# The Linkage between Financial Market and Real Economy: The Analysis with An Agent Based simulation

Yoshito Suzuki, Akira Namatame Dept. of computer science, National Defense Academy, Yokosuka, Japan Email: {em52039, nama} @nda.ac.jp

Abstract— Financial markets are driven by the real economy and in turn also has a profound effect on the financial economy. Understanding the feedback between these two sectors leads to a deeper understanding of the stability, robustness and efficiency of the economic system. In this paper, we investigate the effect of credit linkages on the macroeconomic activity by developing an agent-based model, which allows us to explain some key elements occurred during the recent economic and financial crisis. In particular, we study the linkage dependence among agents (firms and banks) at the micro-level and to estimate their impact on the macro activities such as the GDP growth rate, the size and growth rate distributions of agents.

#### I. INTRODUCTION

In recent decades, a massive transfer of resources from the productive sector to the financial sector has been one of the characteristics of global economic systems. This process is mainly responsible for the growing financial instability characterized by the current global crisis. In production sectors, there has been dramatic increase in the output volatility and uncertainty. Macro economy has created well defined approaches and several tools that seemed to serve us for the past decades. However, recent economic fluctuations and financial crises emphasize the need of alternative frameworks and methodologies to be able to replicate such phenomena for a deeper understanding of the mechanism economic crisis and fluctuation.

To jointly account for an ensemble of these facts regarding both micro-macro properties together with macro aggregates including GDP growth rates, output volatility, business cycle phases, financial fragility, and bankruptcy cascades, agent-based approaches are getting more and more attention recently. We need to analyze explicitly how agents interact with each other.

From this perspective, the network theory is a natural candidate for the analysis of interacting social systems. The financial sector can be regarded as a set of agents (banks and firms) who interact with each other through financial transactions. These interactions are governed by a set of rules and regulations, and take place on an interaction graph

This work was not supported by any organization

Yuji Aruka Faculty of Commerce Chuo University Hachioji, Japan Email: aruka @tamacc.chuo-uac.jp

of all connections between agents. The network of mutual credit relations between financial institutions and firms plays a key role in the risk for contagious defaults.

## II. BACKGROUND

Research on this line has been initiated by the work Delli Gatti, et al. (2005) which, simulating the behavior of interacting heterogeneous firms and one bank, is able to generate a large number of stylized facts. Grilli, et al, (2012) extend their model by incorporating a system of multiple interactive banks. They introduce multiple banks which can operate not only in the credit market but also in the interbank system. They model credit and inter-bank systems as random graphs and study the network resilience by changing the degree of connectivity among the banks' agents.

In their model, firms may ask for loans from banks to increase their production rate and profit. If contacted banks face liquidity shortage when trying to cover the firms' requirements, they may borrow from a surplus bank in the inter-bank system. In this market, therefore, lender banks share with borrower banks the risk for the loan to the firm. Bankruptcies are determined as financially fragile firms fail, that is their net worth becomes negative. If one or more firms are not able to pay back their debts to the bank, the bank's balance sheet decreases and, consequently, the firms' bad debt, affecting the equity of banks, can also lead to bank failures. As banks, in case of shortage of liquidity, may enter the interbank market, the failure of borrower banks could lead to failures of lender banks. Agents' bad debt, thus, can bring about a cascade of bankruptcies among banks.

The source of the domino effect may be due to indirect interaction between bankrupt firms and their lending banks through the credit market, on one side, and to direct interaction between lender and borrower banks through the inter-bank system, on the other side. Their findings suggest that there are issues with the role that the bank system plays in the real economy and in pursuing economic growth. Indeed, their model shows that a heavily-interconnected inter-bank system increases financial fragility, leading to economic crises and distress contagion. However, from the point of view of the average macroeconomist, agent based modeling has the drawback: It makes impossible to think in aggregate terms. The modeler, in fact, can reconstruct aggregate variables only from the bottom up by summing the individual quantities. As a consequence the interpretation of the mechanism of shocks is somewhat arbitrary. If we also consider simulations as experiments, reproducibility is a crucial question. In the context of models created to describe real-world phenomena, emphasis must be put on the reproducibility of experiments to validate the results as a scientific result. If a model cannot generate the same output for the exactly same conditions, its scientific value is questioned.

