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Bank networks and firm credit: an agent based model approach

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Campo de Conhecimento: Finanças

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"It's unbelievable how much
you don't know about the game
you've been playing all your life."
Mickey Mantle

Abstract

Starting from the idea that economic systems fall into complexity theory, where its many agents interact with each other without a central control and that these interactions are able to change the future behavior of the agents and the entire system, similar to a chaotic system we increase the model of Russo et al. (2014) to carry out three experiments focusing on the interaction between Banks and Firms in an artificial economy.

The first experiment is relative to Relationship Banking where, according to the literature, the interaction over time between Banks and Firms are able to produce mutual benefits, mainly due to reduction of the information asymmetry between them. The following experiment is related to information heterogeneity in the credit market, where the larger the bank, the higher their visibility in the credit market, increasing the number of consult for new loans. Finally, the third experiment is about the effects on the credit market of the heterogeneity of prices that Firms faces in the goods market.

Keywords: Agent-Based Models, Computational Economics, Banks and Firms relationship, Networks Theory.

Resumo

Partindo da ideia de que os sistemas econômicos se enquadram na teoria da complexidade, onde seus inúmeros agentes interagem entre si sem um controle central e que essas interações são capazes de alterar o comportamento futuro dos agentes e de todo o sistema, semelhante a um sistema caótico, incrementamos o modelo de Russo et al. (2014) para a realização de três experimentos com foco na interação entre bancos e empresas em uma economia artificial.

O primeiro experimento diz respeito a *Relationship Banking* onde, segundo a literatura, a interação ao longo do tempo entre bancos e empresas é capaz de produzir benefícios mútuos, principalmente devido a redução da assimetria de informação entre eles. O experimento seguinte está relacionado a assimetria de informação no mercado de crédito, onde quanto maior o banco, maior sua visibilidade no mercado de crédito, elevando na mesma proporção as consultar para novos emprestimos. Por fim, o terceiro experimento é relativo aos efeitos no mercado de crédito da heterogeneidade de preços que as empresas se deparam no mercado de bens.

Palavras-chave: Agent-Based Models, Economia Computacional, Relacionamento entre bancos e Firmas, Teoria das Redes.

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List of symbols

i	Firm index
j	Bank index
t	Time index
θ	Productivity factor
β	Output elasticity
π	Profit
δ	Price smooth factor
α	Expected gross profit
η	Risk premium
r^{cb}	Central bank interest rate
ω	Maximum leverage change
ρ	Regulator deposits reserve
μ_p	Price (profit) mean
σ_p	Price (profit) variance
c	Bank operational cost
ϕ	Credit market heterogeneity
h	Environment precision
$\bar{h}$	Idiosyncratic signal noise
κ	Propensity to consult parameter
λ	Capital adequacy rate

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1 Introduction

The financial intermediation done by banks came, among other reasons, from their ability to absorb and manage risk between lenders and borrowers. Possessing liquid liabilities and rigid assets, banks have to manage this relationship, something that is called Asset Liability Management (ALM). The illiquidity of bank assets comes from information sensitivity, where it is not possible to know the borrower, and, and most importantly, the return of investments made through loans.

The intrinsic risk of financial intermediation can be diminished with the access to private information of borrowers, as expected return can be better projected and the decision to lend or not can be made with more safety.

This paper aims to improve the (RUSSO et al., 2014) model in these particular situations, where the relationship between banks and their borrowers can be beneficial mainly for banks, but also to lenders that are focused on firms.

In order to study this relationship, it was proved necessary to build a model where banks and firms interact in an artificial credit market, and firms call for the assistance of banks to fund their projects. This market can be looked at from the complexity theory paradigm, where banks and firms follow their behavioral rules and interact in an informational asymmetric market without the presence of a centralized decision maker. In order to model this, agent-based models that originate an artificial self-evolving environment will be adopted.

In addition, two mechanisms will be described and evaluated. First, price heterogeneity, which will be looked at in order to analyze different profit structures within firms and to understand how banks do in this scenario. Second, the power of a bank in the Credit Market will be studied in order to explain the relationship between large and small banks and firms, considering that the bigger the bank, the bigger its visibility.

This paper is divided into four sections: the second section contains the theoretical framework, with a description of the literature regarding the methodologies that were considered. Section 3 presents the new model and describes the improvements achieved. Results from simulations are shown in Section 4. Our conclusion is presented in Section 5, where further studies are also suggested.

2 Theoretical Framework

Our theoretical framework for this paper starts with the complexity paradigm, that come from the study of natural phenomenons, were we can include the modern economic systems, to try to understand their non linearity of response. After that, in section 2.2, we describe the Agent-based models, a set of tools to model complex systems, once these models can capture the interactions between heterogeneous members in the system, that will be Banks and Firms in our context.

The interaction between Banks and Firms in our model will give rise to networks, that has important insights, and a brief description of their properties and measures can be found in section 2.3. The connection between Banks and their borrowers, Firms in our paper, was extensively studied and is known as Relationship Banking in the literature, that has more details in section 2.4.

2.1 Complexity

In recent years, a new way of seeing the Economic systems has emerged. Considering that the Economy is composed by a vast set of agents that interact with each other in different ways, places and times, this multitude of agents - consumers, firms, banks, investors - is difficult to understand due to, among other reasons, the mechanism of how individual behaviors might react to the pattern they together create after previous movements, and how that pattern would alter their next interactions.

Complexity is a framework which studies how interacting elements in a system create overall patterns, and how these patterns can, in turn, change the interacting elements. This interaction gives us a world that is organic and evolutionary.

In this view, the apparent unpredictability of action of the agents set up a non-quilibrium state in the economy. This state arises endogenously and through the interaction of agents. The assumption of equilibrium from the standard economic doctrine here is but a special case of the non-equilibrium, which is the real natural state of the economy. If equilibrium is the economic rule, "*... there is no scope for improvement or further adjustment, no scope for exploration, no scope for creation*", (ARTHUR, 2013).

Also, according to Arthur (2013)[p.3], non-equilibrium can be explained because of two main reasons. First, the uncertainty that permeates the economic decisions which has its origin in some degree of not knowing, because the agent isn't well informed or cannot make any calculation or, as cited by (SHACKLE, 1992) "*The future is imagined by each man for himself and this process of the imagination is a vital part of the process of*

decision". The second reason is the technological change, which is more disruptive than Schumpeter[1] accounted for because it can set off the development of a sequence of new technologies in a vicious cycle, instead of being only a one-time disruption.

Consider a system composed by individuals with heterogeneous backgrounds and behavior. When these individuals interact in a non-regular way, it means an improvement in the reductionist[2] paradigm that permeates science as a whole, not only Economy. Still, even if we know and understand the entire set of rules that govern the Universe, we cannot recreate it taking into account only a few of its elements, because "*... the behavior of large and complex aggregates of elementary particles, it turns out, is not to be understood in terms of a simple extrapolation of the property of the properties of a few particles.*" (ANDERSON, 1972). In the end of the same paper, Anderson sums up the way we commonly define complexity "*in this case we can see how the whole becomes not only more then but very different from the sum of its parts*".

The definition of a complex system that we will use, from (MITCHELL, 2009) is "*a system in which a large networks of components with no central control and simple rules of operation give rise to complex collective behaviors, sophisticated information processing, and adaptation via learning or evolution. ... a system that exhibits non-trivial emergent and self-organizing behaviors.*" A great example of how simple rules can create complex behaviors is the logistic equation (MAY et al., 1976):

$$x_{t+1} = rx_t\left(1 - x_t\right) \tag{2.1}$$

This equation was first used for the study of populations. The parameter r is the growth rate, calculated from the birth and death rate. For $r < 3$, the population will increase until a fixed value and remain fixed. For example, for $r = 2$, x will converge to 0.5 and stay there. If $r > 3$, the population x never stabilize at any value, and for values closer to 3 an bifurcation occurs and the function presents two periods. If r increases, chaos increases too, the function doesn‘t converge to any fixed value[3]. This complex behavior is summarized in Figure 1 which shows, for values of r, the respective population x:

Another important element in complexity framework is information[4] processing. As previously mentioned, the elements that compose a complex system interact among themselves without the presence of a central control. In other words, the interactive decision is an individual one that each element has to make, following its own beliefs. The elements need to process the information given by an environment and by previous experiences in order to make better decisions, but this available information can come

1 (SCHUMPETER, 1942)
2 Reductionism is an scientific method that tries to describe the system by looking at its constituent parts, where the system is the sum of its parts. For more informations, see (JONES, 2000)
3 A deep understand about this equation can be found in (LI; YORKE, 1975).
4 For an precise definition of information, see (SHANNON, 1948)

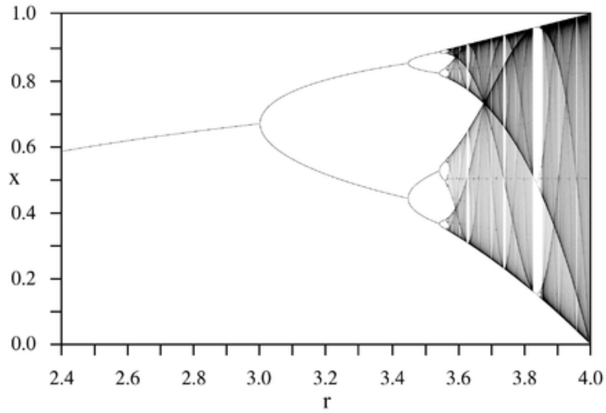


Figure 1 – Logistic Map

with noise or distortions. (WOLFRAM, 1984) offers more details regarding this process of feedback between elements and the environment.

2.2 Agent-Based Models

The class of models that can incorporate the characteristics from complex system theory as described earlier is the Agent-Based Models (ABM). In this theoretical framework, a system is populated by autonomous decision-making agents who individually assess their condition and make decisions based on rules that may or may not depend on environment information. So, with this class of model we can address the key elements in the complexity theory and capture emergent phenomena. As Epstein e Axtell (1996) says, "*ABM can change the way we think about explanation of an observed social sciences.*"

In the economic context, with this class of model, we can incorporate imperfect information, technological change and bounded rationality, because we model the economic heterogeneous agent that interacts in an autonomous way without any central decision force, like the Walrasian auctioneer[5], for example, with limited rationality and following simple rules.

According to Orcutt (1957), "*this type of model consists of various sorts o interaction units which receive inputs and generate outputs*",the outputs being related, in part, to prior events and to the result of random numbers from defined probability distributions.

The paradigm that embraces the agent-based models is the Agent-based Computational Economics (ACE), according to Tesfatsion (2006)[p.832], "... *ACE is the computational study of economic process modelled as dynamic systems of interacting agents.*" Using the growing computational capabilities of computers, an artificial economy

[5] The auctioneer is the core of the price mechanism in Walrasian equilibrium,(WALRAS, 1877), that remains one of the fundamental paradigms that frame the economic theory.

is built where the agent is the unit of observation, which consist of individuals, firms, families, markets or even countries, encapsulated in a piece of software[6].

After setting the initial state of agents and which events they can participate in, the economy evolves solely via agent interaction, with the objective of seeing the evolution of the studied event with the emergence of patterns, rather than the equilibrium state of the system. Agents are autonomous[7] in their decision making, they have the capacity to self-govern.

Agents can be modeled with more realistic social and learning capabilities, like "*social communication skills; the ability to learn about one's environment from various sources, such as gathered information, past experiences, . . . the ability to form and maintain social interaction patterns (e.g., trade networks).* These aspects are private internal characteristics of agents and can be hidden from other agents, which, in turn, have only the ability to see and process determined signals.

