choose a desired level of leverage (i.e. loan demand) and according to the effective amount of credit received they produce final goods. Differently from Riccetti et al. (2013) in our model we assume that banks' loan supply is limited by leverage constraints (as in Delli Gatti et al., 2005) and, thus also banks have to choose a target level of leverage. Similarly to the credit network described in Grilli et al. (2014), the model incorporates rationing mechanisms and prudential behaviors for the banks, which derive from Basel agreements. Finally, both firms and banks make their leverage target choices according to a reinforcement learning mechanism (Tesfatsion, 2005), while in Riccetti et al. (2013) firms' leverage decisions derive only from the observation of previous period profit and production values.

Our work shows that it is possible to analyze economic crises as stemming from the interaction between leverage choices and idiosyncratic shocks amplified and diffused by the credit network. Indeed, the paper describes the emerging properties of a synthetic specifications of the credit network which could offer some perspectives for implementing different configurations of the interactions among banks and firms in the CRISIS model framework. Indeed, the CRISIS European project develops an integrated agent based model aiming at describing European business cycles and the relation between financial crises and the fluctuations of macroeconomic variables.

Simulations are calibrated on a panel of banks and firms quoted in the Japanese stock-exchange markets from 1980 to 2012. This dataset has been analyzed in Marotta et al. (2013), which underlines the complexity of the credit network and focuses on the evolution of firms and banks clusters. The calibration procedure we implement is not based on cluster analysis but is related to the dynamics of aggregate and network connectivity variables. Indeed, simulated business cycle is characterized by properties which emerge from the interactions of agents in a way closely recalling Minsky's cycle (Minsky, 1975, 1982, 1986). Leverage changes generate variations of the output in the opposite direction (see also Adrian and Shin, 2010; Riccetti et al., 2013). However, when leverage increases, the vulnerability of the system to idiosyncratic negative shocks grows, generating the condition for huge output slowdown.[2]

Since the seminal works of Frankel and Rose (1996), Kaminsky et al. (1998), and Kaminsky and Reinhart (1999) several early warning indicators of crises have been detected, using different data sources: aggregate macro variables, interbank networks configurations, international networks of trade and financial data.[3] For instance, Minoiou et al. (2013) through data mining techniques show that financial network measures (connectivity, clustering, neighbor countries' connectivity) may be effectively used to forecast the occurrence of crises. In particular, the financial network connectivity of a country increases consistently before crises augmenting its international exposure.

However, because of the lack of available credit network data at country level and due to the difficulties in embedding credit network dynamics in standard macroeconomic models, the potential of credit networks to provide early warning signals for economic crises has been only partially exploited.

The early warning indicator we propose is based on the analysis of the dynamic configurations of the credit network, which derive from the interactions of banks and firms in the simulated economy calibrated on the Japanese survey. During expansions, simulations show that network concentration rises and the probability of having huge reductions of the output increases. In fact, when some banks are in a central position in the credit network – in terms of both number and size of loans – a shock (for instance, the failure of a large borrower of the bank) may produce a contraction of the loan supply resulting in relevant systemic effects. Thus, not only agent's dimensions but their connectivity has a decisive impact on the economic system, emphasizing the importance of turning policy attention from ‘too big to fail’ to ‘too connected to fail’.

The paper is structured as follows: the second section illustrates the model; the third describes the Japanese credit network dynamics on which the simulations are calibrated. Then the simulated data dynamics are analyzed and a proposed early warning indicator is illustrated and tested in section five. Concluding remarks close the paper.

[2] Let us note that shocks of similar magnitude may produce quite different effects.

[3] The study of early warning indicators of economic crises has gained new momentum after the 2008 financial crash. For a review of the literature see, for instance, IMF (2010), Babeck et al. (2011), and Drehmann and Juselius (2013).

2. The model

Our closed economy, without Government, is populated by M banks and N heterogeneous firms producing the same perishable good using capital as the only input. Firms produce goods by means of capital financed by their internal resources and by bank loans.[4] 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 linear production function:

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

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^d_{it}) and past period loans (ϕL_{it-1}).

$$\Lambda_{it} = (L^d_{it} + \phi L_{it-1})/E_{it}. \tag{4}$$

Thus, loans demand (L^d_{it}) derives from the target leverage chosen:

$$L^d_{it} = \Lambda_{it} E_{it} - \phi L_{it-1}$$

The target leverage is determined by the leverage strategy (η_{it}) that firms chose in each period.

$$\Lambda_{it} = \frac{1}{\eta_{it}} - 1 \tag{5}$$

Thus the loan demand can be re-written as

$$L^d_{it} = \frac{E_{it}}{\eta_{it}} - \phi L_{it-1} - E_{it} \tag{6}$$

The η_{it} parameter is chosen following the reinforcement learning algorithm described in Section 2.4. Firms can choose their leverage strategy (η_{it}) among a finite countable set of strategies H.[5] The lower is η_{it} the higher is the target leverage (Λ_{it}) and, thus, the higher the risk taken by the firm.

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.

$$r_{it} = \alpha \Lambda_{it} + r \tag{7}$$

Profits are given by the difference between revenues ($u_{it} Y_{it}$) and total costs, equal to financing costs and a term, F_f, capturing fixed components.[6] Internal financial cost corresponds to the remuneration of the net worth (rE_{it}). The external financing cost is given by the interests on loans.

$$\pi_{it} = u_{it} Y_{it} - rE_{it} - r_{it} L_{it} - \phi r_{it-1} L_{it-1} - F_f \tag{8}$$

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

[4] See (Delli Gatti et al., 2005, 2008) for the explanation about asymmetric information problems leading to such limited funding strategies.

[5] The set of possible strategies is limited because, on the one hand, η_{it} can not be lower than one: when η_{it} is equal to one firm will not borrow credit, thus they rely only on their net-worth (E_{it}) as financial source. On the other hand, η_{it} has a lower bound because reducing η_{it} the external exposure of the firm increases and, consequently, its riskiness arises. Therefore, after a certain level, reducing further η_{it} is not convenient because banks will not want to lend money to high risk firms or can not offer credit due to financial prudence agreements (as Basilea's agreements). Moreover, increasing η_{it} the debt service arises (Eq. (7)).

[6] The fixed cost F_f is a very small cost that is intended to eliminate very small firms, which have no impact on the aggregate result. We tested the simulation without this cost and we do not have significantly different results. The presence of these costs, eliminating very small firms that may have previous credit linkages, improves the computational efficiency of the simulations.

Stiglitz, 1993):

$$u_{it} = m + \epsilon_{it} \tag{9}$$

$$\epsilon_{it} \sim N(0, \sigma) \tag{10}$$

Thus, net revenues depend on both a fixed component (m) and a stochastic one that represent demand fluctuations not predictable by the firms (ϵ_{it}). Because the expected value of ϵ_{it} is zero, the expected marginal net revenue is equal to m. Firms may take different levels of leverage and there is a maximum level of target leverage (Λ_M) they can choose (corresponding to the riskier leverage strategy allowed in the simulation). When a firm chooses the maximum level of leverage, the loan demanded is charged with a corresponding interest rate following Eq. (7):

$$r_M = \alpha \Lambda_M + r$$

r_M represent marginal costs associated to the loans when a firm chooses the riskier strategy. Once a firm borrows money from the banks, loans are used in production with a marginal productivity equal to ρ. In order to give the possibility for firms to borrow conveniently the amount of loans associated to the maximum level of leverage allowed, the expected net marginal revenue has to be higher than r_M/ρ, in this way marginal revenue is higher than marginal cost for each unit of output produced.

Thus, the expected marginal revenue (m) is assumed to be larger than the marginal cost of loans at the maximum interest rate. Therefore, the expected marginal revenue, m:

$$m = r_M/\rho + \delta \text{ with } \delta > 0 \tag{11}$$

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

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

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 $\eta_{zt} \in H$. 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

$$L^s_{zt} = \frac{E_{zt}}{\eta_{zt}} - \sum_{I_{zt-1}} \phi L_{izt-1} \tag{13}$$

Thus, as for firms, riskier leverage strategies correspond to lower levels of η_{zt}. Indeed, the lower is η_{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 η_{zt} values increase bank leverage and, thus, its riskiness. As for firms, banks have a maximum level of leverage deriving from prudential reasons and in conformity with international credit agreements (Basilea's agreements).

Banks' 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_b).[7]

$$\pi_{zt} = \sum_{I_{zt}} r_{izt} L_{izt} + \sum_{I_{zt-1}} r_{izt-1} L_{izt-1} - BD_{zt} - BD_{zt-1} - r(E_{zt} + D_{zt}) - F_b \tag{14}$$

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

$$\begin{cases} E_{zt} = E_{zt-1} + (1-\tau)\pi_{zt} & \pi_{zt} > 0 \\ E_{zt} = E_{zt-1} + \pi_{zt} & \pi_{zt} \le 0 \end{cases} \tag{15}$$

2.3. Matching among banks and firms

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.

[7] The fixed cost F_b is only a very small cost that is intended to eliminate very small banks, which have no impact on the aggregate result. Thus, this fixed cost slightly decreases computational efforts without modifying simulation results.

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A bank can deny loans to firms that are considered too risky. The probability (p_R) that the demand of loans of firm i is not accepted increases in the firm target leverage (Λ_{it}):

$$p_R = \iota(\Lambda_{it}) \tag{16}$$

Therefore, 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.

In the following periods, each firm expresses its loan demand first of all to its linked banks. At every time t, for each bank z, 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 $t-1$.

$$L^d_{izt} = L^d_{it}\frac{L_{izt-1}}{L_{it-1}} \tag{17}$$

As before, banks may refuse to provide credit to a firm that is considered too financially exposed (following Eq. (16)).

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

$$L_{izt} = L^s_{zt}\frac{L_{izt-1}}{\sum_{I_a} L_{jzt-1}} \tag{18}$$

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.[8]
3. The bank refuses to provide loans because the firm is considered too risky (Eq. (16)).

2.4. Leverage choice

Agents, both banks and firms, in each period choose a target leverage (Λ_{it}). The target leverage (Λ_{it}) derives from the leverage choice (η_{it}) through Eq. (5). Strategies η_{it} are chosen among a limited and countable set H. 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 η_s at time $t-1$ for agent i. In other words, profit is used to value effectiveness of a strategy of leverage η_s, $q(\eta_s)_{it}$:

$$q(\eta_s)_{it} = (1-\chi)q(\eta_s)^F_{it-1} + \pi_{ist-1} \tag{19}$$

Therefore, agents value each possible leverage strategy according to $q(\eta_s)_{it}$, which is updated every time the agent chooses a particular strategy. 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. The higher the profits associated to a strategy, the higher its associated efficiency and, thus, the probability of choosing this strategy in the future periods. At the beginning of each period, the effectiveness of every leverage strategy $q(\eta_s)_{t-1}$ is reduced by a small percentage (ζ): $q(\eta_s)^F_{it-1} = (1-\zeta)q(\eta_s)_{it-1}$, where ζ represents the extent of 'forgetting processes'.

