

Resilience, Leverage and Credit Network in an Agent Based Model

Ermanno Catullo, Mauro Gallegati and Antonio Palestrini

DiSES, Universit Politecnica delle Marche

WEHIA Winter meeting

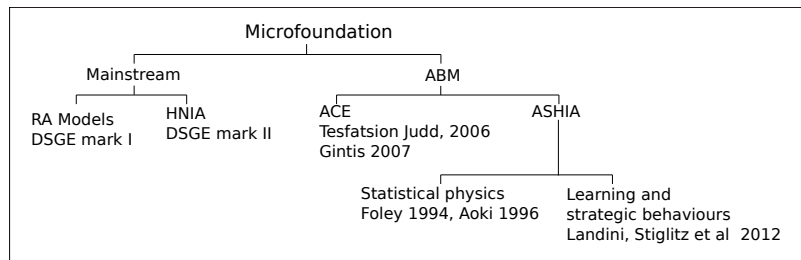
Cats in St.Louis, 1987

Should we take seriously the ABM approach?



Microfoundations

Microfoundations in Macroeconomic Models



Vulnerability of Leveraged and Interlinked Credit Market: an Agent Based Model

Aims

- Resilience of credit network
- Dynamics of output and networks via balance sheet (leverage)
- Early warning indicator

Methodology

Agent based modeling:

- Bottom-up methodology
- ABM within a network: Agents as nodes, links as financial relationship
- Interaction of many HA, which produces a statistical equilibrium
- Emergence: models with HIA where the resulting aggregate dynamics and empirical regularities are not deducible from individual behavior

The Drama

Heterogeneous firms and banks

- Firms and banks have a leverage target, they choose among a limited set of leverage levels (different level of risk)
- Firms are hit by idiosyncratic shocks
- The number of banks and firms is fixed, there are (endogenous) links (credit) between them

The credit network

- Both firms and banks can have multiple credit relationships
- Two period loans contracts
- Banks credit supply and is constrained by minimum net-worth requirements
- The credit network evolve endogenously following individual demand and supply of credit dynamics

The Model

Credit relationships depend on leverage and on market

- The network evolves through credit leverage's conditions

Credit amounts depend on learning

- Basic reinforcement learning algorithm from Tesfatsion 2005: choices derive from past experience but with also small probability of random exploration of the action space

The Model

Firms

Firms production function: capital employed is given by equities (E_{it}) and loans (L_{it}):

$$Y_{it} = \rho K_{it}, \quad (1)$$

where Y_{it} depend on π_{it} *à la* Hommes 2012, $K_{it} = L_{it} + E_{it}$

The interest on loans depends on the target leverage (Γ_{it}):

$$\Gamma_{it} = (L_{it}^d + \frac{1}{\phi} L_{i(t-1)}) / E_{it} \quad (2)$$

$$r_{it} = \alpha \Gamma_{it} + r \quad (3)$$

leading to a trade off between profit opportunities and loans costs in presence of differences among effective and targeted leverage levels (r is the discount rate)

The model

Firms

Profits depend on the difference between idiosyncratic revenues and debt commitments:

$$\pi_{it} = u_{it} Y_{it} - r E_{it} - r_{it} L_{it} - \frac{1}{\phi} r_{i(t-1)} L_{i(t-1)} - F \quad (4)$$

(5)

where F are fixed costs, u_{it} is a normally distributed idiosyncratic shock on profit.

Individual leverage increases production but aggregate leverage depresses it: leverage acts as an externality.

The Model

Banks

Credit supply

$$L_{zt}^s = \frac{E_{zt}}{\eta_{zt}} - \sum_{I_{z(t-1)}} \frac{1}{\phi} L_{iz(t-1)} \quad (6)$$

η_{zt} is updated through reinforcement learning (Tsfatsion 2005).

Banks' profit is given by the sum of interest on lending minus interest payments on borrowing minus bad debts

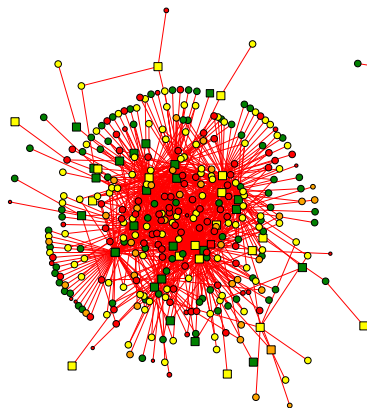
$$\pi_{zt} = \sum_{I_{zt}} r_{izt} L_{izt} + \sum_{I_{z(t-1)}} r_{iz(t-1)} L_{iz(t-1)} - BD_{zt} - BD_{z(t-1)} - r(E_{zt} + D_{zt}) - F \quad (7)$$

where I_{zt} is the set of borrowing firms

Japanese credit network

credit market dataset

- a survey of firms and banks quoted in the Japanese stock-exchange markets
- reporting annual data from 1980 to 2012
- on average 226.18 banks and 2218 firms