Four main objectives are cited by (TESFATSION, 2006) in choosing the ACE paradigm:

Empirical understanding

Try to observe and explain regularities that persist and evolve in the real world. The agents have the same capability of actions as their corresponding entities from reality, and their repeated interaction can show the expected result, according to their own preferences and/or physical circumstances, without any external imposition.

Normative understanding

This methodology can be useful to discover the best economic design for economic policies with the long run objective of a socially desirable economy. The main goal is to see the economic system before and after a determined policy, analyzing if it's more efficient, fair and orderly.

Qualitative insight and theory generation

The objective is to understand the economy and its dynamics through a systematic examination. For example, the self-organizing capabilities of a decentralized market can be explained by a model composed of traders with cognitive capabilities to learn how to make better (not necessarily optimal) decisions about production and price. The main goal is to supply ACE researchers with the best tools to make better models, like programming, visualization and validation.

---

[6] Our agents is a class in the Object-oriented programming (OOP) context, and agents characteristics are methods (COX, 1985).

[7] From (Stan Franklin), . . . *autonomous agent is a system situated within an part of an environment that senses that environment and acts on it, over time, in pursuit of its own agenda and so as to effect what it senses in the future.*

2.3 Networks

As previously discussed, the main characteristic of agent-based models is the possibility of building artificial worlds populated by agents that act according to simple rules and interact among one another. Over the time, this interaction forms networks with characteristics which are fundamental for the understanding of the economy as a whole.

Networks permeate our lives in any context where there is an interaction between two or more parties, agents or not. A network is composed by two main elements. *Nodes*, (or *vertices*) representing the elements of the network (agents in our context) and *edges*, (or *links*) which represent a connection between two nodes. Figure 2 is an example of a simple network:

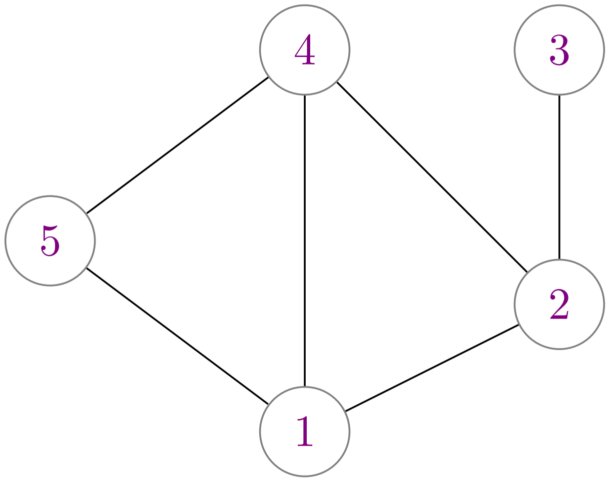


Figure 2 – Network

In this example, following the notation of (JACKSON, 2008), we have $N = \{1, \ldots, n\}$ nodes, with $n = 5$ and 6 edges. We can represent edges by an nxn matrix g, where g_{ij} represent a connection status between pair i, j. This matrix is known as *adjacency matrix*, where $g_{ij} \neq 0$ mean that i and j are connected.

$$g_{ij} = \begin{pmatrix} 0 & 1 & 0 & 1 & 1 \\ 1 & 0 & 1 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 1 & 0 \end{pmatrix}$$

Networks theory is important because with this representation, we can see the indirect influences between nodes. Two nodes may not be directly connected, but their actions affect one another. We can define a path between two nodes i and j by the sequence of links that start in one, say i and finishes in j or otherwise, with this nodes appearing

once in the sequence. A pair of nodes can have one or more paths between its parties, being the shortest path called geodesic.

The links between two nodes can be indirect, as showed in Figure 2, where we can go from node i to j and from j to i without difference. Or a network can have direct links where, for example, we can go directly from i to j but not from j to i directly. This differentiation is important because they change the properties of networks. One important measure of this properties is diameter of a network, defined as the largest distance (number of nodes in their geodesic) between two nodes. Another measure is the average path taken over geodesics.

These two measures are fundamental in social networks because they show the stylized fact of large networks with small diameters and average paths. This characteristic defines networks as *small world networks*, a common phenomenon of social sciences networks, extensively studied and referred to as the “six degree of separation”(TRAVERS; MILGRAM, 1977, p.431).This paper argues that the bigger the number of nodes in a social network, the greater their tendency to exhibit small diameter and, in this case, a small average patch of 6. In other words, the study says that any two people are connected, in average, by six links. Other evidences of this characteristic can be found in (NEWMAN, 2000), (MILGRAM, 1967) and (WATTS, 1999).

The discussion above is focused on the main characteristics of the entire network. Analyzing nodes, we can compare them or see how influent they are in the network, basically looking at their position in that network and how central they are. There are three main measures for this purpose. The first, which is degree, shows how connected a node i is counting the number of connections, $d_i(g)$, it has. We can summary this number in scale $(0, 1)$, computing the centrality degree:

$$\frac{d_i(g)}{n-1} \tag{2.2}$$

The count of connections is an important measure but fails to show how well located a node is in the network, because, despite having many connections, they can be nodes that are not very important for entire network.

The second, which is the closeness, measures how close a given node is of other nodes, and it is represented by

$$\frac{(n-1)}{\sum_{i \neq j} l(i,j)} \tag{2.3}$$

where $l(i, j)$ is the geodesic between i ad j. So, closeness is the inverse average distance between i and the j-th node. The fact that a node has high closeness means that,

in average, it has small geodesics to other nodes in the network.

The measure that will show how relatively well located a node is in a network is betweenness. The bigger the number of geodesic links between two nodes that a node has, the bigger its importance in the network. This index can be written as:

$$\sum_{k\neq j:i\notin\{k,j\}} \frac{\frac{P_i(kl)}{P(kl)}}{\frac{(n-1)(n-2)}{2}} \tag{2.4}$$

Here, $P(kl)$ is the number of geodesic between k and l, and $P_i(kl)$ the geodesic between k and l that i lies, so, their ratio is the importance of i for k and l. Averaging through all pairs of nodes, we can measure the betweenness of the node i.

2.4 Relationship Banking

For banks, the management of the illiquidity of their liabilities in contrast to the liquidity of their assets is a necessity and, therefore, the information regarding borrowers is an important source of competitive advantage. Knowing the counterpart's projects and their intrinsic risk[8] reduces uncertainty of the future. The access to information is directly connected to relationship banking, defined by (BOOT, 2000, p.10) as the policy of a bank of investing on taking customer's specific information and *"evaluate the profitability of these investments through multiple interactions with the same customer over time"*.

The presence of relationship banks is beneficial because the information collected is an intangible asset for the bank who owns it, and this information remains confidential to other players and is improved by interactions over time.

For the borrower, revealing information to banks is a source of scoring contractual benefits, since they can disclose information to a bank without fear of this information being made public and benefiting their competitors. Contrary to what occurs when the source of funding is the Financial Market, which needs public information for investor decision making.

The main contractual benefit from relationship banking is the flexibility, since banks are less rigid for renegotiations of loans than the Financial Market. This flexibility can extend to collateral requirements, more specific contracts and long-run strategies for profits that can accommodate short-term losses for revenues in the future, (BERLIN; MESTER, 1999, p.586).

[8] As described by (BOOT; THAKOR, 1997, p.697)

Relationship banking focuses on soft instead of hard information [9] and its use in risk management is a real advantage in comparison to competitors.

[9] From the definition of (PETERSEN, 2004, p.2), *soft information* is defined as informations difficult to summarize in numbers, and usually comes in the form of text without standard. *Hard information* is that one easy to reduce in a numeric score, like financial statements.

3 Model

Our study is based on the Russo et al. (2014) model. The artificial economy is populated by I firms (indexed by $i = 1, 2, \ldots, I$) that produce goods, and by J banks, (indexed by $j = 1, 2, \ldots, J$) that extend credit to firms. They undertake decisions at a discrete time $t = 1, 2, \ldots, T$.

Two markets coexist in the economy. The Goods Market, where firms sell their goods to consumers, and the Credit Market, where firms take credit from banks to produce their goods. Our focus will be the interaction between banks and firms in the Credit Market.

In the Goods Market, firms sell their production of perishable[1] goods to consumers for an exogenous price, which is determined by a stochastic process. By focusing on the supply side of this market, as stated in Gatti et al. (2010, p. 1631), we assume that price is an increasing function of demand, and "*[...] a high realization of* $u_{i,t}$ (the price random process for the ith firm at time t) *can be thought of as a regime of high demand which drives up the relative price of the commodity in question. In a regime of low demand, the realization of* $u_{i,t}$ *turns out to be low.*". After the selling process, the firm receives revenues, a function of price and the amount produced.

In the Credit Market, the core of our model, firms ask banks for loans according to their needs. At time t, each firm will consult the interest rate offered by a group of banks and choose one of them to take a loan. Both markets and their flows are represented in Figure 3:

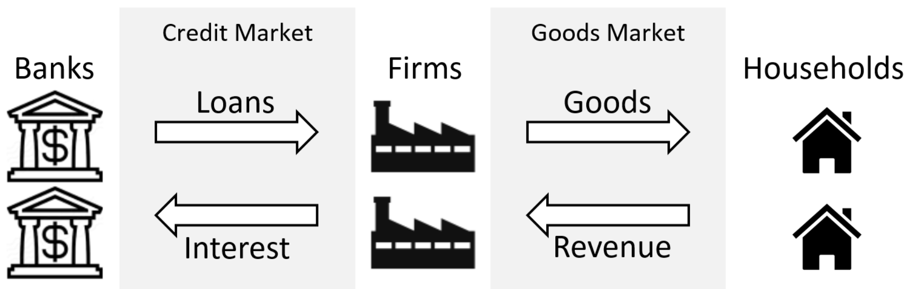


Figure 3 – Firms, Banks and markets

Firms and banks will be connected in time t and $t + 1$ if a loan has been taken at time t and needs to be paid out in the future, because loans last two periods following Russo et al. (2014).

[1] The goods produced at time t need to be sold at same time, firms cannot build inventories to use in the future.

In short, we start creating I firms and J banks. At each time span, each firm computes their leverage target, according to a rule of expected earnings for the next period. With this leverage target, the firm knows the amount of loans that are or not needed. Then it goes to the Credit Market and calls for the interest rates of a selected group of banks. The propensity of a bank to be selected is an increased function of its size. In possession of the interest rates offered by banks, the firm selects the desired bank with a propensity inversely proportional to the interest rate.

Once the loan is taken, the company carries out production and directs it to the Goods Market. For a stochastic price, it sells its goods and calculates its earnings and profits. At the same time span, each bank computes the earnings of its portfolio of loans and its profits. A bank or firm is considered active if their net worth is greater than zero. If not, it will be replaced by another in the beginning of the next time span. The main steps of our model are described in the pseudo code (1). The explanation of the behavior of firms and banks in our model will be in sections 3.1 and 3.2, respectively.

3.1 Firms Behavior

The scale of production of the ith firm at time t is a function of only its capital $(K_{i,t})$. The production function, that generates the output, $Y_{i,t}$ is:

$$Y_{i,t} = \theta K_{i,t}^{\beta} \tag{3.1}$$

Following Greenwald e Stiglitz (1993, p. 88), this function, called "financially constrained output function", is the solution for an optimization problem of a firm's expected profits $E(\pi_i)$ minus an expected real cost of bankruptcy. This function's concavity, as showed by Gatti et al. (2010), express the idea of "decreasing returns" if $0 < \beta < 1$ and $\theta > 0$, parameters uniformly across the I firms.