Agents may choose only among the possible levels of leverage ($H_a \subseteq H$). In fact, because loans have a two-period maturity, agents have to consider also their past debts.[9]

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 η_s) among the levels of leverage allowed (H_a) is given by $p(\eta_s)_{it}$, this probability is different for each agent according to its past profit results:

$$X_{ist} = \left(\frac{q(\eta_s)_{it}}{c}\right)^{\nu} \tag{20}$$

[8] For instance, a firm does not ask for loans at time t, because at time $t-1$ negative profits may have reduced its net-worth, thus the leverage of the agent due to previous loans exceeds the maximum target leverage level allowed.

[9] Thus, if an agent has loans inherited from the previous period, it has to choose a level of leverage that takes into account these past loans, thus starting from a given leverage level that is inherited from the past. For instance, if the level of leverage derived from previous loans is higher than the maximum level of leverage, the agent will not ask or provide any credit. In general, agents that have past debt exposure can not choose among all the set of H possible strategies, but this set is reduced to H_a, thus firms may have not the possibility of choosing strategies that imply lower leverage and lower risk. From a computational point of view, reducing the possible set of strategy allowed has effect on the probability that is associated to each strategy.

$$p(\eta_s)_{it} = \frac{e^{X_{ist}}}{\sum_{Ha} e^{X_{at}}} \tag{21}$$

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 $p(\eta_s)_{it}$. Taking the exponential, strategies that are more efficient (higher $q(\eta_s)_{it}$) 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

To allow a continuous exploration of the action space, there is little probability (μ) that in each period agents may choose their leverage strategy randomly without considering their respective effectiveness ($q(\eta_s)_{it}$). The parameter ζ 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.

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.

However, in this basic learning mechanism, agents do not take into consideration the volatility of profits associated to the different levels of leverage. For this reason, we generalize the Tesfatsion (2005) framework assuming that agents compute also the riskiness of a strategy, say $v(\eta)$, using the variability of profits (σ_π) to correct their leverage decisions. Profit standard deviation (σ_π) is computed on the last twenty values of profit for each leverage level. While $q(\eta_s)_{it}$ is updated using profit level, $v(\eta_s)_{it}$ is updated using profit volatility:

$$v(\eta_s)_{it} = (1-\chi)v(\eta_s)^F_{it-1} + \sigma_\pi. \tag{22}$$

Similarly, $v(\eta_s)^F_{it-1}$ is given by $v(\eta_s)^F_{it-1} = (1-\zeta)v(\eta_s)_{it-1}$. We are now able to compute the probability of choosing a particular level of leverage (strategy η_s) among the target leverage levels allowed (H_a) considering also profit variability. Such probability,

$$X_{ist} = \left(\frac{q(\eta_s)_{it}}{c+\psi v(\eta_s)_{it}}\right)^{\nu} \tag{23}$$

$$p_\sigma(\eta_s)_{it} = \frac{e^{X_{ist}}}{\sum_{Ha} e^{X_{at}}} \tag{24}$$

is denoted by $p_\sigma(\eta_s)$. An important role, investigated in Section 3.1, is played by the parameter ψ, the risk-sensitivity. Indeed, the equation to compute the strength of a strategy (Eq. (23)) differ from the previous one (Eq. (20)) because of the volatility component $\psi v(\eta_s)$. The volatility component has a normalizing effect on the strength of each strategy, reducing the strength of the more volatile ones. Thus, at parity of past profits the leverage strategy with lowest volatility have an higher probability of being chosen. Forgetting and error probability are also applied in this last case, as in the previous specification according to parameters ζ and μ.

3. Japanese and simulated credit networks

The model is calibrated on a dataset based on a survey of firms quoted in the Japanese stock-exchange markets reporting annual data from 1980 to 2012. Each year, on average 226.18 banks and 2218 firms are reported (Marotta et al., 2013).[10] To analyze the aggregate dynamics of the network, we have defined a synthetic indicator: the adjusted out-degree indicator (d_z^+), which tries to capture, at the same time, the level of connectivity and the vulnerability of the credit network. Following Palestrini (2013) and Guzzini and Palestrini (2014), the adjusted out-degree indicator takes into account, at a first order approximation, banks' links and their relevance in the credit market. Assume that the first order approximation of the relationship between firm-i output shock, say y_{it}, and shocks in previous time linked banks, say $b_{1t-1}, \dots, b_{Mt-1}$, may be represented by the following equation:

$$y_{it} = \theta_{1i} b_{1t-1} + \cdots + \theta_{Ni} b_{Mt-1} + \varepsilon_{it} \tag{25}$$

with ε_{it} as an idiosyncratic component, and $i = 1, \dots, N$.

Putting all the y_{it} in the vector $y_t = [y_{1t}, \dots, y_{Nt}]^T$, we may write the system of equations

$$y_t = \Theta b_{t-1} + \varepsilon_t \tag{26}$$

[10] We use only the data referring to banks and firms with positive net worth, thus we do not consider other financial institutions that are reported in the survey.

where y_t is the N-dimensional vector of firm shock. According to the above equation firm-i's shock may be explained by an N-vector of idiosyncratic (white noise) component ε_{it} - whose generic element has expected value μ_ε - and by the links with the M banks at time $t-1$ according to the time homogeneous $N \times M$ matrix of weighted links Θ.[11] Now we are interested in the dynamic of *weighted* aggregate shocks, that we may, for example, measure as the weighted mean μ_w of the firms' shock at time t using a vector of weights w, that is

$$\mu_{wt} = w^T y_t.$$

By multiplying by w^T Eq. (26), the aggregate dynamics becomes

$$\mu_{wt} = w^T \Theta b_{t-1} + w^T \varepsilon_t. \tag{27}$$

As shown in Palestrini (2013) the weighted mean generates

$$w^T \Theta = (d_1^+, \ldots, d_N^+)^T.$$

the vector of weighted *out-degree* between banks and firms. In this way, the aggregate effect of the banking system is given by

$$w^T \Theta b_{t-1} = (d_1^+, \ldots, d_M^+)^T b_{t-1} = \sum_{z=1}^{M} d_z^+ b_{zt-1}. \tag{28}$$

The above equation shows that the (first order) effect on firms output shock is given by a combination of banks shocks with adjusted out-degree as weights. In the following empirical analysis we use the quantity $M^{-1}\sum_{z=1}^{M} d_z^+$ to analyze the effect of the banking sector to the real economy since it has a very simple interpretation.[12] It represents the average effect on output when all banks are hit by a unitary shock. In our work, the degree distribution is related to the amount of loan, say $l_z = \sum_i^N l_{iz}$, of every bank. Furthermore, the degree indicator is adjusted to consider variations of bank's connectivity and riskiness. We use an adjusted degree indicator, $d_z = a_z l_z$, with $a_z = n_z \lambda_z$ which includes the normalized number of credit links (n_z) of a bank[13] and the level of leverage of the bank (λ_z) to weight for its riskiness: That is,

$$d_z^+ = n_z \lambda_z l_z \tag{29}$$

Each period of the simulation is considered as a quarter of a year to allow the comparison of simulated data with empirical ones. The artificial economy is populated by 500 firms and 50 banks, which is the approximate Japanese database proportion (1 bank every 10 firms). Simulations are calibrated to reproduce empirical aggregate regularities. The aggregate output growth rate standard deviation of Japanese firms is similar to the one of simulated data (around 0.07 of output Δ log) and, in line with empirical data, the simulated output growth rate is positively auto-correlated.

Moreover, IRFs of VARs implemented on simulated data give coherent results with respect to the empirical ones. Thus, to allow comparison among empirical and simulated data, we consider the effect of aggregate shocks on macro variables. The small duration of the time series, thirty annual data, allows us to implement only simple VARs with one lag. VARs are computed to have a qualitative and synthetic representation of the jointed dynamics of the variation of the aggregate output, the aggregate leverage of banks, as a measure of systemic riskiness, and the average adjusted degree indicator.[14] In particular, in both empirical and simulated data, a positive output shock impacts positively on the adjusted degree growth rate (Figs. 1 and 2, upper right panel). Moreover, the increase of the aggregate bank leverage reduces the output growth rate the following year and increases the adjusted degree (Figs. 1 and 2, middle left and right panels). An interpretation of these last IRFs is that growth of leverage and connectivity may increase the vulnerability of the credit network, causing the decrease of the output in the next periods. Indeed, the diffusion and amplification of local shocks is determined by the strength of the connection between agents (i.e.; following Eq. (28)). High levels of leverage augment the exposure of both firms and banks, thus the probability of failure increases with high leverage. Moreover, higher leverage implies high levels of connectivity (i.e.; the higher the leverage, the higher the amount of loans asked and offered in the economy), thus, shocks may be easily diffused and amplified: the failure of an agent may trigger the failure of other agents or the reduction of the loans offered leading to a significant aggregate output contraction.

[11] As said above, the specification of the links structure implicitly assumes a Markovian property regarding the y_t vector. The analysis can be easily generalized adding more lags to the y_t specification. The matrix Θ is a *simple adjacency matrix*.

[12] Note that since we have a fixed number of banks, using $M^{-1}\sum_{z=1}^{M} d_z^+$ or $\sum_{z=1}^{M} d_z^+$ gives the same results once we adjust for the scaling factor M.

[13] That is equal to the number of out-degrees divided by the number of firms.

[14] In Figs. 1 and 2, the logarithmic difference of the aggregate output is indicated as *dout*, the aggregate leverage of banks is *dlev* and the mean of the adjusted degree indicator is *dadeg*, which are covariance stationary (Dickey Fuller test). We use the Cholensky decomposition to identify shocks of the system; the ordering restrictions implied seem to hold, at least approximately, in the model. In the simulations shocks derive from idiosyncratic firms' revenue variations which, affecting agents' net-worth and profitability, impact on the aggregate leverage. Afterwards, shocks directly or through leverage variations affect the credit network and, in particular, the adjusted degree indicator.