Network Analysis

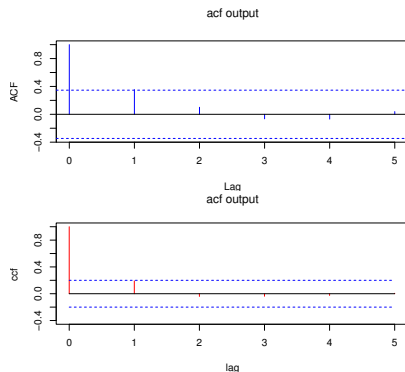
How to measure network resilience

- Banks loans structure and leverage determine shocks diffusion and amplification
- According to Palestrini (2013) 'Deriving Aggregate Network Effects in Macroeconomic Models', it is possible to infer the system effects of idiosyncratic shocks from weighted outdegrees
- The adjusted degree (*adeg*) is the mean of the banks normalized degree times the total amount of loan they provide times leverage ($adeg = deg \cdot loan \cdot lev$)

Credit networks

Empirical and simulated data

- Output growth standard deviation is similar
- Growth rate is autocorrelated
- The adjusted degree (*adeg*) growth anticipates output growth
- The adjusted degree growth is positively correlated to output growth in simulations



Credit networks

Empirical and simulated data

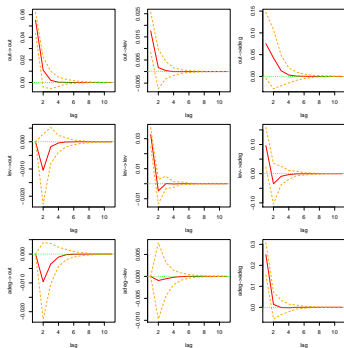
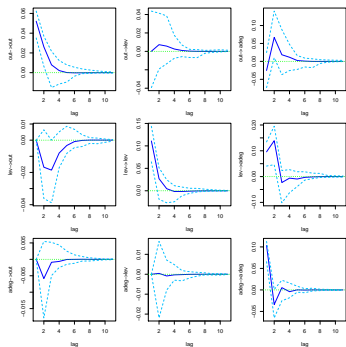
- Output growth is Laplacian
- Firms' and Banks' size distribution has fat tails
- The aggregate leverage anticipates downturn, while recovery comes after deleveraging
- Inequality in come distribution is counter-cyclical
- Expansions and recessions are asymmetric (duration, phases, steepness end deepness)
- Connectivity is pro-cyclical

Calibration: IRFs

VAR with one lag log differences variables: output (*out*), bank leverage (*lev*) and the mean adjusted degree (*adeg*)

IRF on empirical data

IRFs on simulated data



- If leverage and connectivity increase (endogenously and because of shocks) then system vulnerability rises leading to successive output contractions

Simulated economy dynamics

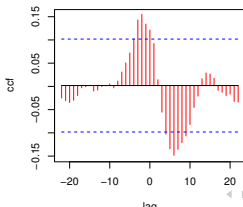
From the interaction of individual agents behaviors emerge aggregate dynamic patterns (Minsky, 1975, 1982) **interaction produces emergence**

- Safe expansion (SE): output growth with low leverage
- Fragile expansion (FE): output growth with increasing leverage
- Fragile contraction (FC): output decrease with high leverage
- Safe contraction (SC): output decrease with low leverage

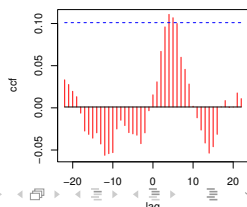
| | output | leverage |
|----|--------|----------|
| SE | ↑ | ↓ |
| FE | ↑ | ↑ |
| FC | ↓ | ↑ |
| SC | ↓ | ↓ |

leverage dynamics

Ccf Output and Firm Leverage

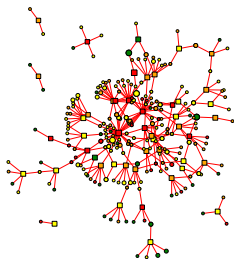


Ccf Output and Excess Credit Demand



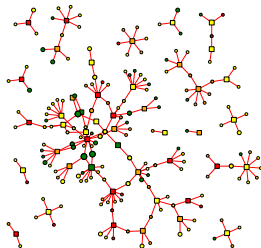
Systemic risk indicator

Network before the crisis



cycle 400

Network after the crisis



cycle 410

Before the crisis high levels of the risk indicator:

- Leverage of both banks and firms is increasing
- The credit network is strongly connected (prone to domino's effect)

Systemic risk indicator

k-indicator: adjusted degree concentration

- The systemic risk represents a synthetic measure of the concentration of leverage, credit capabilities and connectivity of banks

$$k_t = \frac{\sum_{z \in 10d} adeg_z}{\sum_z adeg_z} \quad (8)$$

- We define a crisis as an output drop above 15% in 5 consecutive years.