Capital, $K_{i,t}$, is the only input of the production function. Indeed, in order to set its level of activity, a firm needs to change this variable. At time t, capital is defined by:

$$K_{i,t} = E_{i,t} + L_{i,t} + L_{i,t-1} \tag{3.2}$$

Where $E_{i,t}$ is the firm's equity, $L_{i,t}$ the loan taken at time t and $L_{i,t-1}$ the loan taken at time $t-1$. Following Riccetti, Russo e Gallegati (2013), we assume that the debt lasts for two periods. Therefore, in order to change the production level, the firm needs to manage its loans.

We will follow the dynamic trade-off theory for the capital structure of firms. In this theoretical framework, an evolution of the original trade-off theory proposed by Jensen

(1976) and Myers (1977), firms have long-run leverage targets that maximize their value, persuading them, in the short-run, to doing adjustments towards the target (FRANK; GOYAL, 2008).

The leverage[2] target is a function of expected earning. If the expected price is greater than the expected interest rate, then the firm increases the previous leverage target by a factor $\omega\psi$, where ω is a parameter that represents the maximum change in the leverage and ψ is a random number with uniform distribution between 0 and 1. Equation 3.3 summarizes this rule:

$$l^*_{i,t} = \begin{cases} l_{i,t-1}(1+\omega\psi) & \text{if } \bar{p}_{i,t} \geq r^e_{i,t} \\ l_{i,t-1}(1-\omega\psi) & \text{if } \bar{p}_{i,t} < r^e_{i,t} \end{cases} \tag{3.3}$$

where $\psi \sim \mathcal{U}(0,1)$

The expected price $\bar{p}_{i,t}$ is given by an exponential smoothing,(JR., 2006) of the last observed prices with parameter δ (Equation 3.4).

$$\bar{p}_{i,t} = \delta p_{i,t-1} + (1-\delta)\bar{p}_{i,t-1} \tag{3.4}$$

Prices will be explained later. The expected interest rate, $r^e_{i,t-1}$, is given by an static adaptive expectation, where $r^e_{i,t} = r_{i,t-1}$.

With the leverage target of the current period determined, the loan target, $L^*_{i,t}$, can be found following Equation 3.5:

$$L^*_{i,t} = E_{i,t} l^*_{i,t} \tag{3.5}$$

If the previous loan $L_{i,t-1}$ is greater than the loan target $L^*_{i,t}$, the firm didn't need to take a new loan because the leverage target is reached only with $L_{i,t-1}$. So, the loan demand for the current time is:

$$L_{i,t} = max(0, L^*_{i,t} - L_{i,t-1}) \tag{3.6}$$

Once the firm decides the amount of the loan, it will consult a group of banks according to the mechanisms described in subsection 3.3.1 and subsection 3.3.2. Once the process of borrowing is complete, the output is computed. As we've said earlier, the entire output will be sold in the Goods Market at price $p_{i,t}$.

[2] Leverage is defined as $\left(\dfrac{L_{i,t} + L_{i,t-1}}{E_{i,t}}\right)$

Price here can be interpreted as the, "*. . . stochastic gain on a unit of output that contains the stochastic price net of the expenses for producing the output itself.* " (RICCETTI; RUSSO; GALLEGATI, 2013). In mathematical terms:

$$p_{i,t} = max(0, \alpha_i + \gamma_{i,t}) \tag{3.7}$$

Where $\gamma_{i,t} \sim \mathcal{N}(\mu_p, \sigma_p)$ is the random component with normal distribution for each firm i at time t. Expected gross profit per unit, α_i, is net of financial costs, constant over time and different for each firm, with uniform distribution in range $[\alpha^{min}, \alpha^{max}]$.

For firm i at time t, the income statement will be:

Revenues	p_tY_t	Revenue
Expenses	r_tL_t	Current Loans
	$r_{t-1}L_{t-1}$	Previously Loans

Table 1 – Firm Income Statement

From Table 1 we can derive the profit equation:

$$\pi_{i,t} = p_{i,t}Y_{i,t} - r_{i,t}L_{i,t} - r_{i,t-1}L_{i,t-1} \tag{3.8}$$

We will suppose that the entire profit will be reinvested. So, the firm's equity for the next period will be:

$$E_{i,t+1} = E_{i,t} + \pi_{i,t} \tag{3.9}$$

In accounting notation, the firm's balance sheet at the end of time t:

Assets		Liabilites	
K_t	Capital	L_{t-1}	Previously Loans
		L_t	Current Loans
		Net Worth	
		E_t	Equity
		π_t	Profit

Table 2 – Firm Balance Sheet

If the firm's net worth is less than 0, then it goes bankrupt and is out the next period and, therefore, a new firm will enter the market with a small random equity.

In this light, the firm's net worth is composed by its equity and previous profit, E_t and π_{t-1}, so, it goes bankrupt only if previous profit is a loss (negative profit) greater than current equity, $-\pi_{t-1} < E_t$.

3.2 Banks Behavior

Firms and banks interact in the Credit Market, as introduced in the beginning of this chapter. Banks are consulted by firms who are looking for loans, as described in section 3.1. Each bank consulted by a firm at time t will return the interest rate, $r_{j,i,t}$ composed by three terms:

$$r_{j,i,t} = f_1(E_{j,t}) + f_2(l^*_{i,t}) + r^{cb} \tag{3.10}$$

In Equation 3.10, the first term, $f_1(E_{j,t})$, represents the bank structure component in the interest rate of the loan. Following (RUSSO et al., 2014) and (GATTI et al., 2009), the functional form of this term is:

$$f_1 = \eta E_{j,t}^{-\eta} \tag{3.11}$$

The logic behind this relationship is that large banks use their market power to extend credit in favorable terms, with lower interest rates than small banks, following (KASHYAP; STEIN, 2000, p.410) and (GAMBACORTA, 2008, p.798).

$$\frac{\partial f_1}{\partial \eta} < 0$$

$$\frac{\partial^2 f_1}{\partial \eta^2} > 0$$

The bigger the bank in terms of its equity, the lower the interest rate in a decreased way. The term η is the risk premium parameter, fixed and equal for all banks.

The second component that composes the interest rates, as described in the Equation 3.10, $f_2(l^*_{i,t})$ tries to grasp the borrower's credit risk, which will increase with their leverage, $l^*_{i,t}$. We are considering a decreasing risk premium in relation to the size of the firm, estimated by $\left(\frac{E_{i,t}}{E_t^{max}}\right)$. The equation is:

$$f_2 = \eta \left[\frac{l^*_{i,t}\left(1 + \frac{1}{h + \bar{h}k_{i,j}}\right)}{1 + \frac{E_{i,t}}{E_t^{max}}} \right] \tag{3.12}$$

Here we are including the term $\left(1 + \frac{1}{h + \bar{h}k_{i,j}}\right)$ in the original function proposed by (RUSSO et al., 2014). Aligned with our objective, this term will include the relationship in loan price determination. As described by (BOOT, 2000), the relationship between a bank and a firm can produce benefits for banks as they are able to better understand

their clients. Following (ACEMOGLU; BIMPIKIS; OZDAGLAR, 2014), the variable $k_{i,j}$ represents a truthful private signal. Bringing this idea to our context, $k_{i,j}$ is the number of times that a firm i has been connected to a bank j.

The other two terms, h and $\bar{h}$ are, respectively, the state (environment) precision[3], and the idiosyncratic noise of the signal, or, better put, how well the information can be processed by a bank, its ability to assimilate the signal sent by firms.

We can see that our expression for f_2 is a general case of the original expression proposed by Russo et al. (2014), where banks know the leverage of a firm from the start:

$$\lim_{k_{i,j}\to\infty} f_2 = \eta\left(\frac{l^*_{i,t}}{1+\dfrac{E_{i,t}}{E^{max}_t}}\right)$$

In other words, we are including a friction in the beginning of the relationship between bank and firm, as we can see in Figure 4.

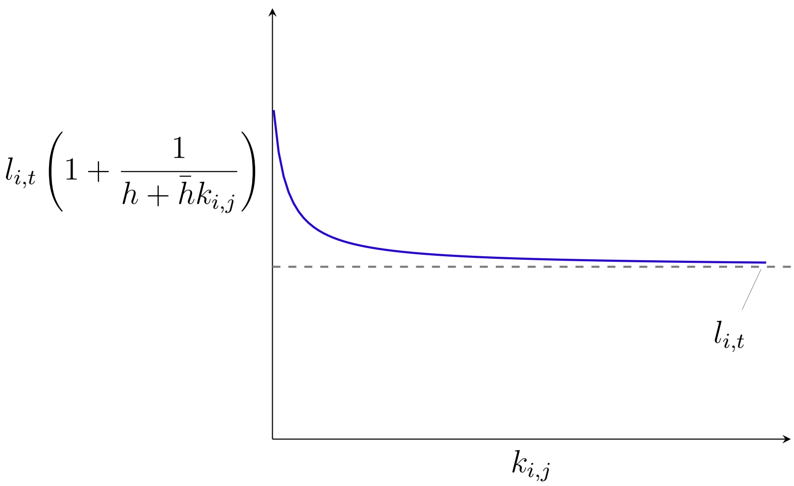


Figure 4 – Number of connections, $k_{i,j}$, and leverage, $l_{i,t}$, relationship over time.

After computing the interest rate $r_{j,i,t}$, if the firm chooses the j-th bank, the loan asked will then be provided. At the end of every period, banks have extended credit for firms, receive interest rate from previous loans and incur losses from bankrupted firms. The income statement of the bank will be:

From Table 3, we can derive the profit expression:

$$\pi_{j,t} = \sum^{i} r_{i,j,t}L_{i,j,t} + \sum^{i} r_{i,j,t-1}L_{i,j,t-1} - r^{cb}D_{j,t} - cE_{j,t} - bad_{j,t} \tag{3.13}$$

[3] This equation is part of the expected profit of an agent taking an action after observing k truthful private signals in an connected network.

Revenues	$\sum^{i} r_{i,t} L_{i,t}$	Current loans revenue
	$\sum^{i} r_{i,t-1} L_{i,t-1}$	Previously loans revenue
Expenses	$r^{cb} D_t$	Deposits return
	cE_t	Operational Cost
	bad_t	Bad Loans

Table 3 – Bank Income Statement

Where $\left(\sum^{i} r_{i,j,t} L_{i,j,t} + \sum^{i} r_{i,j,t-1} L_{i,j,t-1}\right)$ is the revenue from loans extended to firms.

The first costs component of a bank is $r^{cb} D_{j,t}$, the deposits payment, the second is the operational cost, proportional to bank's asset $cE_{j,t}$. The third component of the function of the profit of a bank is the loss from loans made to bankrupted firms $bad_{j,t}$. Here we consider the loss as the sum of all loans made to bankrupted firms, the net of legal expenditures (Le) fixed for all firms, and the net of recovery rate (RR):

$$bad_{j,t} = \sum^{i} \left[L^{npl}_{i,j,t} (1 - RR_{i,t})(1 - Le) \right] \tag{3.14}$$

One less the recovery rate (RR), as described in Basel. . . (1987), is the loss given default rate (LGD). Here we will consider this terms as the ratio of a firm's assets and their loans at bankruptcy moment and the payment capability of a firm at default time:

$$(1 - RR_{i,t}) = LGD_{i,t} = \left(\frac{E_{i,t}}{L_t + L_{t-1}} \right) \tag{3.15}$$

Bank risk management follows BIS I capital adequacy. The parameter λ is the capital adequacy rate, corresponding to 8% of their total risk-weighted loans in portfolio. [4].