## III. STUDY POLICY

In the first part of our work, we replicate and extend the model of Delli Gatti et al.(2005) and that of Grilli et al. (2012). We then address the questions of validating and verifying simulations. We propose the model refinement strategy which validate through some universal laws and properties based on empirical studies revealing statistical properties of macro-economic time series. We begin the presentation with the widely acknowledged "stylized facts" which describe the firm (and bank) growth rates of fat tails, tent distribution, volatility, etc., and recall that some of these properties are directly linked to the way time is taken into account (Stanley, et al.(1996)).

It is well known that the growth of firm size, the distribution of firm sizes, the distribution of sizes of the new firms in each year are be well approximated by a log-normal. We investigate whether the simulation results shown in Fig.1, the logarithmic distribution of the growth rates with a fixed growth period of one year as Y, and companies with approximately the same size S as X, obeys an exponential form.

Fig. 1 shows our simulation result for the growth rate of firms. It allow us to be able to attest because it is very sufficiently similar in "stylized facts".



Fig. 1 Growth rate of firm as the simulation result



We validate our simulation results in this way and analysis them. In the second part of our work, we investigate the linkage between financial markets and the real economy using the validated agent-based modeling. We especially investigate the effect of credit linkages on the firms' activities to explain some key elements that occurred during the recent economic and financial crisis. In particular, we study the repercussions of inter bank connectivity on agents' performances, bankruptcy waves and business cycle fluctuations. The purpose of the model is to build up the dependence among agents (firms and banks) at the microlevel and to estimate their impact on the macro stability. Fig. 2 shows an example of our simulation result for the rate of banks' bankruptcies by time steps, where  $\beta$  is output elasticity of capital of firms' production function. When  $\beta$ increases, the rate of banks' bankruptcies also increases. By this result, it is evident that the change of firms has an effect on banks through the linkage between firms and banks.

# IV. OVERVIEW OF AGNET MODEL

Our model is based on Grilli, et al (2012). We consider two types of agents, ,firm agent and bank agent.

# A. Firm agent

The firm agent *i* has net worth  $A_{i,t}$  and loan  $L_{i,t}$  at time step *t* and produce an output  $Y_{i,t}$ . At Grilli's model, production function is defined as

 $Y_{i,t} = \phi(A_{i,t} + L_{i,t})$  However, it is well

known that production function is not a liner function and the liner product function affects the growth rate of firms than actuals value. Therefore, we define production function as

$$Y_{i,t} = \phi(A_{i,t} + L_{i,t})^{\beta}$$

where  $\phi$  is the capital productivity and  $\beta \in [0,1]$  is output elasticity of capital. If  $\beta = 1.0$ , our model equals Grilli's model. The firm product's price is the selling price  $P_{i,t}$ , which is assumed to be a random value with the average price  $P_t$ . Wedefine the relative price ui,t as the ratio of Pi,t to Pt, which has the normal distribution with a certain mean and finite variance. Firms pay back their debt commitment according to

$$\overline{L}_{i,t} = \frac{1}{\tau} \qquad {}^t_{t-\tau} (1 + r_t^{i,j}) L_{i,t}$$

where  $r_t^{i,j}$  is the interest rate of the loan from bank *j*. The net worth is updated with firms' profit  $\pi_{i,t}$ , given  $u_{i,t}$ ,  $Y_{i,t}$  and  $\overline{L}_{i,t}$ , as

$$\pi_{i,t} = u_{i,t}Y_{i,t} - \overline{L}_{i,i}$$

At each step, firm maintain their capital stock  $K_{i,t} = A_{i,t} + L_{i,t}$  in the optimal stock

$$K_{i,t}^{*} = \frac{\phi}{2c\phi(\lambda r_{t}^{i,j} + (1-\lambda)l_{i,t})} + \frac{c\phi A_{i,t}}{2c(\lambda r_{t}^{i,j} + (1-\lambda)l_{i,t})}$$