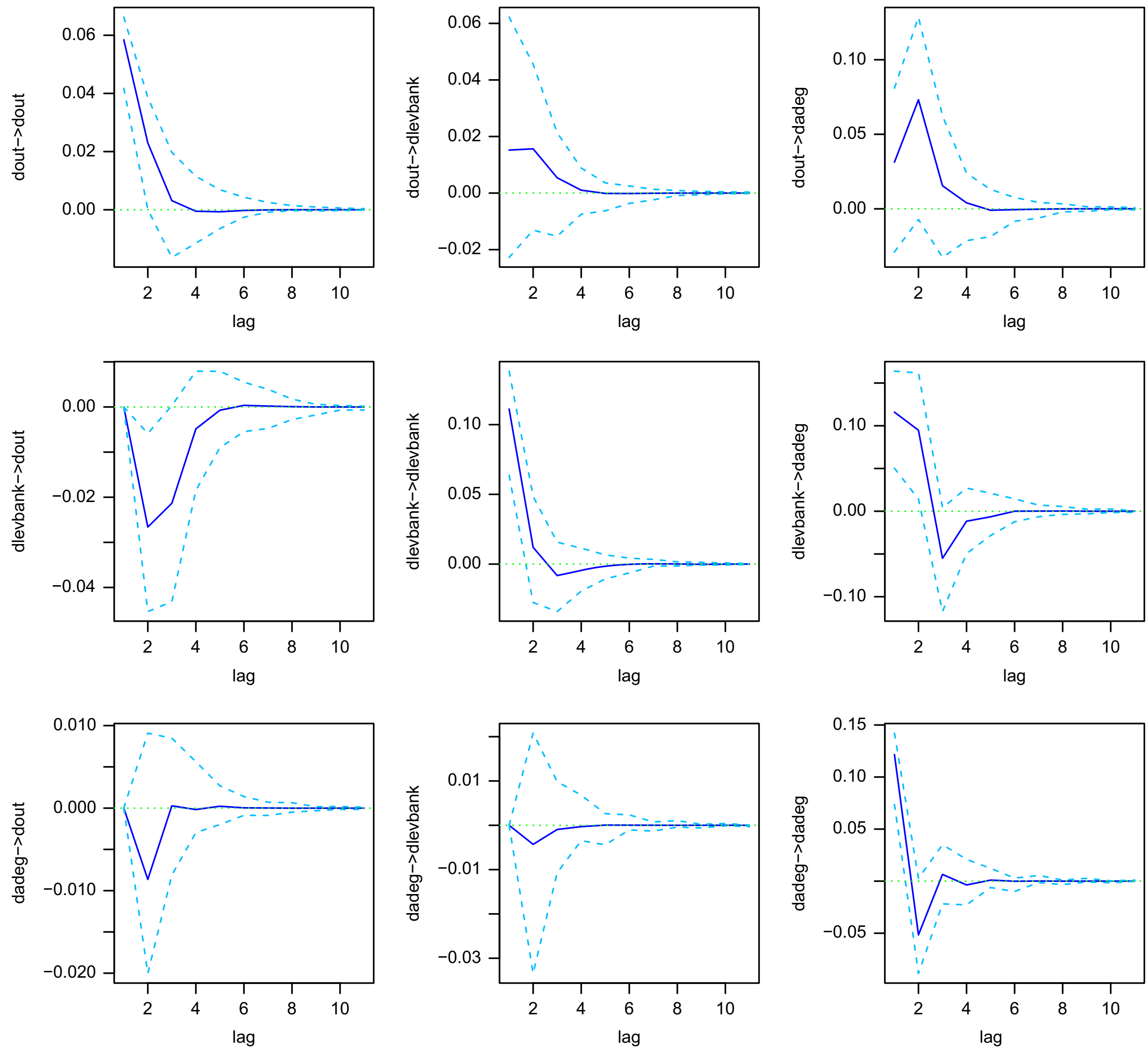

Fig. 1. Impulse-response functions on empirical data. IRFs are computed assuming Cholensky decomposition of the error term on logarithmic variations. *dout* is the output variation, *dlevbank* is the variation of the leverage, *dadeg* the variation of the adjusted degree.

3.1. Micro and meso patterns of the simulated economy

It is possible to have some insights into the inner dynamics of the artificial economy considering cross correlation functions between the cyclical component of macro variables, taking quarterly data of the simulations (in effect looking at simulated periods separately).

Output is positively correlated (at time zero) with leverage levels (leverage computed both on firms and on banks) and with the adjusted degree (Fig. 3).[15] When the leverage is higher, adding loans to their own resources, firms have higher productive capacity, this on average leads to higher production levels. Higher leverage, in particular when it is combined with a relatively large total amount of loans, increases the average adjusted degree, which combines the level of connectivity with the amount of banks' loans and leverage.

Output dynamics slightly anticipate firm leverage and the adjusted degree: when output starts growing the aggregate leverage and the connectivity of the system augments with a certain delay. In part, this is due to the fact that banks need some time to increase their net worth and, therefore, their loan capacity. In effect, excess credit demand positively anticipates output. Moreover, output is positively correlated with the level of riskiness of the strategies chosen by the agents, i.e. agents tend to follow riskier strategies during expansions (Fig. 4). However, leverage increases the system vulnerability to local shocks. Indeed, the number of firm failures and the volume of bad debts are positively correlated with

[15] In the figure the cross correlation functions $c(X,Y)$ are defined as $c(X_{t+\tau},Y_t)$, where $X_{t+\tau}$ is the first variable (lagged variable) at time $t+\tau$ and Y_t is the second variable. For instance, in Fig. 3 upper left panel, the X variable is output and the second variable Y is bank leverage.

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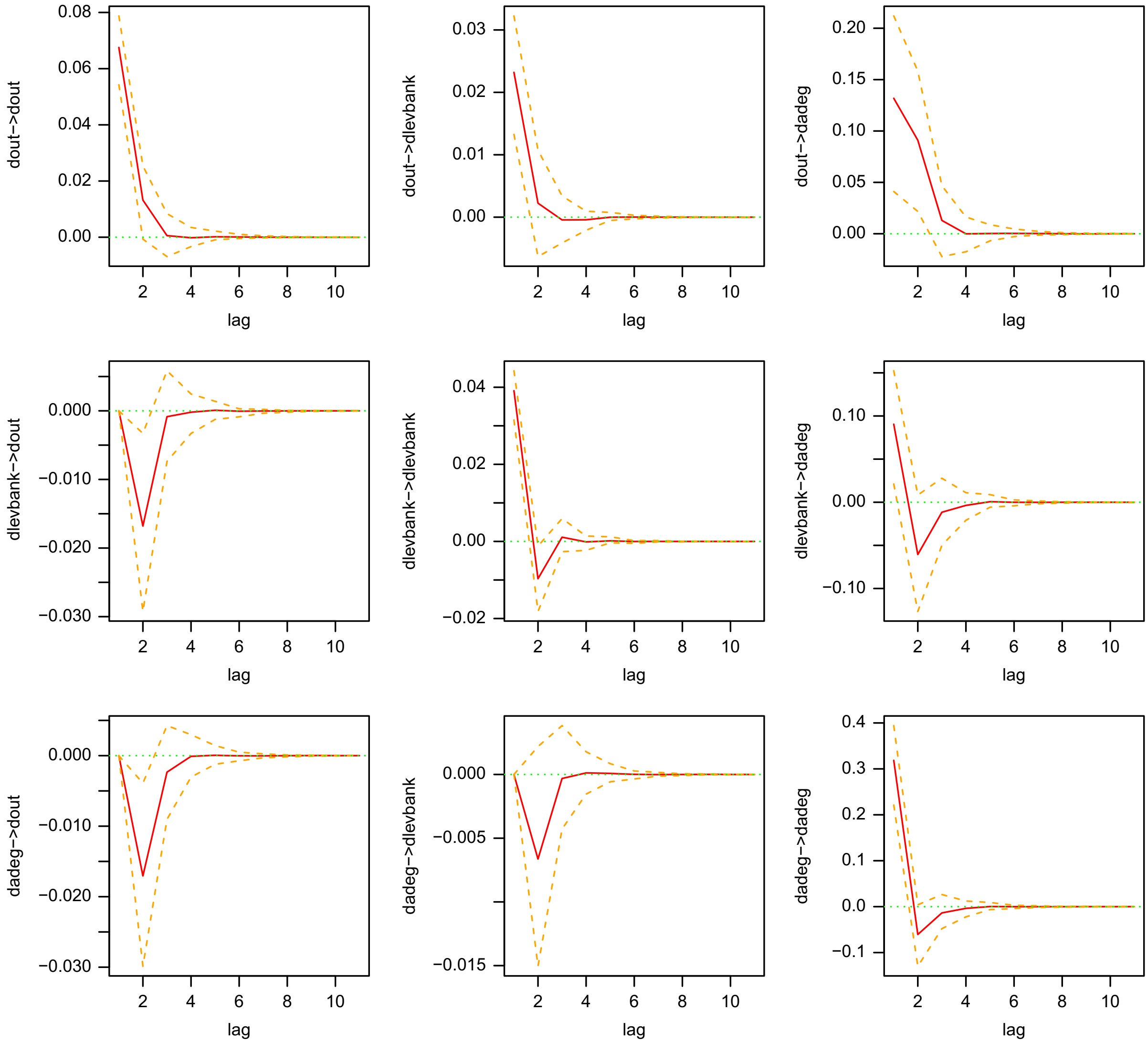

Fig. 2. Impulse-response functions on simulated data (Averages over 50 Monte Carlo simulation runs). IRFs are computed assuming Cholensky decomposition of the error term on logarithmic variations. *dout* is the output variation, *dlevbank* is the variation of the leverage, *dadeg* the variation of the adjusted degree.

the level of aggregate firm leverage. The increasing leverage during expansionary phases seems to create endogenously the conditions for the following contraction. Furthermore, when the increasing leverage is associated with a relatively high concentration of the adjusted degree, the possibility of the occurrence of a huge output contraction increases. Indeed, from Eqs. (28) and (29) we see that to understand network effects, at a first approximation, the sum of the weighted degree distribution is important. Moreover, the numerical analysis below shows that the effect is not symmetric with respect to negative and positive shocks. With negative shocks the degree distribution and in particular its concentration (see Section 4) plays a key role in understanding output dynamics. Localized bankruptcy of big firms/banks may produce avalanches leading or amplifying the crisis. Therefore, the early warning indicator we propose on Section 4 is based on the concentration of the adjusted degree.

Some general dynamical features of the model which emerge from the simulations are worth noting.