Assets		Liabilites	
$\sum^{i} L_{i,t}$	Current loans	$D_t(1-\rho)$	Net deposits
$\sum^{i} L_{i,t-1}$	Previously loans	Net Worth	
$\lambda\left(\sum^{i} L_{i,t} + \sum^{i} L_{i,t-1}\right)$	Capital reserve	E_t	Equity
		π_t	Profit

Table 4 – Bank Balance Sheet

From the Balance Sheet of a bank, Table 4, we can determine deposits as an exogenous component. Deposits are a net of regulators reserves, captured by the parameter

[4] By simplification, we will consider a risk weight of 100% for all loans. Then, the expression for bank's capital is $\lambda\left(\sum^{i} L_{i,t} + \sum^{i} L_{i,t-1}\right)$. For more informations about the Basel I framework, see (BASEL. . . , 1987)

ρ. A bank isn't constrained to extend credit for firms by capital, since deposits are determined as exogenous:

$$D_{j,t} = \frac{(1+\lambda)\left(\sum^{i} L_{i,j,t} + \sum^{i} L_{i,j,t-1}\right) - E_{j,t}}{1-\rho} \tag{3.16}$$

3.3 Agents Interaction

Banks and firms will interact in two different moments for every period. At first, when the firms that need loans go to the Credit Market to call for the interest rates for those loans in a few banks.. Then, after those firms select one of the banks consulted and actually take the loan. These two moments will be explained in details in the next two sections.

3.3.1 Banks to consult

A firm will call for the interest rate for a set $\Phi \in$ J, of size ϕJ, where $0 < \phi < 1$ is the parameter that captures the heterogeneity in the Credit Market. The intuition here is that a firm doesn't have all the possible information about the market structure, and, therefore, it cannot ask the entire market for interest rates.

In (RUSSO et al., 2014), the firm randomly selects the Φ set. Here, we will use a propensity rule to select banks. The rule is:

$$pa_j = \left(\frac{E_t}{E_t^{max}}\right)^{\kappa} \tag{3.17}$$

The propensity pa_j of being consulted is directly proportional to the size of a bank. The bigger the bank, the less the asymmetry incurred and the greater the chance of it being consulted by firms. The parameter κ changes the pa_j propensity shape, as shown in Figure 5:

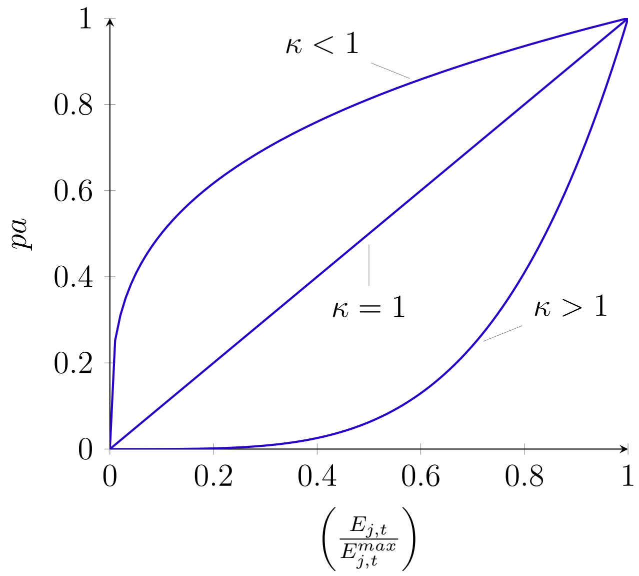


Figure 5 – Propensity to be consulted, pa, and Equity Ratio relationship for different values of κ

If $\kappa < 1$, pa is concave ($\frac{\partial^2 pa}{\partial \kappa^2} < 0$), then, the propensity is diminishing with $\left(\frac{E_{j,t}}{E_{j,t}^{max}}\right)$. Likewise, for $\kappa > 1$, pa is convex ($\frac{\partial^2 pa}{\partial \kappa^2} > 0$) with increasing values. For each bank asked, the firm sorts a random number and if the random number is inferior to the propensity of the bank, this bank will be selected, until Φ is complete.

3.3.2 Partner Selection

As mentioned previously, for the set Φ of selected banks, the firm will call for the interest rates for the desired loan and the banks will then reply using the rules described in equation 3.10. Following (GATTI et al., 2010), a firm will switch banks with a propensity ps. If the interest rate of the new potential lender, r_{t*}, is inferior to the interest rate offered by the previously lender, r_{t-1} the propensity ps will increase following the difference between r_{t*} and r_{t-1}. The expression is:

$$ps_j = 1 - e^{\left(\frac{r_{t*} - r_{t-1}}{r_{t*}}\right)}, \text{ if } r_{t*} < r_{t-1} \tag{3.18}$$

Figure 6 shows the relationship of ps and the differences between interest rates:

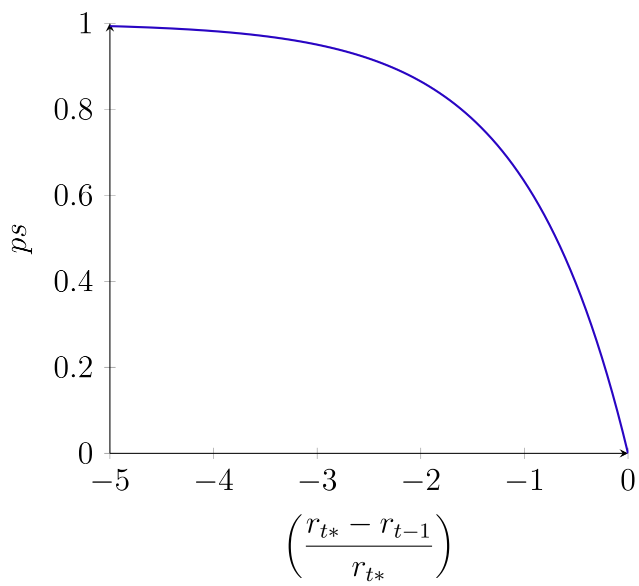


Figure 6 – Propensity of a partner be selected, ps, and interest rates r_{t-1} and r_{t*} relationship.

For consulted banks with an interest rate inferior to the previous interest, the propensity ps_j is computed and if it is greater than a random uniform number in $(0, 1)$, then, the bank is selected as the lender for the current period.

3.4 Network Evolution

In every period, firms who need new loans in order to satisfy their leverage target go to the Credit Market to search for lenders. As we've described, the firms will consult only a set Φ of all available banks, because there is an heterogeneity in this Market. They will then take a loan from a new lender with a propensity that increases along with the difference between the previous and the new interest rates offered.

Once the loan has been taken, the firm will remain connected with its lender. Using names from network theory, banks and firms will be vertices and the node will be the loan that connects them. The mechanisms described in the previous sessions will give rise to an endogenous evolution of the credit network.

In every time span, firms can be connected to two banks, because the debt lasts for two periods. This inter-temporal characteristic of debts is important to simulate the rigidity that firms face in the real world. Changes in capital structure rarely can be made in the short run. For example, (ALMEIDA; CAMPELLO; LARANJEIRA, 2011, p.10) shows that maturity compositions of the debts of a firm are an important characteristic to measure how firms have been affected by the 2007 credit crisis, since maturity is fundamental for financial flexibility.

The dynamics that govern our model starts with the leverage target of a firm. If the firm has experienced profit in the previous period and expects the interest rate to be lower than the profit rate, it is eager to increase its leverage in order to increase production. Banks will consider this increased leverage as an increase in the firm's fragility, and will then rise the risk premium, which will be lower if the firm is known, if there has already been a past relationship between the two agents, firm and bank. Interest rate also depends on the size of the assets of a bank. The growth of a bank depends on how wealthy its portfolio is and on its previous lending strategy, as we can see in Equation 3.13, which refers to the profit composition of a bank.

These two mechanisms, the size of a bank and its previous relationship with a firm, have an effect on reducing interest rates, encouraging firms to increase their leverage. An increase in leverage, in turn, pushes interest rates up, because high leverage is seen by banks as an increase in the risk of a firm leading to an increase in loan costs for that firm, Equation 3.8, and reducing profits. These forces, together with the competition among banks in the Credit Market will cause network formation that evolves according to the interactions between firms and banks.

3.5 Model Simulation

The simulation begins, following algorithm 1, with the creation of the initial I firms and J banks. The amount of firms and banks is constant throughout the simulation, so, when a firm goes bankrupt,[5], it is replaced by a new one with initial equity equal to 5% percentile of healthy firms. The same happens with banks, both in the beginning of each new time span.

In each time span, firms, in random order, evaluate their leverage target for that period, according to Equation 3.3 and if their current levels aren't sufficiently high, they go to the Credit Market to take a new loan. They ask the banks for the interest rates and take their loans as described in subsection 3.3.2. Once the capital structure is decided, the firms produce and sell their goods in the Goods Market with price derived from Equation 3.7. Thereafter, the firm computes revenues and profits for the current period.

Once all active firms have gone through these steps, active banks compute the profits from their loans portfolios. Once the simulation begins, the system evolves with no external influence, following the ACE paradigm discussed in section 2.2. We can

[5] section 3.1

summarize these steps through the algorithm below:

```
Algorithm 1: Model Steps
Input: Parameters
begin
    Create Firms
    Create Banks
for time = 0 to t do
    Replace Dead Firms and Banks
    foreach Active Firm do
        Compute leverage target
        Define loans demand
        if Need loan then
            Ask the interest rate from a group of banks
            Take loan from an selected bank
        Produce goods and sell them
        Compute revenues and profit
    foreach Active Bank do
        Compute Loans Portfolio
        Compute Profits
    Compute Active Firms and Banks
    Replace dead Firms and Banks
```

We will consider the same value for parameters as (RUSSO et al., 2014), which are shown on Table 5. The level of each variable was determined and stressed by the authors, and a complete sensitivity analysis for all parameters can be found at (RICCETTI; RUSSO; GALLEGATI, 2011).

Moreover, we will consider a scenario in which price, the main source of heterogeneity in the model, is parameterized as a constant, with $\sigma_p = 0$. With this configuration, that we will refer to as steady state, we are able to validate the model's regularity and the level of model variables in equilibrium.

With this configuration, the sources of variation come from the decisions made by firms of raising or cutting their leverage target, which should stabilize at the time when the interest rate is equal to the price. With this equality, the company will increase its leverage, which, in turn, will be perceived by the bank as an increase in risk entailing a rise in the interest rate. In the next moment, with interest rates higher than the prices, leverage is reduced. This mechanism is evident in the comparison between charts at Figure 7 below, which show the average (blue), percentile 10th and percentile 90th (black) from firms'

Parameter	Description	Value
T	Periods	1000
I	Firms	500
J	Banks	50
$L_{i,t=0}$	Firm initial leverage	1
$E_{i,t=0}$	Firm initial equity	10
$E_{j,t=0}$	Bank initial equity	10
θ	Firm's productivity	3
β	Firm's production elasticity	0.7
δ	Exponential smoothing parameter	0.5
ω	Maximum leverage change	0.1
μ_p	Price mean	0.0
σ_p	Price variance	0.1
r^{cb}	Central bank interest rate	0.02
η	Risk premium	0.02
ρ	Regulator deposits reserve	0.1
c	Bank operational cost	0.05
Le	Legal expenditures	0.1
ϕ	Credit market heterogeneity	0.1
λ	Capital adequacy rate	0.08

Table 5 – Baseline model parameters

interest rates and leverage across time[6], both in steady state and original model.