If  $A_{i,t}$  is under  $K_{i,t}^*$ , the firm asks banks for the loan

$$L_{i,t}^d = K_{i,t}^* - A_{i,t}$$

# B. Bank agent

Bank agents have the equity  $E_{j,t}$ , and deposits  $D_{j,t}$ . Then, Banks' have the credit supply  $S_{j,t}$  limited by their equity  $E_{j,t}$ and uniform value  $\alpha$ 

$$S_{j,t} = \frac{E_{j,t-1}}{\alpha}$$

When banks are asked a loan by firms, banks check firm's demand of loan  $L_{i,t}^d$  and investment risk  $p_t^{j,i}$  according to

$$p_t^{j,i} = 1 - \chi(\frac{\overline{G}_{i,t}}{S_{j,t}})^{\psi}$$

where  $\overline{G}_{i,t}$  is the amount of firm's debt. When  $p_t^{j,i}$  is 0.1  $p_t^{j,i}$ , this means that one out of ten banks lend money to a firm. If the bank *j* credit supply is  $S_{j,t} < L_{i,t}^d$ , bank *j* asks other banks through the inter-bank market. The lender bank *k* checks the demand of credit supply  $S_{kj}$  and borrower bank's investment risk  $p_t^{k,j}$ . The lender bank *k* makes a loan to firm *i* or bank *j* with interest rate based on the leverage of borrower firm or bank. Then, the bank's profit is defined as

$$\pi_{j,t} = \frac{1}{\overline{\tau}} \Big[ \sum_{z,t-\tau \le t' < t} L_{z,t'} r_{t'}^j \Big] - \overline{r}_{j,t} \Big( D_{j,t-1} + E_{j,t-1} \Big)$$

where z is index of borrower firm or bank.

# C. Network Structure

Our model makes two networks. One of the networks is the linkage between firms and banks. If the firm i has a chance to offer a loan to bank j, it is regard credit linkage from firm i to bank j (it means that it is not necessarily required to borrow a loan). And if the firm's net worth becomes negative, the firm i undergoes bankruptcy and imposes a loss based on their loan at a rate from ten to ninety percent on the lender bank j through the credit linkage. Another network is the linkage called interbank network and is formed between banks to be able to borrow from or lend to a loan. It is to transfer the damage from the bank going bankruptcy to lending bank through interbank network. The two networks have different network topologies. The firm-bank network topology is random graph. At each step, a firm can randomly choose three or less banks. For example, firm i chooses three banks at step t, then step, firm i chooses one bank that is not the same bank at step t. On the other hand, interbank network is a two-type network topology. One of them is also a random graph. The banks choose partner banks less than a number limited by the network density at random and, after several steps, change a partner bank chosen randomly into other bank which is not linked. Other network topology is similar in the real network. A bank cut off a partner bank which has the lowest number of partner banks and cooperate with a new partner bank which has a larger number of partner banks than the cut off bank and has an equity which is greater than itself.

## V. SIMULATION SETTING

The model is done for the combination of the output elasticity of capital  $\beta$  and the interbank network connectivity. From the result of preliminary experiment, "Big firm", which is 1010 times larger than other firms, appear if  $\beta$  is 0.86 on more. Therefore, we simulate in the environments where there are no "Big firm" ( $\beta = 0.8$ ), a few "Big firm"

(  $\beta\!=\!0.86$  ) and almost half of firms that are "Big firm" (  $\beta\!=\!0.9\,$  ).