1. Agents' heterogeneity generates path-dependence mechanisms. In fact, the dynamical adjustments have to trickle down the whole distribution of agents financial conditions.
2. An impulse forced upon the system propagates in a non-linear way. Therefore, aggregate fluctuations are quite large and persistent because firms turnover and the changing composition of the credit network amplify the effects of small shocks (Fisher, 1999; Williamson, 1996);

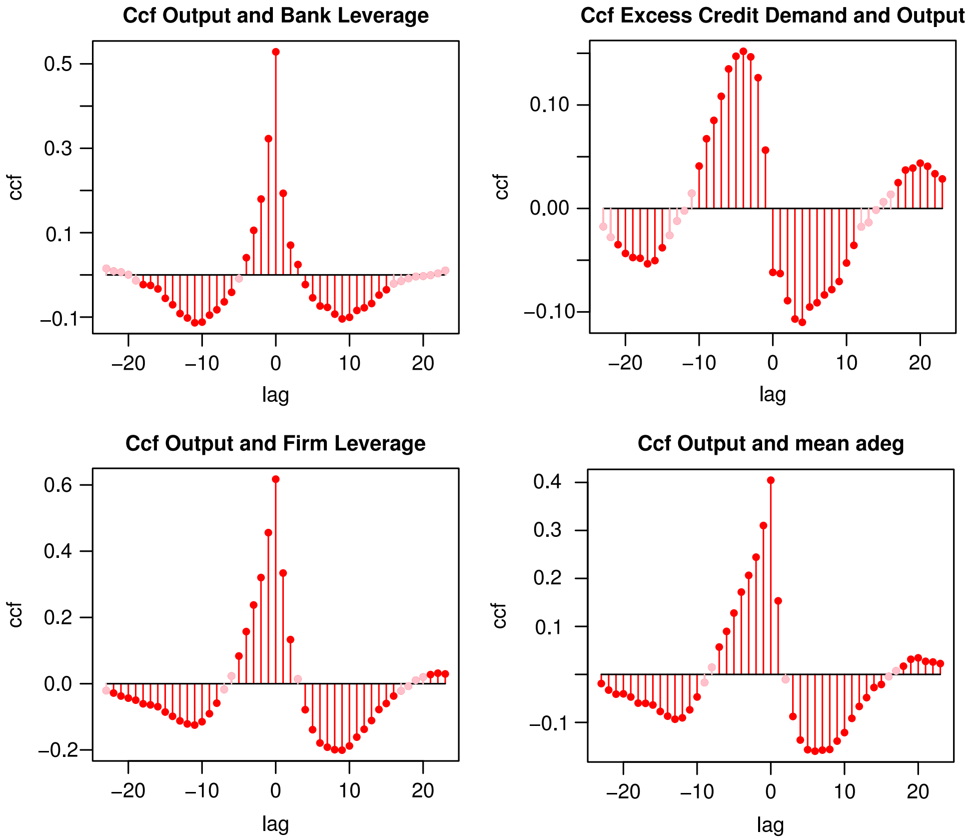

Fig. 3. Cross correlation functions between simulated macro variables. Variable is detrended through HP filtering. (Averages over fifty Monte Carlo simulation runs, in lighter shade values that are not significant at 5%). In the upper left panel, cross correlation between aggregate output and aggregate bank leverage. In the upper right panel, cross correlation between excess credit demand and aggregate output. In the lower left panel, cross correlation between aggregate output and aggregate firm leverage. In the lower right panel, cross correlation between aggregate output and the average adjusted degree of banks.

3. Stationarity properties of aggregate variables are distribution dependent: The notion itself of long run equilibrium is ambiguous in this framework. Indeed, the distribution of the adjusted degree may be crucial to determine the occurrence of crises and, thus, the stability of the system.

Stochastic impulses and the non-linearity of the underlying dynamic setting are the sources of erratic and complex behavior. There is no sequence of stages in the fluctuations, but one can detect that, because of the stochastic nature of profits and the changing composition of the credit network, the frequency, amplitude and timing of the business fluctuations change over time and the relationships between aggregate output and leverage change from cycle to cycle. All the fluctuations, however, are led by a change in financial fragility which determines output behavior: business cycles are financially driven. In an attempt to provide a qualitative description of the intertwined dynamics of financial fragility and aggregate output during a financially driven business cycle, we identify *à la* Minsky,[16] two stages of the expansion from trough to peak (*financially hedge phase*, *financially fragile boom*) and two stages of the recession from peak to trough (*speculative recession*, *hedge recession*).

At the bottom of the cycle and the beginning of a *tranquil era*, i.e. at the lower turning point, a wave of bankruptcies has cleared up the economy eliminating fragile firms: therefore, the leverage decreases. As firms balance sheets become more robust, output and profits increase, while debt commitments become lighter. This scenario describes a virtuous circle in which the growth of investment and profits is paralleled by a decline of debt. This phase does not go on forever. Positive profit opportunities speed up production and firms' demand for external finance soars. Therefore, aggregate debt goes up and eventually determines the transition to the *financially fragile boom*, characterized by increasing average leverage. The system reaches the peak but balance sheets deterioration leads to the endogenous downturn. The recession begins. Right after the upper turning point, during the *speculative recession*, the decline of profits depresses output. Firms financial

[16] We borrow from Minsky (Minsky, 1975, 1982, 1986) the taxonomy of industrial units according to their degree of financial fragility. A hedge unit has a leverage low enough to rule out any risk of bankruptcy. A speculative unit is more financially fragile (has a higher leverage) than a hedge unit but is still lingering on the threshold of survival. A Ponzi unit postpones bankruptcy as long as it can access credit in order to reimburse the preexisting debt.

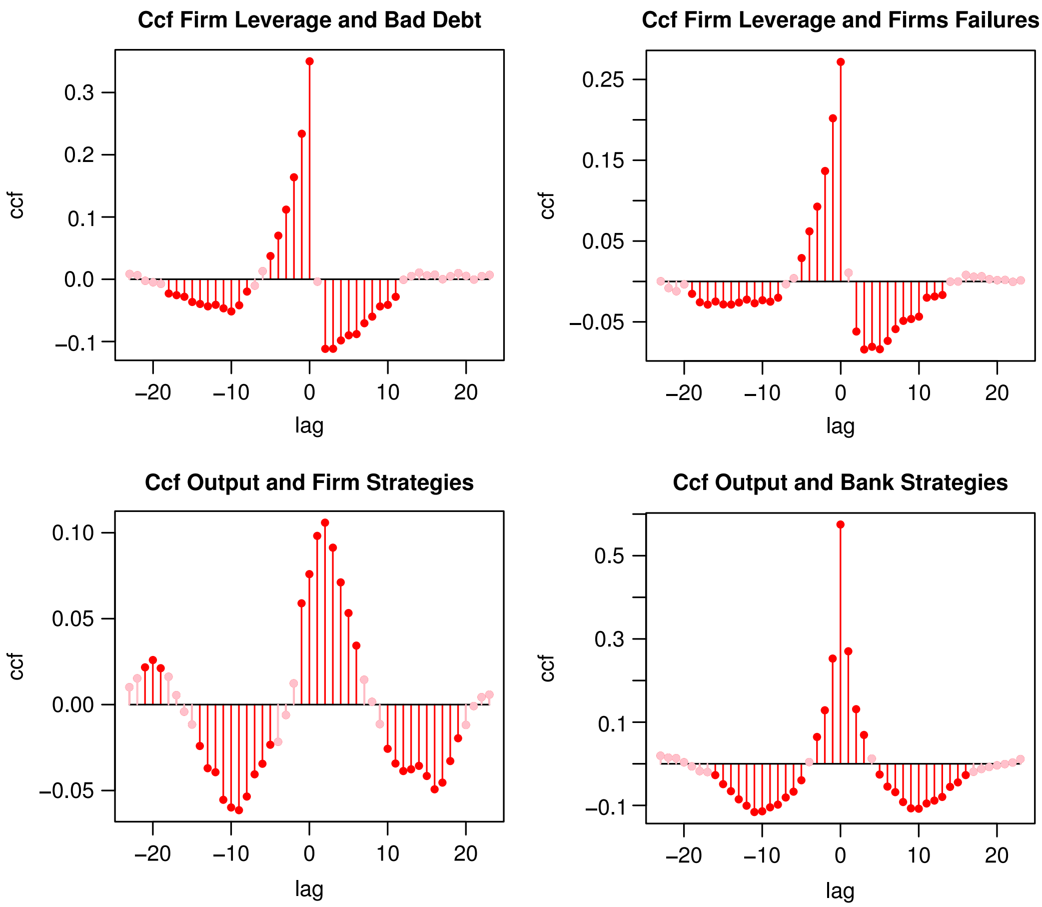

Fig. 4. Cross correlation functions between simulated macro variables. Variable is detrended through HP filtering. (Averages over fifty Monte Carlo simulation runs, in lighter shade values that are not significant at 5%) In the upper left panel, cross correlation between aggregate firm leverage and aggregate volume of bad debts. In the upper right panel, cross correlation between aggregate firm leverage and the number of firm failures. In the lower left panel, cross correlation between aggregate output and the average leverage strategy chosen by firms. In the lower right panel, cross correlation between aggregate output and the average leverage strategy chosen by banks.

conditions are still unsound: the leverage goes further up. The intermediate stage of the recession is the *safe contraction*, i.e. financially robust contraction. The leverage goes down and once in the *hedge depression* the leverage stabilizes. At the end of *hedge depression*, investment becomes greater than saving, a turning point in the business cycle occurs and a new recovery sets in.

If banks are not able to absorb the negative shocks, the economic slow down may bypass the *weak contraction* phase and enter directly in a *robust contraction* phase. The production slow down consistently affects more exposed banks, their net-worth and supply of loans decrease, reducing aggregate leverage and the credit network connectivity.

The macro dynamics are the result of agents' choices and their interactions. In particular, risk perception is crucial in determining agents behavior in the credit market. Introducing sensitivity to profit volatility (parameter ψ in Eq. (24)), thus the possibility for each agent of choosing leverage levels considering both past profits and profit volatility, has a strong impact on the macroeconomic dynamics. Sensitivity to profit volatility reduces output variability and the probability of having huge output slowdown (Fig. 5).

More in general, looking at macro variables cross correlation functions, output dynamic is no longer anticipated by the other macroeconomic variables (Figs. 7 and 8). Indeed, increasing individual leverage the amplification of both positive and negative shocks for firms augments (following Eq. (8)). Thus, higher levels of leverage are associated with higher levels of volatility. However, the higher the sensitivity to profit volatility, the lower is the probability of choosing high levels of leverage. Therefore, following more prudential leverage strategies, agents reduce the possibility of triggering positive or negative feed back mechanisms, implying lower cross-correlation of aggregate variables through time.