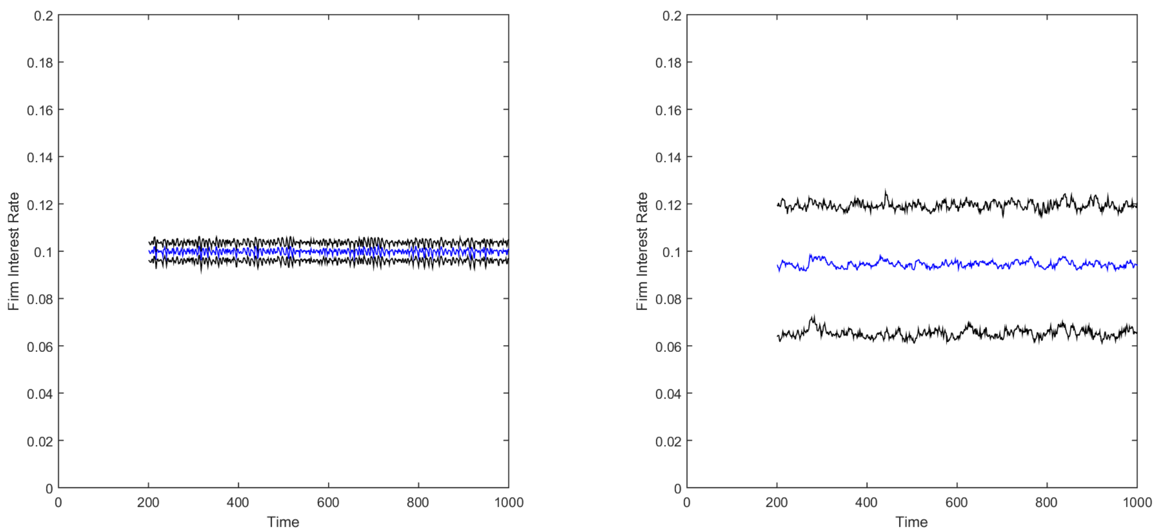


Figure 7 – Firm interest rate at steady state, left, and at original model. The black lines are the percentiles 10th and 90th, and the blue line is mean.

6 All results and charts consider only time greater then 200, because first periods are needed to start the simulation.

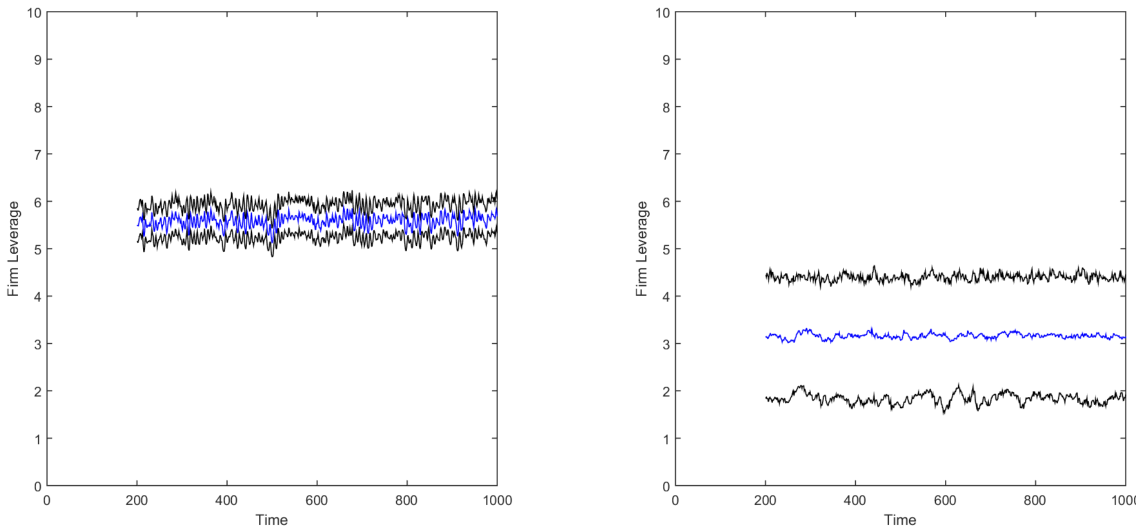


Figure 8 – Firm leverage rate at steady state, left, and at original model. The black lines are the percentiles 10th and 90th, and the blue line is mean.

Analyzing profits, as expected, for firms they are near 0 on average because, with constant price and leverage at a level where the interest rate is equivalent to price, the financial expense will be equal to the revenues. Accordingly, there are no bankruptcies for firms in this scenario. Profit for banks, on the other hand, is a function of the credit portfolio granted to companies that randomly sought them, from revenues perspective. From costs perspective, even if the bank has not granted a single loan, there is a fixed a cost that will erode part of its capital. For this reason„ the mean of profit of banks is below 0, with a big standard error, as shown in Table 6.

	Mean	Standard Error
Firms	0.0001	0.0005
Banks	-2.6727	8.7689

Table 6 – Steady State profits

We will consider these two scenarios, the baseline from (RUSSO et al., 2014) and the steady state to seek to understand the effects of our improvements on the characteristics of firms and banks and in the environment of our artificial economy. We are including five new parameters to address our questions, as described in Table 7. The first two, h and $\bar{h}$ address our discussion about relationship banking and how this relationship can offer advantages (or disadvantages) both for bank and for firm.

The third, κ, aaims to improve the way firms select banks, as a function of the assets of a bank, here the bigger the bank, the greater the chance of it being seen in the Credit Market, addressing our discussion about heterogeneity in the Credit Market. The last two parameters, α^{min} and α^{max} include heterogeneity in firms price structure.

Parameter	Description	Value
h	Environment precision	1
$\bar{h}$	Idiosyncratic signal noise	1
κ	Propensity to consult parameter	0.2
α^{min}	Expected gross profit	0.1
α^{max}	Expected gross profit	0.2

Table 7 – New model parameters

4 Results

In order to try to understand how our agents are going to act, interact and evolve in a slightly modified environment with the purpose of addressing our questions, in the next three sections, we will separately analyze each of them, always comparing them to the original model results and the steady state configuration.

4.1 Relationship Banking

Our first question is about relationship banking. As discussed in section 2.4, a better knowledge of the counterpart of a credit operation is crucial for banks because it provides them a better understanding and a correct pricing of risk. This happens because the flow of information between banks and customers is intensified through relationship.

To simulate this, we altered the way banks set their interest rates, as described in Equation 3.12, including a term which increases the knowledge a bank has of the risk of a firm that seeks a loan, so long there has already been a prior relationship between them. Thus, banks are able to set a more assertive interest rate. In order to isolate this effect, the parameters of the other changes are turned off so that they have no influence over the results. The value of parameters can be found in Table 8.

Parameter	Description	Value
h	Environment precision	1
$\bar{h}$	Idiosyncratic signal noise	1
κ	Propensity to consult parameter	0
α^{min}	Expected gross profit	0.1
α^{max}	Expected gross profit	0.1

Table 8 – Parameters for Relationship Banking

The first comparison we can make is of the effect of relationship banking in interest rate, as shown in Table 9:

	Steady State		Original Model	
		With Relationship		With Relationship
Mean	0.0998	0.0998	0.0941	0.0942
Standard Error	0.0010	0.0011	0.0011	0.0013

Table 9 – Comparative between interest rate with or without relationship banking

Relationship banking has no ability to lower interest rates. Its effect is more related to banks keeping their customers, considering that those who do not have a prior relationship lose competitiveness when compared to those who have. This is reflected on the maintenance of the loans portfolio of the bank, and here an important effect is perceived.

Comparing the distribution of equity between banks, Figure 9 on the left shows the trajectory of the equity of a bank over time in steady state and the right that same trajectory in steady state, but with the existence of relationship banking.

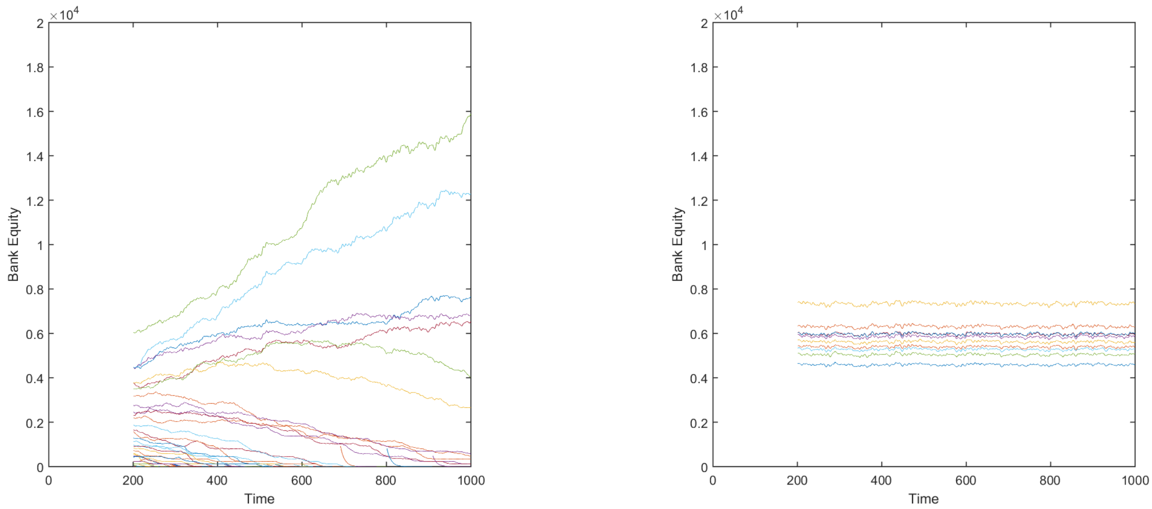


Figure 9 – Bank's equity over time at steady state on the left, and with relationship banking on the right.

The mechanism acts on repelling new loans to firms without a prior relationship. The lack of a prior relationship makes the requested bank offer loans at higher interest rates, whereas the bank that possesses the credit history of a firm, offers them a lower interest rate. This reflects on equity stability over time and banks maintain their loans portfolio.

When we place the relationship mechanism in the dynamic environment of the original model, the conclusion is the same. Comparing the number of bankruptcies of banks we have a mean of 0.3237 bankrupt banks (one bank failing every 3 time spans) over 0.0812 at steady state environment, which is four times lower.

Lastly, the equity of a bank is positively correlated to the average number of interactions between banks and firms, according to Figure 10, where we have the pair mean of interactions of clients in a bank's portfolio and the bank's equity.

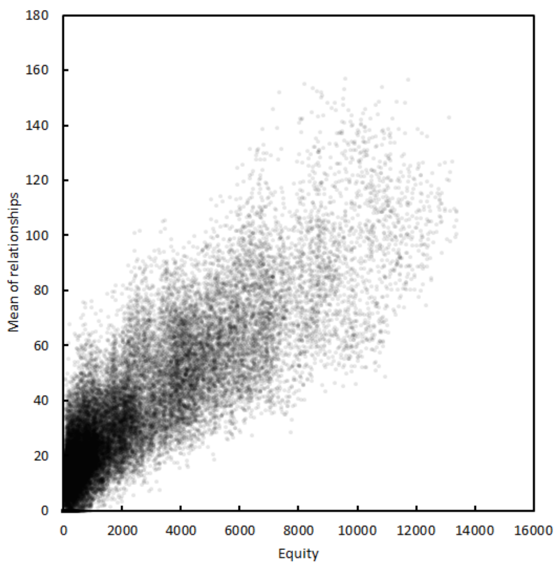


Figure 10 – Positive relation between Bank's equity and relationship. Each dot represent an bank at time t.

4.2 Credit market heterogeneity

As proposed by (RUSSO et al., 2014), when a firm needs a loan, it chooses a random subset of all active banks at a given instant in time. Here we will try another mechanism, as described in subsection 3.3.1, with three different values to parameter κ, which will produce three different shapes for probability to be consulted, pa, of a determined bank as a function of their equity relatively.

So, as κ decreases, the lower the probability (pa) of a small bank being consulted by firms that are looking for loans is, as shown in Figure 11.