Fig. 3 Firm growth rate distribution  $\beta$ =0.9 (left side: random network, right side: real network)

Miguel, Amblard, Barceló & Madella (eds.) Advances in Computational Social Science and Social Simulation Barcelona: Autònoma University of Barcelona, 2014, DDD repository <a href="http://ddd.uab.cat/record/125597">http://ddd.uab.cat/record/125597</a>



Fig. 4 Firm growth rate distribution  $\beta$ =0.86 (left side: random graph, right side: real network)



Fig. 5 Firm growth rate distribution  $\beta$ =0.80 (left side: random graph, right side: real network)



Fig. 6 Small firm size distribution  $\beta$ =0.9 (left side: random graph, right side: real network)

![](_page_3_Figure_7.jpeg)

Fig. 7 Small firm size distribution  $\beta$ =0.86 (left side: random graph, right side: real network)

![](_page_4_Figure_1.jpeg)

Fig. 8 Small firm size distribution  $\beta$ =0.8 (left side: random graph, right side: real network)

![](_page_4_Figure_3.jpeg)

Fig. 9 GDP growth rate  $\beta$ =0.9 (left side: random graph, right side: real network)

![](_page_4_Figure_5.jpeg)

![](_page_4_Figure_6.jpeg)

Fig. 11 GDP growth rate  $\beta$ =0.8 (left side: random network, right side: real network)

We investigate that the alteration of firms' production function influences bank's growth and GDP through firmbank linkage. There is an upper limit with interbank network topology. A maximum number of links are defined by network density. The network density is divided into three levels: low connectivity, middle connectivity and high connectivity. The maximum possible number of links are six, twelve, twenty five. In random graph topology, the maximum link limit is maintained until final step. However, in similar real network topology, the limit is applied only in the first step. By this way, we observe what kind of effect the difference of interbank network topology has on macro economy.

## VI. DISCUSSION

Fig. 3, 4 and 5 show firm growth rate distribution at each environment. The distributions are similar in "stylized facts" except for the shift at the top of their distribution. By this result, our model has enough reasonability. Fig. 6, 7 and 8 show firm size distributions which are  $\beta = 0.90$  except for "Big firm". Big firms almost behave in a power low fashion and, in fact, it is well known that firms' size distribution is a power law distribution. This simulation result also provides the validity of our model.

We compare the firms' size distribution with different combination of the output elasticity of capital  $\beta$  and the interbank network connectivity to estimate the effect of the network topology. In the case that the network topology is a random graph, firms' size probability increases if the network density increases. However, in the real network topology, firms' size probability does not necessarily increase when the network density increases. There is empirical evidence that as the connectivity of an interbank network increases, there is an increase in the network performance, but at the same time, there is an increase in the chance of risk contagion which is extremely large. Allen and Gale (2000) introduced the use of network theories to enrich our understanding of financial systems and studied how the financial system responds to contagion when financial institutions are connected with different network topologies. Furthermore, we observe that the change of network topology has an effect on the economy. We also compare the GDP growth rate. Fig.9, 10 and 11 show that the range of change of GDP growth rate depend on  $\beta$ . Basically, when  $\beta$ increases, the range spreads out. However, in the real network topology, the maximum range is produced when  $\beta = 0.86$  and the network density is high. By this result, the network topology not only amplifies economic trend simply, in this particular case, but also takes on complexity to economic activity.

#### References

- Allen, F. and Gale, D. "Financial contagion", J. Political Econ. 108(1), 2000,pp.1–33.
- [2] Delli Gatti, D. Di Guilmi, C. Gallegati, M. Palestrini, A. "A new

approach to business fluctuations: heterogeneous interacting agents, scaling laws and financial fragility", Journal of Economic Behavior and Organization. vol.56,2005,pp.489 – 512

- [3] Grilli, R, Tedeschi, D, Gallegati, M. "Markets connectivity and financial contagion", Universita Politecnica Delle Marche, DISES, working paper, 2012.
- [4] Legendi, R, Gulyas, L. "Replication of the MacroABM Model", CRISIS, working paper, 2012.
- [5] Stanley, M, et al "Scaling behavior in the growth of companies", NATURE, vol. 379, 1996, pp. 804-806