Besides, we implemented simulation with different mnemonic capabilities of the agents (Fig. 6) regarding profit volatility, i.e.; modifying the length of the profit time series on which agents compute profit standard deviation. Memory reduces volatility in terms of both output growth standard deviation and number of crises. However, increasing the memory after 20 period does not seem to have significant impact on volatility. Indeed, when the time series used to compute

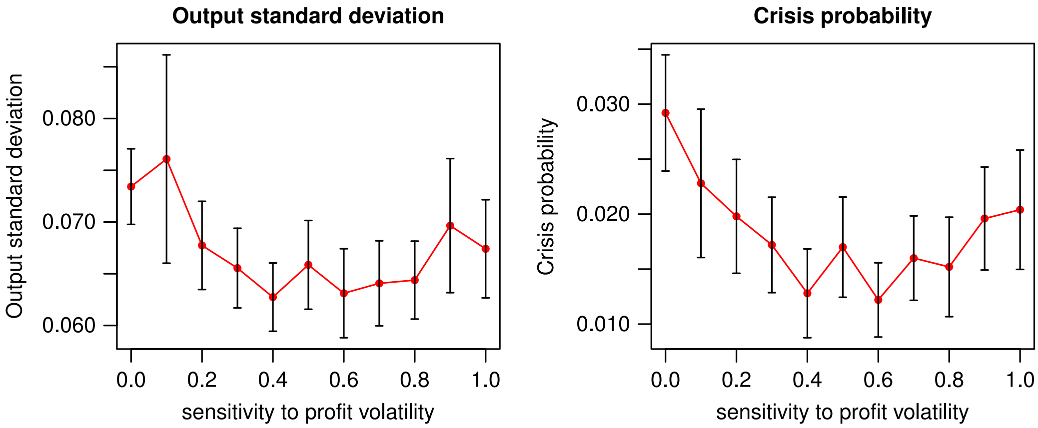

Fig. 5. Output standard deviation and sensitivity to profit volatility, ψ. In the standard simulation specification $\psi = 0$. In the left panel, output standard deviation and sensitivity to profit volatility. In the right panel, probability of having a crisis and sensitivity to profit volatility. (Averages over 50 Monte Carlo simulation runs for each sensitivity level, ψ, with 95% CI bars on means).

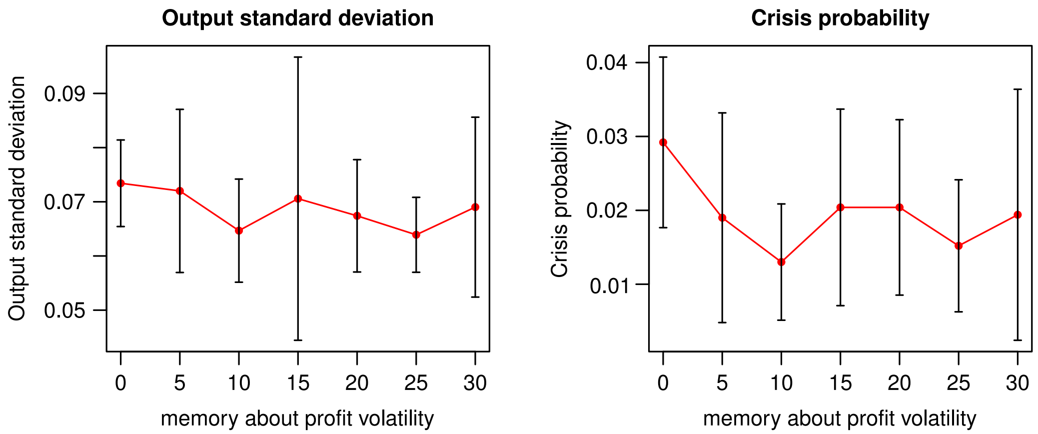

Fig. 6. Output standard deviation and memory about profit volatility, ψ. In the left panel, output standard deviation and memory. In the right panel, probability of having a crisis and memory. (Averages over 50 Monte Carlo simulation runs for each memory level with 95% CI bars on means).

volatility is too long, it is possible that agents' choices derive excessively from past results and, thus, their choices are not so effective to cope with the actual state of the economic system.

4. The early warning indicator

Credit network analysis (Eq. (28)) suggests that when the connectivity of the network, i.e. the adjusted degree indicator, increases local shocks may be amplified and diffused with higher probability. As shown in Fig. 9, before a crisis the leverage of the agents and the connectivity of the system is high, while after the crisis both leverage and connectivity goes consistently down.

In particular, when the concentration of the adjusted degree indicator is high, the possibility of having huge reductions of the output increases. Thus, the level of concentration of the adjusted degree among banks may be used as an early warning indicator for crisis. In fact, when the adjusted degree is too concentrated, if one of the banks with high adjusted degree is hit by a local shock, the effect of the consequent loans contraction on the aggregate supply of credit may be massive. The failure of one or just a few firms may trigger a crisis: the failed firms do not pay back their loans to lenders, this may cause creditors' failure or a significant worsening of creditors' balance sheets. Creditors' failures or the worsening of their balance sheets may consistently reduce the overall banks' lending capacity in the following periods. When the adjusted degree is highly concentrated, the possibility that banks which are central in the credit network are hit by firms' failures increases and, thus, the following contraction of credit supply may be large enough to have a significant negative impact on the whole economic system.

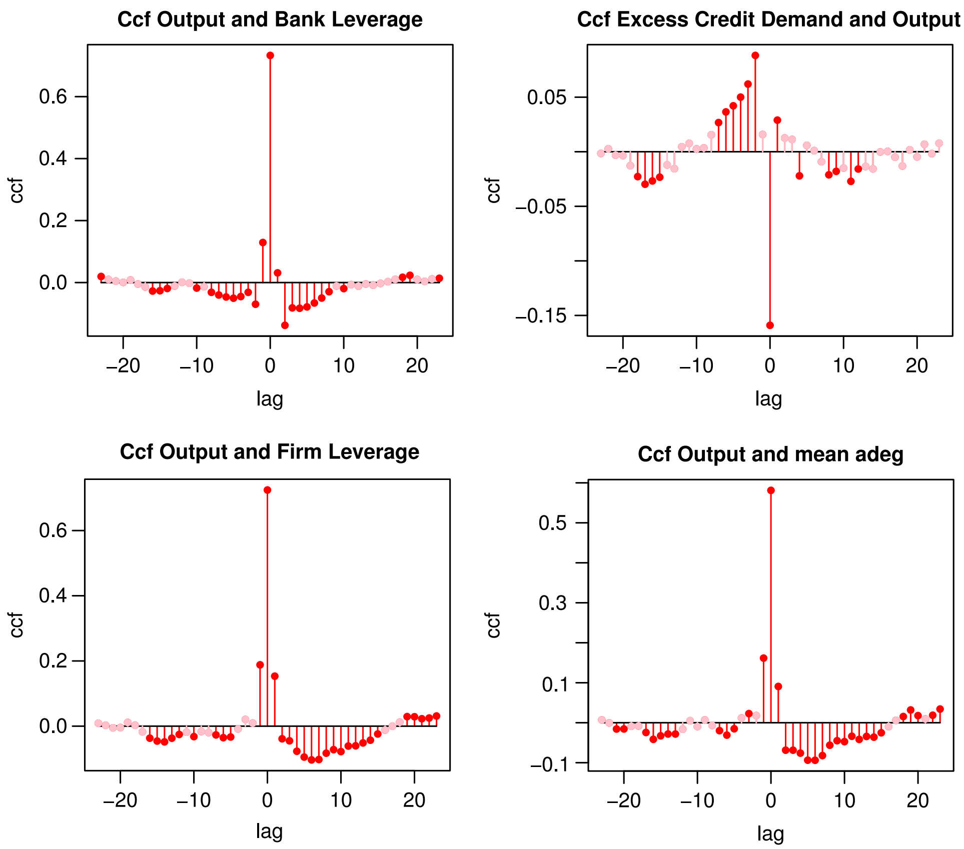

Fig. 7. Cross correlation functions between simulated macro variables with sensitivity to profit volatility. Variable is detrended through HP filtering. (Averages over 50 Monte Carlo simulations, in lighter shade values that are not significant at 5%). In the upper left panel, cross correlation between aggregate output and aggregate bank leverage. In the upper right panel, cross correlation between excess credit demand and aggregate output. In the lower left panel, cross correlation between aggregate output and aggregate firm leverage. In the lower right panel, cross correlation between aggregate output and the average adjusted degree of banks.

We define the concentration indicator (k_t) as the sum of the adjusted degree of the banks in the last percentile, say p_{95}, of the distribution ($\sum_{z \in p_{95}} d_z^+$) divided by the total sum of the adjusted degree of all the banks ($\sum_z d_z^+$):

$$k_t = \frac{\sum_{z \in p_{95}} d_z^+}{\sum_z d_z^+} \tag{30}$$

The concentration indicator (k_t) is positively correlated with output, leverage and connectivity. Moreover, the concentration indicator anticipates negativity output: high levels of the indicator may lead to future output low levels (Fig. 10). During expansionary phases the concentration of the adjusted degree tends to increase. However, when the level of concentration becomes too high the vulnerability of the credit network and, thus, the probability of a contraction of the economic system arises.

In line with the dimension of the crisis observed in 2010 in the Japanese data, a crisis event, say C, is simply defined as an annual output reduction of more than -15% or a geometric growth rate of -5% in three consecutive years. The higher the level of the concentration indicator, the higher the possibility of having a crisis. The effectiveness of this measure as an early warning signal, on the one hand, depends from the conditional probability of having a crisis in the three subsequent years, say $p(C|k)$, when the concentration indicator reaches a relatively high level (Fig. 11). On the other hand, the conditional probability, say $p(k|C)$, is relevant to reach a certain level k of the indicator before a slow down occurs (i.e. Alessi and Detken, 2009; Cohen et al., 2009; Jorda et al., 2011; He and Krishnamurthy, 2013).[17]

The relation between the two conditional probabilities ($p(C|k)$ and $p(k|C)$) may be expressed trough the trade-off between *hit ratio* and *false alarm ratio*.[18] For instance, when the level of the concentration indicator reaches high levels (for example, when $k=0.5$), the probability of having a huge output reduction increases sharply, as shown by the reduction

[17] Different time span may be used, three years seems a short-medium period which may be sufficient for implementing structural preventive intervention on the credit structure of an economy (IMF, 2010; Drehmann and Juselius, 2013)

[18] Hit ratio=n.crises/n. crises predicted, False alarm ratio=(n. indicator activations-n. crises predicted)/(n. observation-n. crises). The larger the distance of the curve from the diagonal axis the higher the early warning efficiency of the indicator. See, for instance, for applications of the ROC curves in