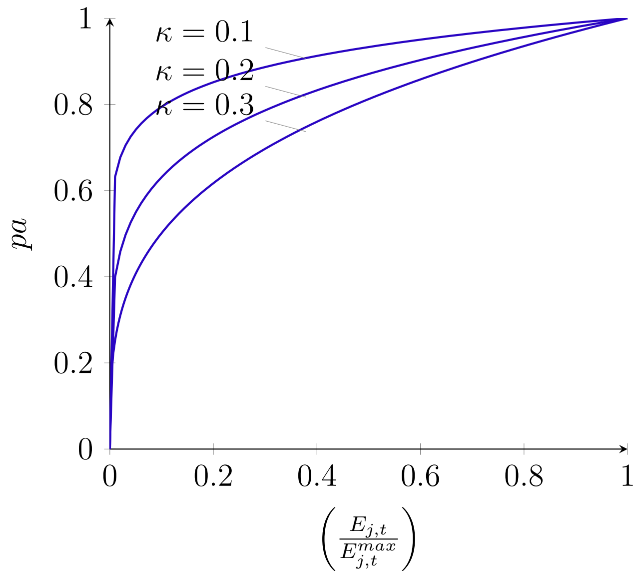


Figure 11 – Propensity of a bank be selected, pa and their relative equity for selected values of κ

Again, we will isolate the effect of our other experiments, setting parameters as shown in Table 10. Being more frequently consulted may be an advantage for large banks, and if they have the best rates, the further they will grow.

Parameter	Description	Value
h	Environment precision	∞
$\bar{h}$	Idiosyncratic signal noise	0
κ	Propensity to consult parameter	[0.1,0.3]
α^{min}	Expected gross profit	0.1
α^{max}	Expected gross profit	0.1

Table 10 – Parameters for Credit Market Heterogeneity

The higher the parameter κ, the higher the distance between banks, considering their equity. This effect can be seen in Figure 12, the results from one iteration, where one bank grows at a high rate and others follow this expressive growth, but at a given moment, they start to decrease. These results came from our steady state environment.

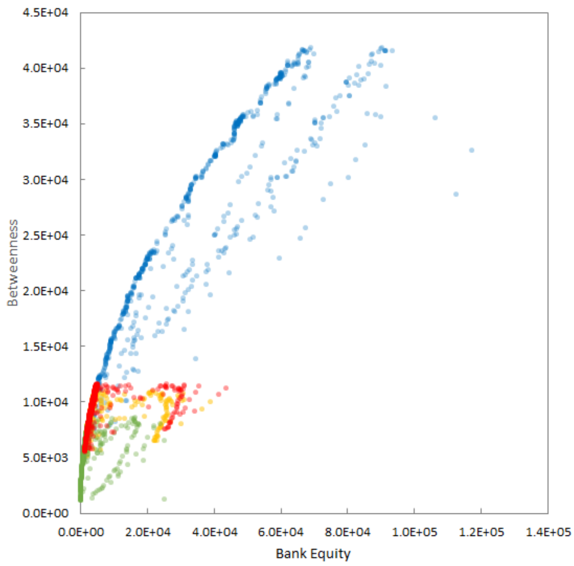


Figure 13 – Betweenness and equity to the four big banks with $\kappa = 0.2$

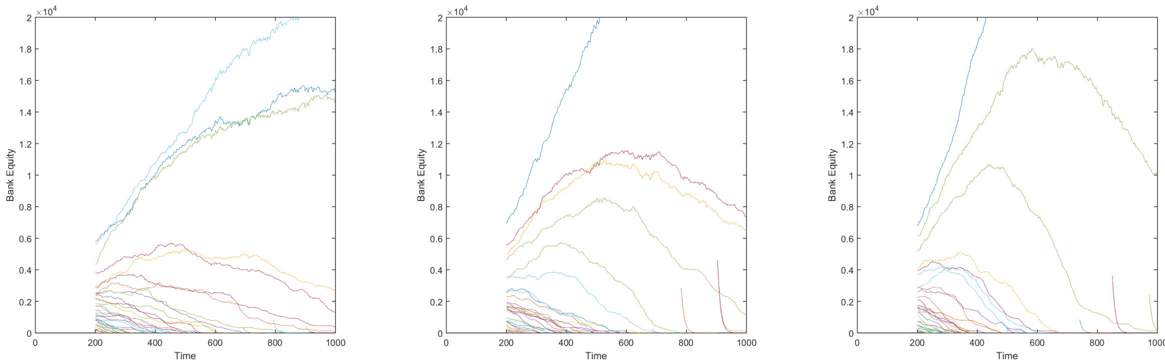


Figure 12 – Bank's equity over time for $\kappa = 0.1$ on the left, $\kappa = 0.2$ center, and $\kappa = 0.3$ on the right. The higher the κ higher concentration.

Analyzing the results for $\kappa = 0.2$, we can see that for the four largest banks, the betweenness index and the equity of a bank have a positive relation, as shown in Figure 13. Considering the second largest bank (red), it grew in a time interval smaller than 600, and from then on, it only decreased. This growth is primarily organic, from the increase in the portfolio value and not the amount of lenders, since the betweenness does not grow above a certain level, despite the fact that the capital shows growth.

4.3 Price Heterogeneity

Our next experiment consists in relaxing the assumption of expected gross profit (α)uniformly across firms. We will sort a number between 0.1 and 0.2 from a uniform distribution for each firm, and this parameter will be fixed across time. The parameters

values are described in Table 11.Once a bank makes price discrimination [1], we expect a higher interest rate for firms with a high α value.

Parameter	Description	Value
h	Environment precision	∞
$\bar{h}$	Idiosyncratic signal noise	0
κ	Propensity to consult parameter	0
α^{min}	Expected gross profit	0.1
α^{max}	Expected gross profit	0.2

Table 11 – Parameters for Price Heterogeneity

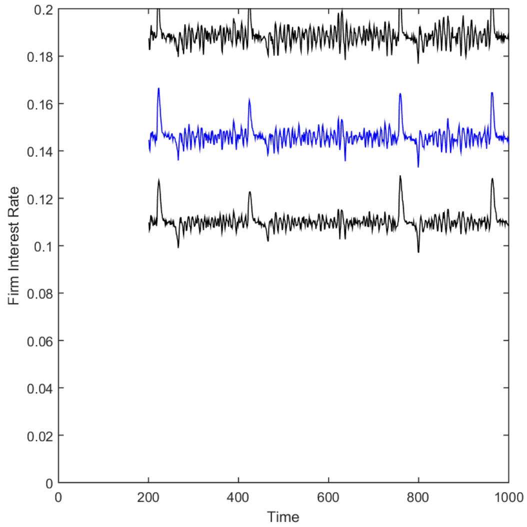
Considering the steady state, as Table 12 shows, we have an increasing interest rate for higher α values, hence, high leverage, once price is constant.

α value	Interest Rate (mean)	Leverage (mean)
[0.1,0.11)	0.1017	5.2523
[0.11,0.12)	0.1085	5.6180
[0.12,0.13)	0.1192	6.1854
[0.13,0.14)	0.1280	6.6522
[0.14,0.15)	0.1376	7.1532
[0.15,0.16)	0.1469	7.6385
[0.16,0.17)	0.1568	8.1522
[0.17,0.18)	0.1668	8.6734
[0.18,0.19)	0.1758	9.1433
[0.19,0.2]	0.1878	9.7721

Table 12 – Average interest rate and Leverage for α intervals, at steady state

However, when we look at an environment where price isn't constant, this price discrimination disappears, and the interest rate stays at a level that is close to the one found in Table 9, where the effect of price heterogeneity is nonexistent. Figure 14, shows the interest rate average and percentiles at steady state on the left chart, and Figure 14 the interest rate average as in the original model on the right chart.

[1] To set firm's interest rate, bank use the leverage from firm, according to Equation 3.12



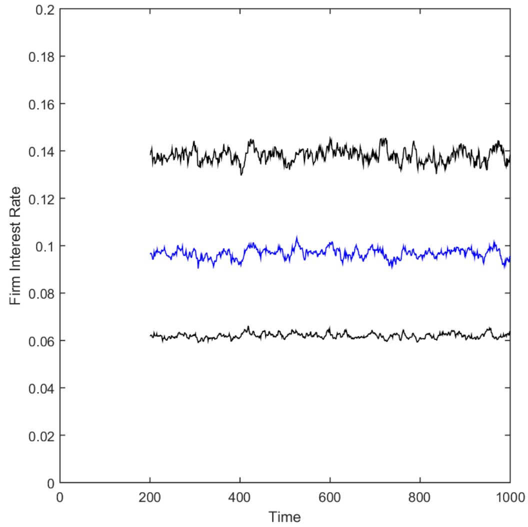


Figure 14 – Steady state interest rate over time on the left and original model interest rate on the right.The black lines are the percentiles 10th and 90th, and the blue line is mean.

In other words, when prices are determined by a stochastic process, interest rates exhibit a lower level than in an environment with fixed prices. This occurs because firms with high values of α have a lower life expectancy. While a firm with α in the range of 0.1 has an expectancy of 175 time spans in average, one with α greater than 0.19 has the expectancy of only 46.95 time spans.

interval	Time Spans
[0.1,0.11)	174.06
[0.11,0.12)	154.83
[0.12,0.13)	110.41
[0.13,0.14)	85.29
[0.14,0.15)	68.74
[0.15,0.16)	63.84
[0.16,0.17)	57.09
[0.17,0.18)	52.81
[0.18,0.19)	49.76
[0.19,0.2)	46.95

Table 13 – Firm's average life for α value interval.

A firm's life expectancy decreases as α gets higher because with high prices, the firm will raise leverage, and once leverage is high, there is an increase in the fragility of the firm. Figure 15 shows the relationship between leverage and price. This relationship isn't linear, firms with low α have lower leverage, with low dispersion while firms with α (and consequently high prices), have a great dispersion in leverage (light blue in picture).

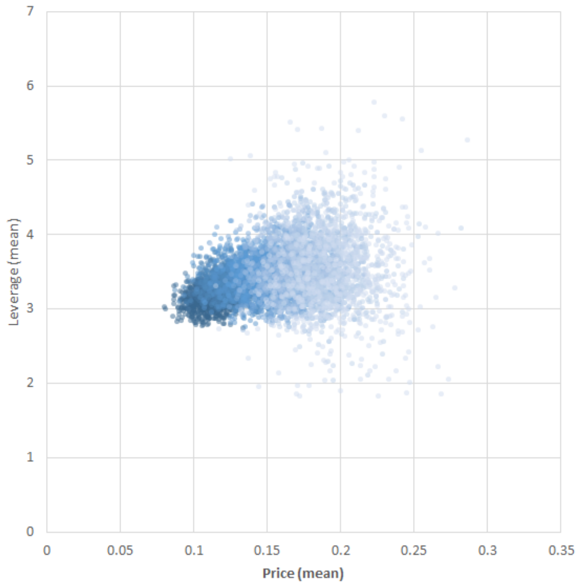


Figure 15 – Relationship between Firm's leverage and price. Each dot is an Firm at time t over iterations, and the weaker the shade of blue, the greater the α value.

4.4 Full model

The last experiment is the analysis of the three mechanisms acting simultaneously. For this, we considered parameters from Table 14.

Parameter	Description	Value
h	Environment precision	1
$\bar{h}$	Idiosyncratic signal noise	1
κ	Propensity to consult parameter	0.2
α^{min}	Expected gross profit	0.1
α^{max}	Expected gross profit	0.2

Table 14 – Parameters for all mechanisms simultaneously

For firms, when comparing this configuration with results from the original model, leverage and interest rate exhibit the same characteristics. These results were expected because, as explained in the previous sections, not all of our improvements have a real effect on firms. The only one that has is price heterogeneity, where for the interest rate there was a function of parameter α, but only in the particular configuration of steady state.