Hit ratio represents the capacity of predicting future crisis when the indicator is activated

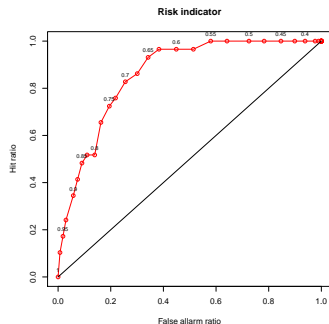
$$\text{Hitting ratio} = \frac{n. \text{ crises predicted}}{n. \text{ crises}}$$

False alarm ratio represents the propensity of the indicator to be activated without a crisis will successively occur

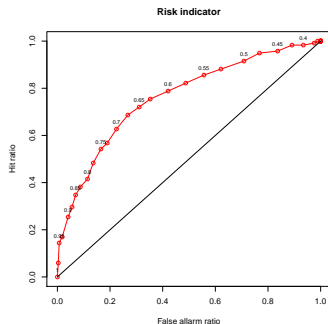
$$\text{False allarm ratio} = \frac{n. \text{ indicator activations} - n. \text{ crises predicted}}{n. \text{ observation} - n. \text{ crises}}$$

Systemic risk indicator

Risk indicator one year before the crisis



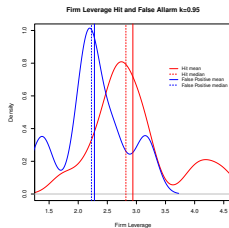
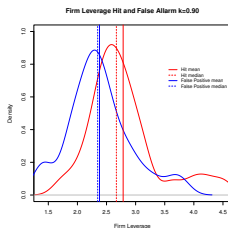
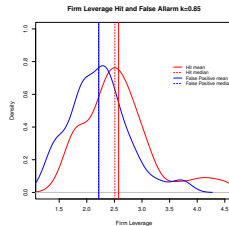
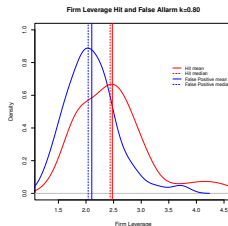
Risk indicator five years before the crisis



- This systemic risk indicator may be conceived as an early warning indicator

Systemic risk indicator

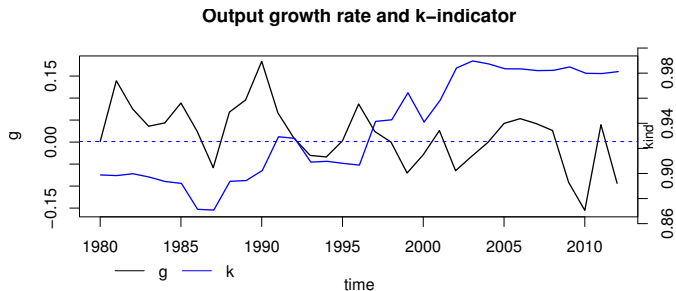
False Positives and Leverage Level



- False positive are related to lower aggregate leverage: the higher the risk indicator the greater the leverage level difference between false positives and hits

Systemic risk indicator

Risk indicator and output in the Japanese sample



- Increase of connectivity concentration since the late eighties bubble
- High connectivity concentration associated with low growth and output drops

Concluding Remarks and Perspectives

Remarks

- The model replicates several endogenous aspects of the Japanese credit network dynamics
- Idiosyncratic shocks to firms may be amplified by leverage of firms and banks
- Leverage choices and accumulation processes shape the credit network and influences system vulnerability
- The credit network configuration determines the diffusion of idiosyncratic shocks and, thus, the systemic vulnerability
- The predictive alarm warning indicator for crisis foresees fluctuations too

Perspectives

- Improving calibration and validation of the model
- Counterfactual experiments for policy measures through simulations

Concluding remarks: economy as a complex adaptive system

- Their interaction leads to empirical regularities, which emerge from the system as a whole and cannot be identified by looking at any single agent in isolation these emerging properties are the main distinguishing feature of a complex system
- The focus on interaction allows us to abandon the heroic and unrealistic RA framework, in favor of the science of complexity.
- ABM (and complexity) approach is a tough line of research whose results are very promising (despite me)

Merci!