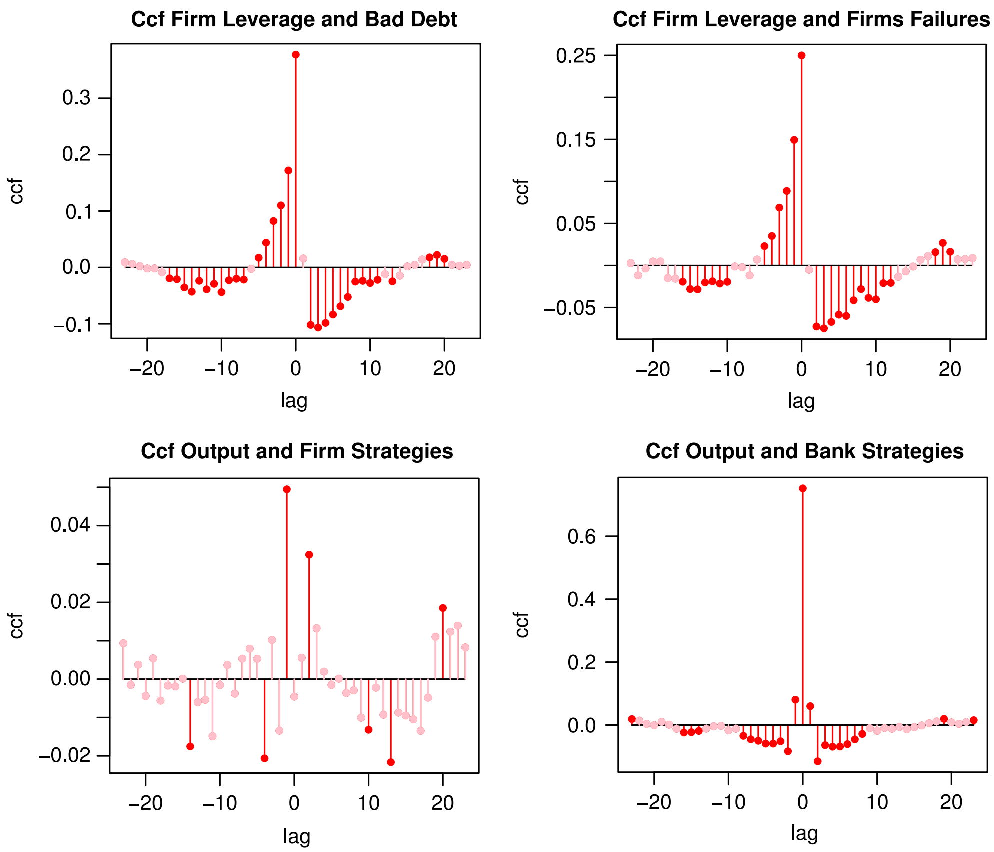

Fig. 8. Cross correlation functions between simulated macro variables with sensitivity to profit volatility. Variable is detrended through HP filtering. (Averages over 50 Monte Carlo simulations, in lighter shade values that are not significant at 5%). In the upper left panel, cross correlation between aggregate firm leverage and aggregate volume of bad debts. In the upper right panel, cross correlation between aggregate firm leverage and the number of firm failures. In the lower left panel, cross correlation between aggregate output and the average leverage strategy chosen by firms. In the lower right panel, cross correlation between aggregate output and the average leverage strategy chosen by banks.

of the false alarm ratio. On the other hand, when the concentration indicator rises, the hit ratio goes down: crises may be generated by other factors that are not expressed through the concentration indicator as the level of firm leverage (Fig. 12).

After a crisis, the value of the concentration indicator (k) tends to decline. In effect, the distribution of the adjusted degree after a crisis shows that, in general, the level of the adjusted degree is lower and the distribution is steeper implying lower concentration (Fig. 13, left panel). Moreover, in the year that follows the crisis, the average variation of the concentration indicator is significantly negative (Fig. 13, right panel). The leverage of the economic system and the connectivity goes down, thus the potential for having another crisis declines.

The resilience of the credit network also depends on the leverage of firms. When the concentration indicator (k_t) is high, a crisis may not occur if the level of firm leverage is relatively low. Low firm leverage reduces the vulnerability of the credit network even if its concentration is high. Indeed false positives (high values of the concentration indicator that do not lead to a crisis) show in mean and median lower firm leverage. As shown in Fig. 14, firm leverage for different levels of the concentration indicator (k_t) is lower in the case of false positives.[19] In fact, the predictive capacity of the concentration indicator conditional to having an high level of aggregate firm leverage increases (Fig. 15).[20]

Once controlled for firm leverage, the timing and extent of an eventual macro-prudential policy intervention is strongly influenced by the trade-off between hit and false alarm ratio (IMF, 2010, 2011; Drehmann and Juselius, 2013). On the one hand, if the policy intervention starts when the level of the indicator is too low, it may avoid crises but it may be expensive

(*footnote continued*)
economics (Granger and Machina, 2006; Jorda et al., 2011; Drehmann and Juselius, 2013; Subrahmanian, 2013; Minoiu et al., 2013; Schularick and Taylor, 2012).

[19] In Fig. 14, the black dashed curve represents the distribution of firms leverage when the concentration indicator is activated but a consistent output slow down does not occur (false positives); in the lighter shade (red) the distribution of the firm leverage before a crisis.

[20] The indicator is activated only once firm leverage is higher than its average, otherwise it assumes a zero value. The indicator conditional to firm leverage shows a lower hit false alarm trade-off. In effect, in Fig. 15 the black dashed shade curve (conditional trade-off) dominates the red solid one (nonconditional trade-off).

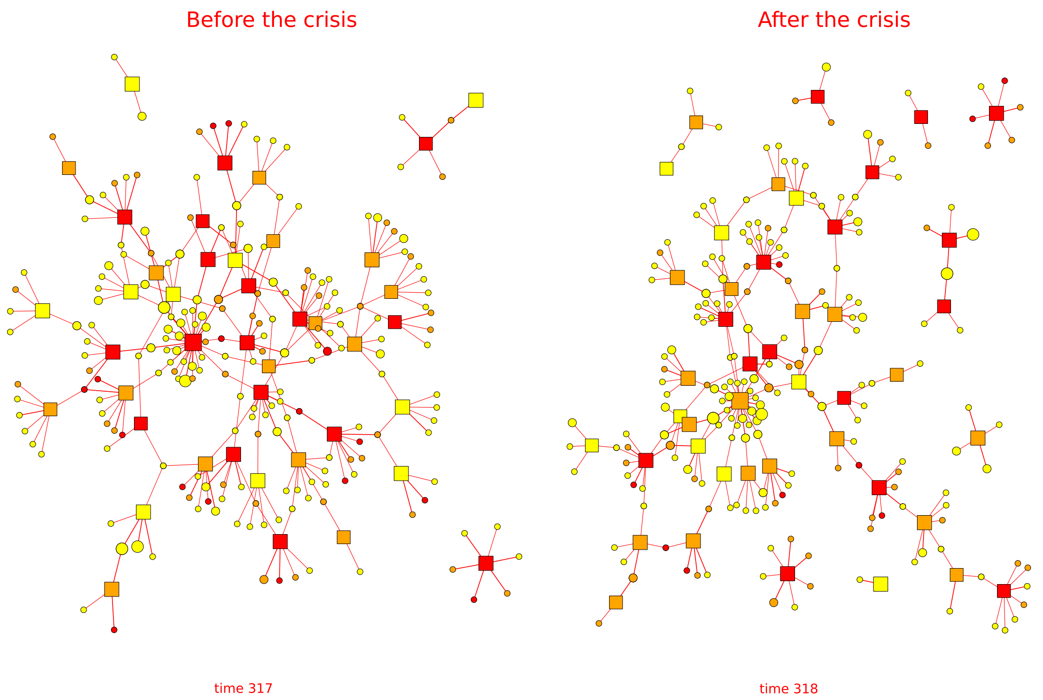

Fig. 9. Credit network before and after a crisis (output reduction of more than −15%). Squares represent banks, circles are firms, links are credit relationships. The level of leverage of the agents is shown by color: the darker (tending to red) the higher the leverage level. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

considering the relatively high probability that the indicator is giving a false alarm. On the other hand, if policy makers react when the indicator is already too high, false alarms are avoided, but at risk to intervene when it is too late for contrasting effectively the crisis.

The importance of the concentration of the credit network, at least qualitatively, in determining the conditions for the manifestation of huge output contraction may be observed in the Japanese data-set (Fig. 16). Actually, this was the inspiring figure of our work and for this reason should be put at the beginning of a the paper. We had to insert it at the end for the simple logical reason that to compute it we need, before, to define a concentration index.

Considering the Japanese credit network, the concentration indicator (k_t) started to increase at the end of the eighties (Marotta et al., 2013). Indeed, after the bubble of the late eighties the Japanese credit network went through a period of deep reconstruction leading to a significant increase of its concentration. Since 2003, the concentration indicator (k_t) arrives at high levels, high credit concentration may have increased the vulnerability of the system. This may be one of the factors that enhanced the transmission of the global financial crisis, which are reflected by the output reduction in the 2009 (−9%), in 2010 (−0.16%). After the crisis of 2009–2010, in 2011 the concentration indicator starts to increase again and in 2012 there is another huge output slow down (−9%). In effect, the concentration of the indicator is low in the '80s where we have a recession in '86. The indicator increases in the '90s and we have two recessions in 1999 and 2002. The indicator reaches the highest level since 2002 and we have two huge recessionary events in 2009 and 2012. Thus, the indicator starts to increase in the '90s and, in 2002 reaches higher levels, before the 2009 and 2012 crises. Indeed, the indicator value shows high values before the occurrence of huge output contractions. Future line of research will be testing the indicator on other datasets, hopefully larger and with higher frequency data (for instance, quarterly data). However, the access to credit network information is quite restrict in reason of the extreme sensitivity of these data for economic agents and policy makers.

5. Concluding remarks

Following the credit network financial accelerator approach (Delli Gatti et al., 2010; Riccetti et al., 2013), this paper defines an early warning indicator of crises based on the configurations of the credit network between firms to banks. The indicator derives from the analysis of the dynamics of a simulated economy where agents endogenously determine the evolution of the credit network through leverage decisions. Simulations are calibrated on the data of a survey of Japanese firms and banks (Marotta et al., 2013), reproducing basic aspects of the dynamics of the output and its correlation with leverage and network connectivity.