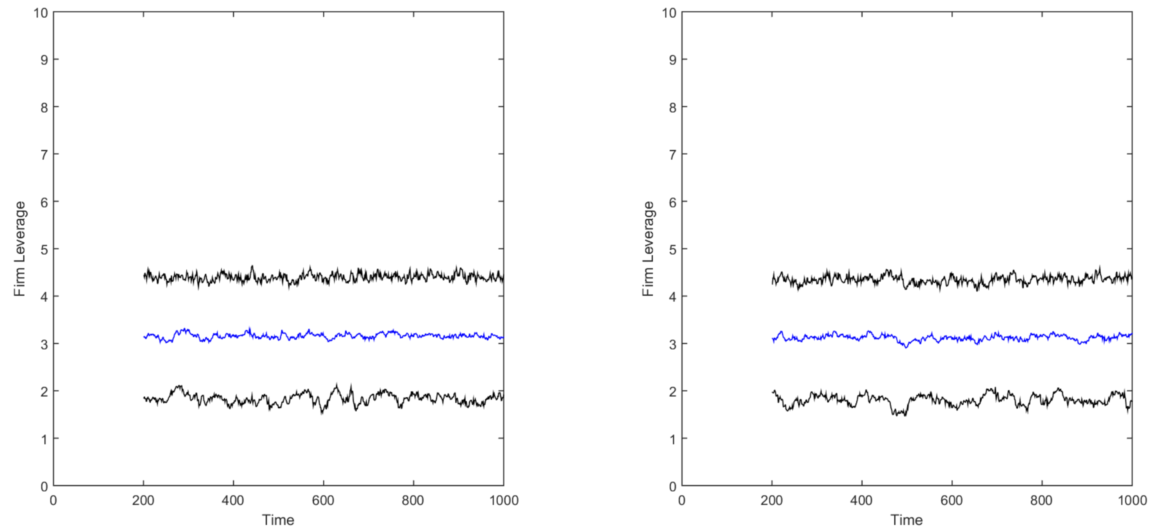


Figure 16 – Firm's Leverage over time from original model on the left, and with all mechanisms on the right. The black lines are the percentiles 10th and 90th, and the blue line is mean.

Figure 16 shows the leverage distribution for firms in the original model on the left and in our modified environment on the right, respectively. As for the interest rate, results can be seen in Figure 17.

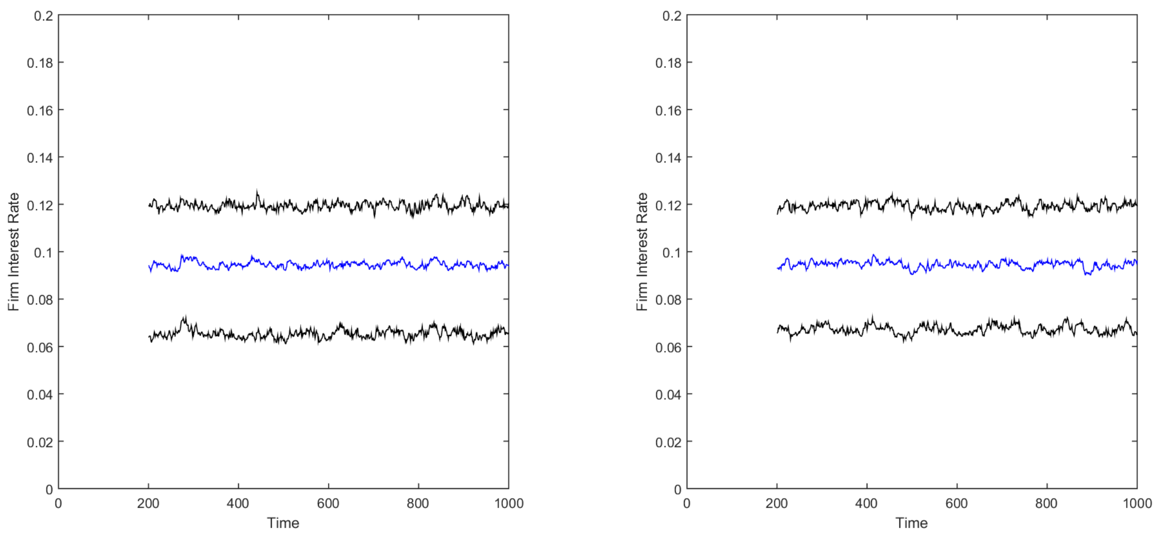


Figure 17 – Firm's price over time from original model on the left, and with all mechanisms on the right. The black lines are the percentiles 10th and 90th, and the blue line is mean.

Looking for banks, despite the effect of concentration of banks that came from our mechanism of selection based on bank's size, we can observe an process of concentration slower then observed on the original model, Figure 18 on the left, and Figure 18 on the

right, where the blue line, bank's mean equity decreases over time contrary to what occurs in the original model, and the 90th percentile maintain at same level.

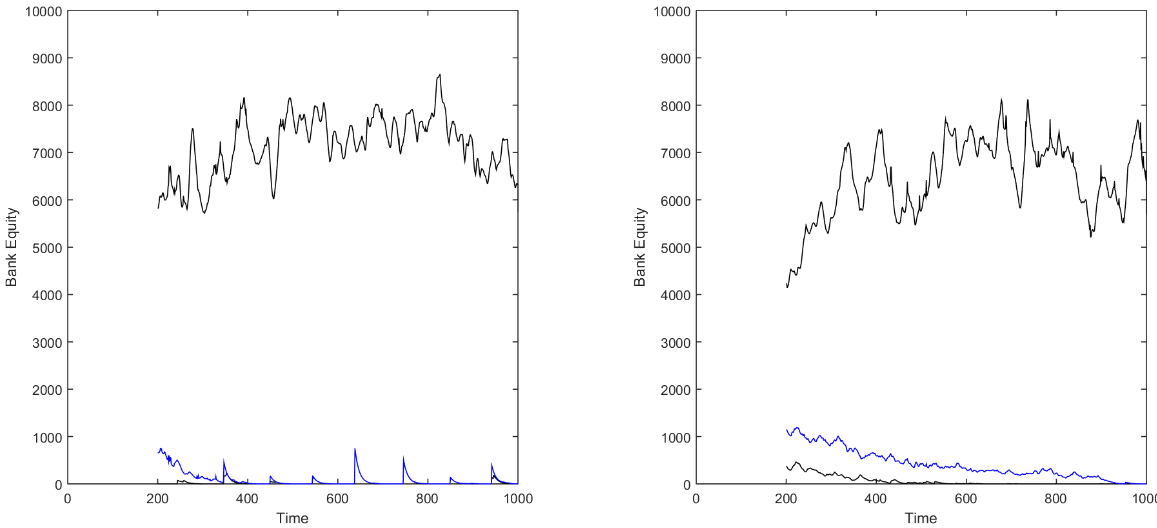


Figure 18 – Bank's equity over time from original model on the left, and with all mechanisms on the right. The black lines are the percentiles 10th and 90th, and the blue line is mean.

Another difference is the expected profit for banks. As a result of the changes we've made, which can be seen in Table 15, banks have an average profit closer to zero than what is perceived in the original model. This is derived basically from the relationship mechanism, which makes the portfolios of banks more stable over time, without entries and exits.

	Original Model	Full Model
Mean	-2.116	-0.084
Standard Error	8.130	6.974

Table 15 – Comparative between interest rate with or without relationship banking

As for the definition of interest rates by banks, it is apparent that the bigger the bank, the lower the intrinsic component of the interest rate, Equation 3.11, therefore, a bank will only lose a borrower to another bank if it is smaller or if the borrower has a greater previous relationship with the other bank, which will result in a better estimation of the risk of the firm, Equation 3.12.

The four images below compare the network from the original model and our full model in two different moments in time. Red dots represent banks and the blue ones are firms, as to the size their equities. In the first two, Figure 19 we can observe more concentration in the original model than in our model, where there are small banks that

maintain relationships with firms. As discussed above, our model tends to concentrate too, but in a lower degree than the original model. With $t = 1000$, Figure 20, the network density for the original model is closer than at t = 500. In our model, however, we can see the emergence of one large bank, on the right chart.

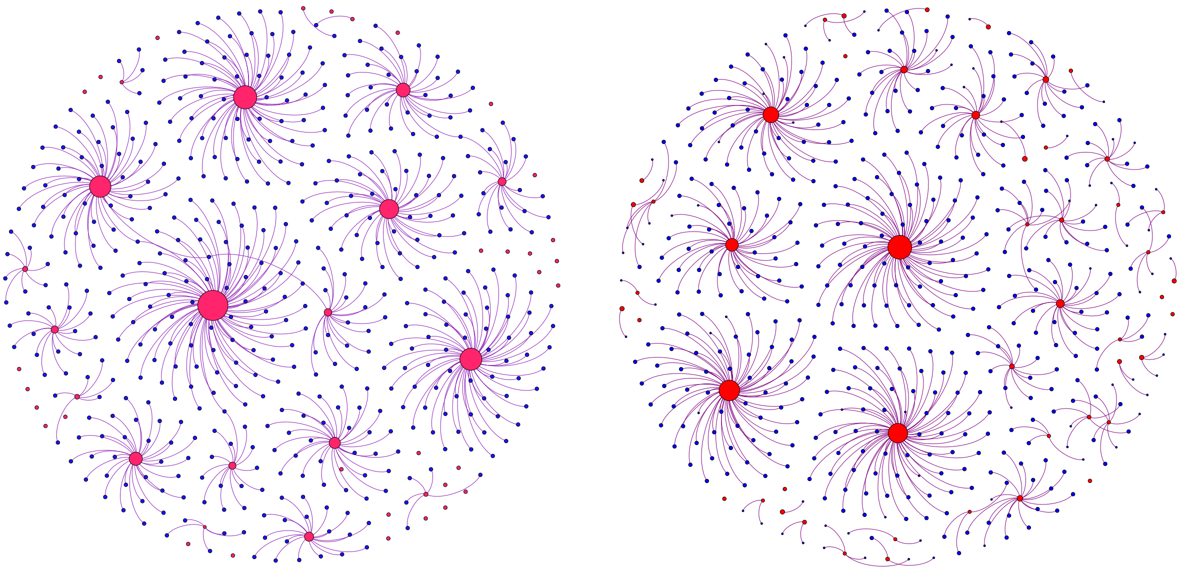


Figure 19 – Network configuration at $t = 500$, original model on the left and the full model on the right. Red dots are banks, blue dots are firms. The dot's size is proportional to agent equities.