Simulations show that both agents' leverage and their connectivity are strictly interrelated with the business cycle. Indeed, the model underlines the importance of the credit network in influencing the resilience of the system to idiosyncratic shocks: when the connectivity of the network and the leverage level are high even small idiosyncratic negative

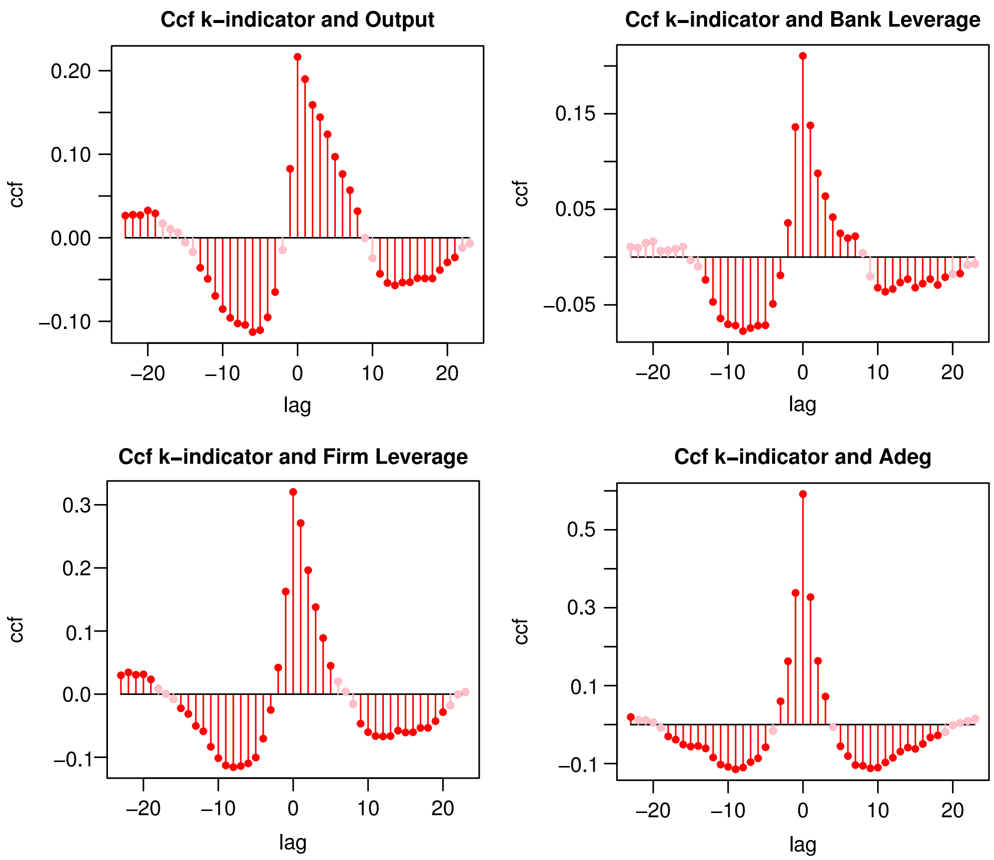

Fig. 10. Cross correlation functions between simulated macro variables and the early warning indicator (k_t) (Averages over fifty Monte Carlo simulation runs). In the upper left panel, cross correlation between the concentration indicator (k) and aggregate output. In the upper right panel, cross correlation between the concentration indicator (k) and aggregate bank leverage. In the lower left panel, cross correlation between the concentration indicator (k) and aggregate firm leverage. In the lower right panel, cross correlation between the concentration indicator (k) and the average adjusted degree of banks.

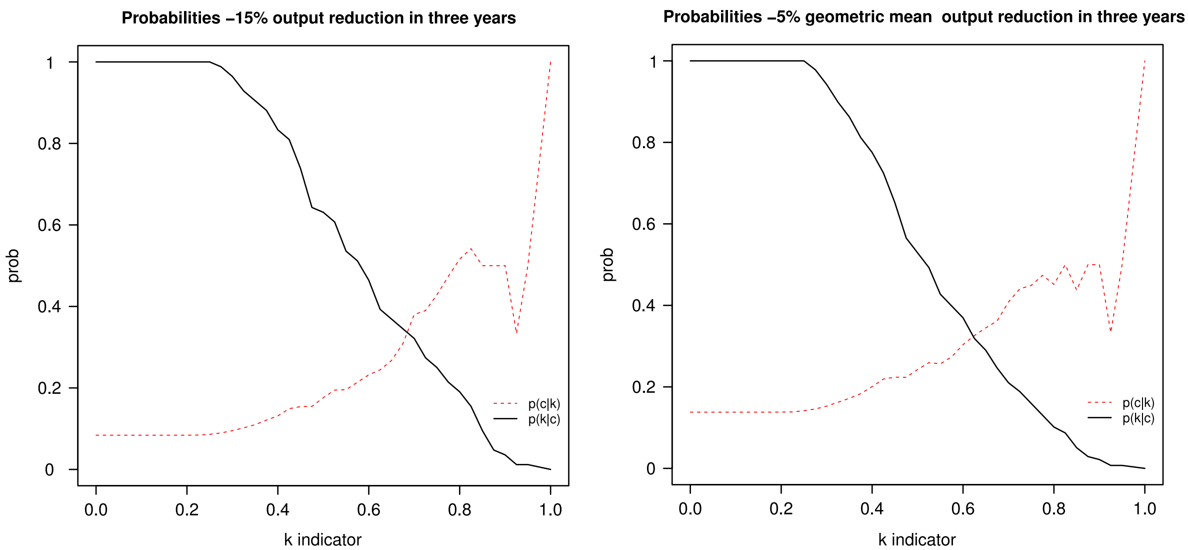

Fig. 11. Probability of a consistent output slowdown. In the left panel, the probabilities of a slow down of more than −15% in at least one of the next three years. In the right panel, the probabilities of a slow down with a growth rate of −5% in the next three years (probabilities derive from one-thousand Monte Carlo simulation runs). $p(C|k)$ is the probability of having a crisis given the indicator k level, $p(k|C)$ is the probability that the indicator reaches the level k when a crisis occurs.

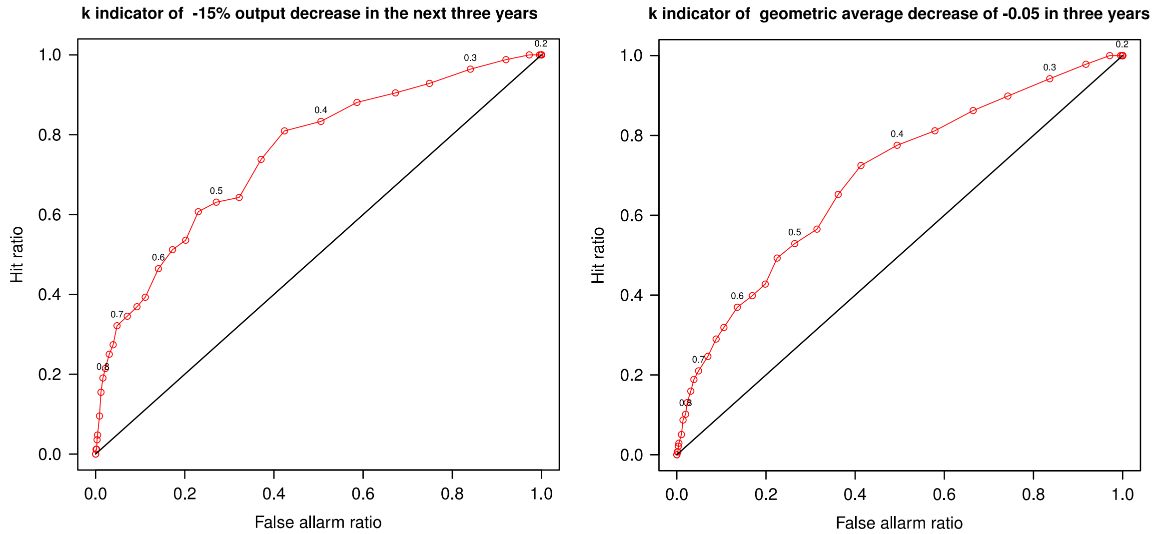

Fig. 12. Simulated hit ratio and false alarm ratio with different levels of the concentration indicator k. The two ratios are extracted from one-thousand Monte Carlo simulation runs. Values of the k indicator are expresses near the curve, indicating the hit and false alarm ratio associated to the different levels of the indicator.

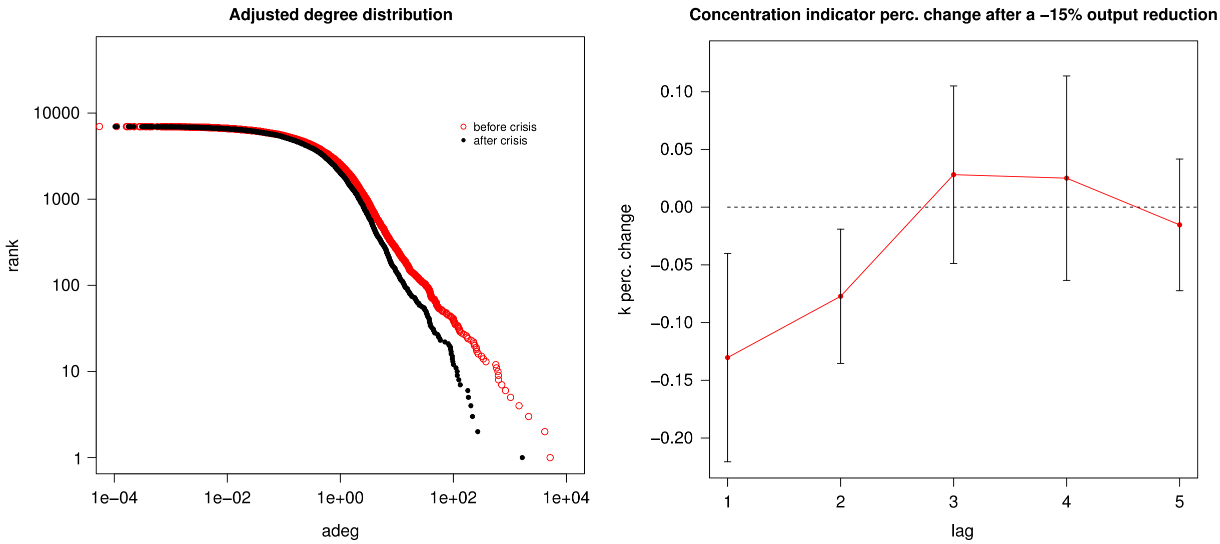

Fig. 13. In the left panel, the adjusted degree distribution of banks before and after a crisis, Zipf logarithmic rank/frequency distribution. The two distributions are different according to the Kolmogorov–Smirnov test. In the right panel, concentration indicator variation (percentage change) after a crisis, lags represent years, bars are 95% confidence interval on means. Distributions are extracted from one-thousand Monte Carlo simulation runs.

shocks may have strong systemic effects. Consequently, an early warning indicator of crises is defined considering the concentration of banks' network connectivity, adjusted for banks' leverage and volume of loans.

This indicator seems to be able to anticipate huge output contractions. The indicator effectiveness improves when the aggregate level of firm leverage is taken into consideration: the probability of having a crisis increases when the value of the early warning indicator grows and, at the same time, the aggregate firm leverage level is relatively high. The effectiveness of this early warning indicator is also suggested by the Japanese survey data on which the simulated model is calibrated. Thus, the agent based model we have presented in this paper and the early warning indicator we propose may represent a coherent theoretical and empirical framework which may be useful for tuning and timing macro prudential interventions (IMF, 2010, 2011; Drehmann and Juselius, 2013). Emphasizing the role played by agents connectivity in determining aggregate results, policy makers may direct preventive and regulatory interventions paying more attention to credit networks configurations shifting from 'too big to fail' to 'too connected to fail'.

A future line of research will be that of increasing the effectiveness of the indicator without excessively enlarging the informative set on which the indicator is based. Moreover, the model can be extended in different prospectives. First, the

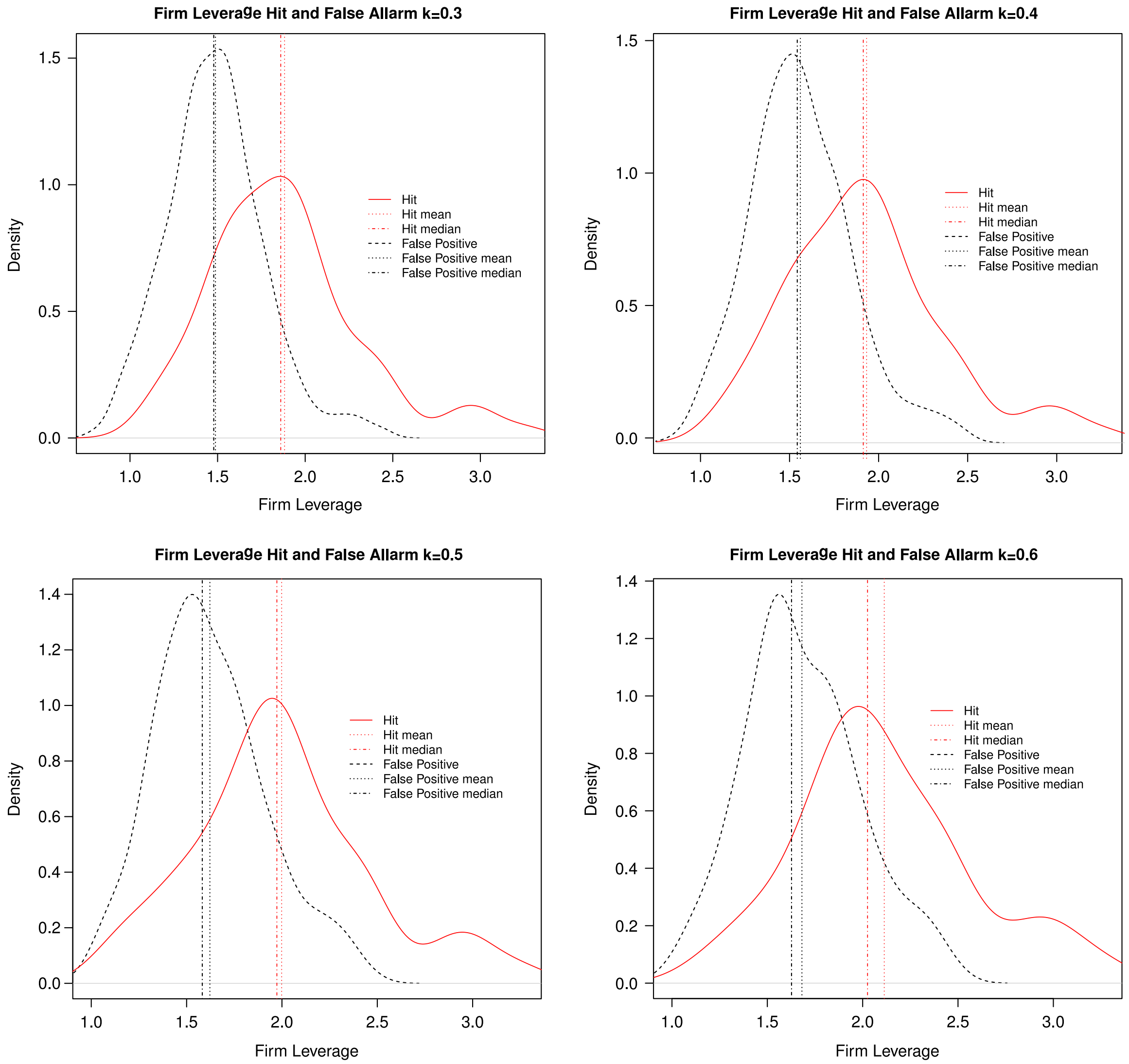

Fig. 14. False positives: Concentration indicator and leverage. The averages of the two distributions are different in a statistically significant level (t-Tests). Distributions are extracted from one-thousand Monte Carlo simulation runs. The black dashed curve shows the distribution of firm leverage in case of a false alarm for different levels of the risk indicator k. The red solid curve shows the leverage level when the indicator anticipates a crisis (hit). (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

model can be enriched to simulate different policy measures aimed at reducing the vulnerability of the credit network. Indeed, the resilience of the system may be improved isolating single banks or clusters (Bargigli and Gallegati, 2011, 2012) of banks and firms which are too exposed and connected. Second, simulations show the importance of individual risk perception in determining macro results and the model could easily incorporate different learning mechanisms (Brock and Hommes, 1997; Anufriev and Hommes, 2012; Anufriev et al., 2013). Third, the model can be modified to cope with a larger set of stylized facts observed in the Japanese credit network survey or to be calibrated on larger time span datasets.

Simulation parameters

Simulations last 500 periods, there are 500 firms and 50 banks. This proportion between firms and banks reflect the relation of one bank for each ten firms that roughly is found in the Japanese dataset. The initial value of firms' equity is $E_i = 1$, that of bank's equity is $E_z = 5$. With these equity levels, given the leverage strategies H, at the beginning in average aggregate supply of loan is equal to demand for loans.

Firms and banks with nonpositive 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 $E_i \sim U(0.1, mf)$ and entering banks have $E_z \sim U(1.0, mb)$, with mf the average size of firms and mb the average size of banks; the minimum levels of equities of firms and banks are respectively: 0.1 and 1.0; while the maximum levels are 0.5 and 5. From one hand, this entry condition

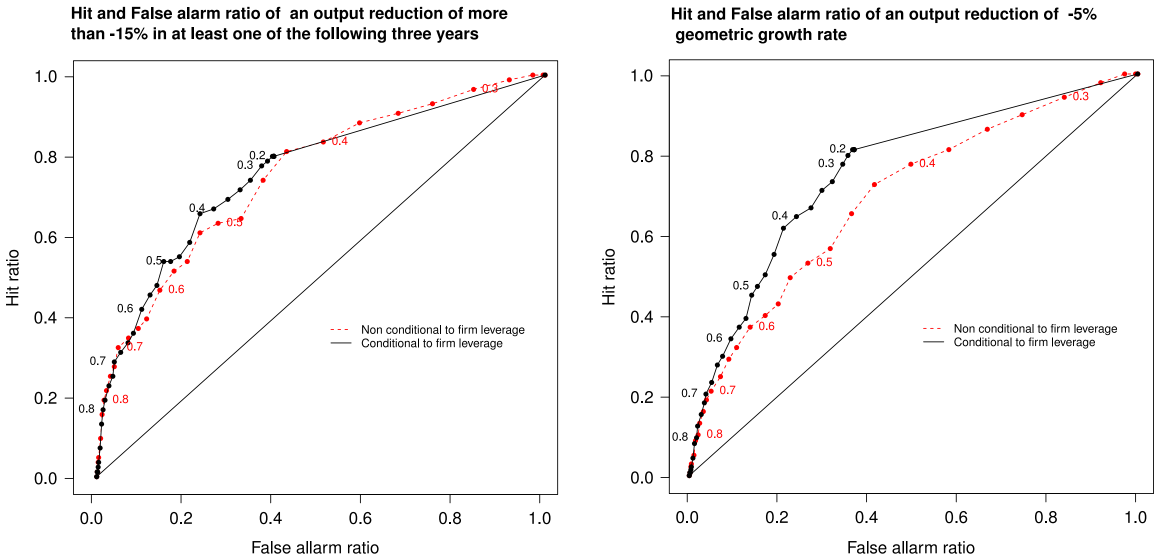

Fig. 15. Simulated hit ratio and false alarm ratio with the concentration indicator k conditional to firm leverage. The two ratios are extracted from one-thousand Monte Carlo simulation runs. Values of the k indicator are expresses near the curve, indicating the hit and false alarm ratio associated to the different levels of the indicator.

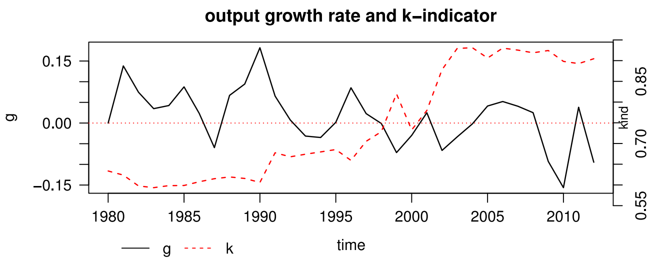

Fig. 16. Growth rate and the concentration indicator k of the credit network observed in the Japanese data set, 1980–2012. On the left axis the growth rate g, on the right axis the concentration indicator k.

assures that enterers have a size that is in line with the one of other competitors. On the other hand, with maximum and minimum level fixed, the entry condition reduces the possibility of having exponential growth (decline) of agents dimensions during booms (contraction).

The set of leverage value is $H=\{1.0, 1/1.5, 1/2.0, 1/2.5, 1/3.0, 1/3.5, 1/4.0, 1/4.5, 1/5.0, 1/5.5, 1/6.0, 1/6.5, 1/7.0, 1/7.5, 1/8.0\}$, in average reflecting the leverage of firms in the dataset.

System		Learning	
α	1/300	χ	0.2
ϕ	0.5	ν	0.5
ρ	0.1	c	0.01
τ	0.4	ζ	0.05
δ	0.001	μ	0.05
F	0.01		
σ	1.0		
ι	1/300		
r	0.01		

- F is a fixed cost equal for both firms and banks. F has a low value to eliminate very small banks and firm that do not impact on the aggregate dynamics, thus allowing to foster computational efficiency.
- ϕ is chosen for simplicity as 0.5, loans capital reimbursement is divided equally in the two periods of loans maturity.
- The profit margin δ is a very small value to allow a minimum level of profitability for loans associated with the highest levels of interests.
- σ for simplicity is chosen equal to one. The other variable related to productivity (ρ), profit share that is not accumulated (τ) and the sensitivity to leverage in risk premium component of the interest rate (α) are linked together by Eq. (11).

Therefore, they are fixed in order to assure a relative stability of the system in order to avoid explosion or implosion of the aggregate output produced.

- The sensitivity to firm leverage for credit rationing (ι) is chosen as equal to the sensitivity to leverage in the risk premium component of the interest rate (α), because both refer to the same process of risk evaluation.
- r is the discount interest rate is fixed as a small constant percentage.
- ζ is the 'forgetting' parameter and μ the 'error' parameter, in learning literature they are usually small percentages.
- χ value is chosen to limit the impact of past value of strategy effectiveness to allow agents to rapidly adapt to the changing conditions of the economic system.
- c and ν values are chosen in order to mitigate the effect of the exponential value at which leverage. strategies are valued in Eqs. (20) and (23).

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