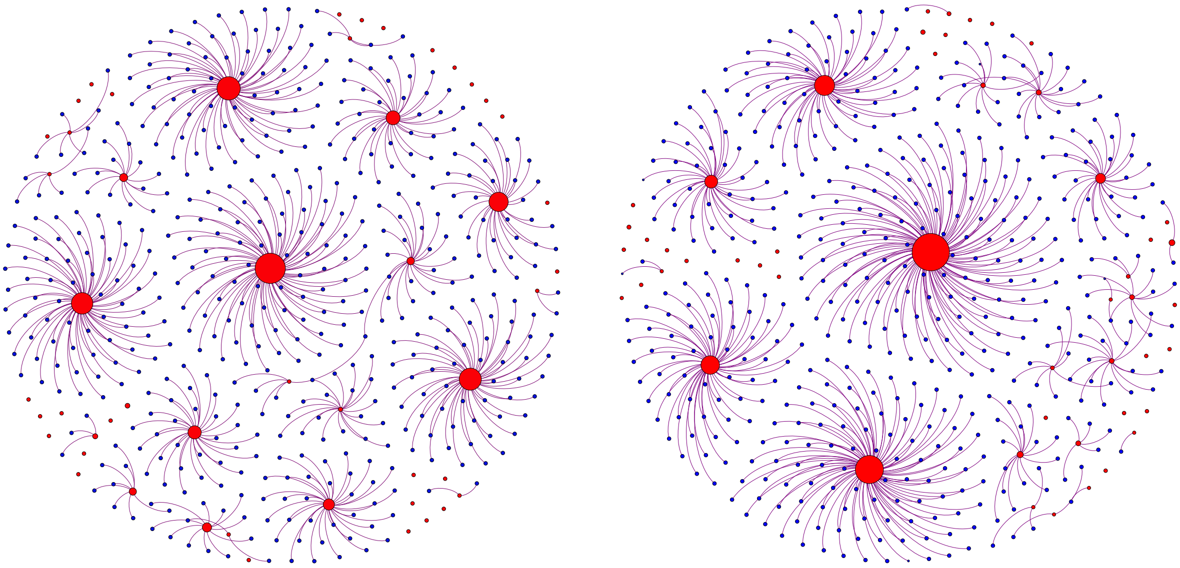


Figure 20 – Network configuration at $t = 1000$, original model on the left and the full model on the right. Red dots are banks, blue dots are firms. The dot's size is proportional to agent equities.

5 Conclusion

In this paper, we bring an contribution to Russo et al. (2014) model, including an mechanism to study relationship banking and analyzing the effects of heterogeneity in the credit market and price heterogeneity that firm's faces in the goods market.

The relationship banking mechanism has an effect related to banks maintain their costumers, once previously relationship increases the mutual benefits between banks and firms, as stated by theory. For firms, a lower interest rate, and for banks portfolio stability. This effect is best understood without price's exogenous randomness at goods market (steady state), having an effect of maintenance of bank's equity, without competition between them.

For credit market heterogeneity scenario, higher the parameter κ, lower the probability of small banks be selected to be asked for loans. This mechanism alone leads to a monopoly situation, where only one bank takes over all the market, killing the others. The main reason for this characteristic is that we have a decreasing relationship between bank 's equity and interest rate. So, as the monopolistic grows, lower the interest rate offered in new loans.

Our last simulation, including price heterogeneity for firms in the goods market, has an effect of heterogeneity of interest rate, in another words, banks has the ability of capture the surplus of firm's profit. But this only occurs at steady state, where prices are fixed. When we include the price's variance, this effect disappears because firms with favorable prices structure will increase the leverage, and high leverage decrease firm's life expectancy.

Bibliography

ACEMOGLU, D.; BIMPIKIS, K.; OZDAGLAR, A. Dynamics of information exchange in endogenous social networks. *Theoretical Economics*, Wiley Online Library, v. 9, n. 1, p. 41–97, 2014. Cited at page 27.

ALMEIDA, H.; CAMPELLO, M.; LARANJEIRA, B. *Corporate debt maturity and the real effects of the 2007 credit crisis*. [S.l.], 2011. 3-58 p. Cited at page 31.

ANDERSON, P. W. More is different. *Science*, v. 177, n. 4047, p. 393–396, 1972. Cited at page 15.

ARTHUR, W. B. Complexity economics: a different framework for economic thought. *Complexity Economics, Oxford University Press (forthcoming)*, 2013. Cited at page 14.

BASEL II: International Convergence of Capital Measurement and Capital Standards: a Revised Framework. Bank for International Settlements, 1987. Cited at page 28.

BERLIN, M.; MESTER, L. J. Deposits and relationship lending. *Review of Financial Studies*, Soc Financial Studies, v. 12, n. 3, p. 579–607, 1999. Cited at page 20.

BOOT, A. W. Relationship banking: What do we know? *Journal of Financial Intermediation*, v. 9, n. 1, p. 7 – 25, 2000. ISSN 1042-9573. Cited 2 times at page 20 and 26.

BOOT, A. W.; THAKOR, A. V. Financial system architecture. *Review of Financial studies*, Soc Financial Studies, v. 10, n. 3, p. 693–733, 1997. Cited at page 20.

COX, B. J. Object oriented programming. Addison-Wesley, Reading, MA, 1985. Cited at page 17.

EPSTEIN, J. M.; AXTELL, R. *Growing Artificial Societies: Social Science from the Bottom Up*. [S.l.]: The MIT Press, 1996. Cited at page 16.

FRANK, M. Z.; GOYAL, V. K. Chapter 12 - trade-off and pecking order theories of debt*. In: ECKBO, B. E. (Ed.). *Handbook of Empirical Corporate Finance*. San Diego: Elsevier, 2008, (Handbooks in Finance). p. 135 – 202. Cited at page 24.

GAMBACORTA, L. How do banks set interest rates? *European Economic Review*, v. 52, n. 5, p. 792 – 819, 2008. ISSN 0014-2921. Cited at page 26.

GATTI, D. D. et al. Business fluctuations and bankruptcy avalanches in an evolving network economy. *Journal of Economic Interaction and Coordination*, Springer-Verlag, v. 4, p. 195–212, 2009. Cited at page 26.

GATTI, D. D. et al. The financial accelerator in an evolving credit network. *Journal of Economic Dynamics and Control*, v. 34, n. 9, p. 1627 – 1650, 2010. ISSN 0165-1889. Computational perspectives in economics and finance: Methods,dynamic analysis and policy modeling. Cited 3 times at page 22, 23, and 30.

GREENWALD, B. C.; STIGLITZ, J. E. Financial Market Imperfections and Business Cycles. *The Quarterly Journal of Economics*, v. 108, n. 1, p. 77–114, February 1993. Cited at page 23.

JACKSON, M. O. *Social and economic networks*. [S.l.]: Princeton University Press Princeton, 2008. v. 3. Cited at page 18.

JENSEN, W. H. M. M. C. Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, v. 3, n. 4, 1976. Cited at page 24.

JONES, R. *Reductionism: Analysis and the Fullness of Reality*. [S.l.]: Bucknell University Press, 2000. ISBN 9780838754399. Cited at page 15.

JR., E. S. G. Exponential smoothing: The state of the art—part {II}. *International Journal of Forecasting*, v. 22, n. 4, p. 637 – 666, 2006. Cited at page 24.

KASHYAP, A. K.; STEIN, J. C. What do a million observations on banks say about the transmission of monetary policy? *American Economic Review*, JSTOR, p. 407–428, 2000. Cited at page 26.

LI, T.-Y.; YORKE, J. A. Period three implies chaos. *The American Mathematical Monthly*, Mathematical Association of America, v. 82, n. 10, p. pp. 985–992, 1975. ISSN 00029890. Cited at page 15.

MAY, R. M. et al. Simple mathematical models with very complicated dynamics. *Nature*, London, v. 261, n. 5560, p. 459–467, 1976. Cited at page 15.

MILGRAM, S. The small world problem. *Psychology today*, New York, v. 2, n. 1, p. 60–67, 1967. Cited at page 19.

MITCHELL, M. *Complexity : a guided tour*. [S.l.]: Oxford University Press, 2009. Cited at page 15.

MYERS, S. C. Determinants of corporate borrowing. *Journal of Financial Economics*, v. 5, n. 2, p. 147–175, 1977. Cited at page 24.

NEWMAN, M. Models of the small world. *Journal of Statistical Physics*, Kluwer Academic Publishers-Plenum Publishers, v. 101, n. 3-4, p. 819–841, 2000. Cited at page 19.

ORCUTT, G. H. A new type of socio-economic system. *The Review of Economics and Statistics*, The MIT Press, v. 39, n. 2, p. pp. 116–123, 1957. ISSN 00346535. Cited at page 16.

PETERSEN, M. A. *Information: Hard and Soft*. 2004. Cited at page 21.

RICCETTI, L.; RUSSO, A.; GALLEGATI, M. *Leveraged Network-Based Financial Accelerator*. [S.l.], 2011. Cited at page 33.

RICCETTI, L.; RUSSO, A.; GALLEGATI, M. Leveraged network-based financial accelerator. *Journal of Economic Dynamics and Control*, v. 37, n. 8, p. 1626 – 1640, 2013. Rethinking Economic Policies in a Landscape of Heterogeneous Agents. Cited 2 times at page 23 and 25.

RUSSO, A. et al. Network analysis and calibration of the "leveraged network-based financial accelerator". *Journal of Economic Behavior and Organization*, v. 99, p. 109 – 125, 2014. Cited 11 times at page 6, 7, 13, 22, 26, 27, 29, 33, 35, 39, and 49.

SCHUMPETER, J. A. *Capitalism, socialism, and democracy*. New York: Routledge, 1942. Cited at page 15.

SHACKLE, G. L. S. *Epistemics and economics*. [S.l.]: transaction publishers, 1992. Cited at page 14.

SHANNON, C. E. A mathematical theory of communication. *The bell system technical journal*, v. 27, n. 1, p. 379–423, 1948. Cited at page 15.

TESFATSION, L. Agent-based computational economics: A constructive approach to economic theory. *Handbook of computational economics*, Elsevier, v. 2, p. 831–880, 2006. Cited 2 times at page 16 and 17.

TRAVERS, J.; MILGRAM, S. An experimental study of the small world problem. In: LEINHARDT, S. (Ed.). *Social Networks*. [S.l.]: Academic Press, 1977. p. 425 – 443. ISBN 978-0-12-442450-0. Cited at page 19.

WALRAS, L. *Elements of Pure Economics: Or the Theory of Social Wealth*. [S.l.]: Routledge, 1877. (Elements of Pure Economics, Or the Theory of Social Wealth). ISBN 9780415313407. Cited at page 16.

WATTS, D. J. *Small worlds: the dynamics of networks between order and randomness*. [S.l.]: Princeton university press, 1999. Cited at page 19.

WOLFRAM, S. Universality and complexity in cellular automata. *Physica D: Nonlinear Phenomena*, Elsevier, v. 10, n. 1, p. 1–35, 1984. Cited at page 16.

6 Annex

6.1 Model Code

Here we provide the three main codes of our model.

6.1.1 Environment Code

```
%------------------------------------------------------------------------%
%  Bank networks and firm credit: an agent based model approach
%  Henrique Teixeira
%  Jun/2015
%------------------------------------------------------------------------%
%  Definition...: Base model: Riccetti(2013) model
%------------------------------------------------------------------------%


%% Options
format long %Bank %shortG
clear;

%% Parameters
%->Firms
v_Params.f_qtt = 500;
v_Params.f_start_networth = 10;
v_Params.f_productivity = 3;
v_Params.f_elasticity = 0.7;
v_Params.f_leverage_adjust = 0.1;
v_Params.f_assimetry_banks = 0.1;
v_Params.f_legal_expediture = 0.1;

%->Banks
v_Params.b_qtt = 50;
v_Params.b_start_networth = 10;
v_Params.b_capital_coef = 0.05;
v_Params.b_reserve_coef = 0.05;
v_Params.b_risk_premium = 0.02;
v_Params.b_operational_cost = 0.1;

%->Environment
v_Params.central_bank_rate = 0.02;
v_Params.price_alpha_min = 0.1;
v_Params.price_alpha_max = 0.2;
v_Params.price_mu = 0;
v_Params.price_sigma = 0.1;
v_Params.price_smooth = 0.5;

v_Params.h = 0.000000001;
v_Params.h_bar = 100000000;
v_Params.bank_propensity = 0.2;
v_Params.time = 1000;
v_Params.t = 0;
```

```
v_Params.time_now = datestr(now,'yyyy-mm-dd_HH-MM-SS');

%->Variables
t0_Bad_Rate = 0;
v_Params.NWmax = v_Params.f_start_networth;
v_Params.agregate_BR = 0;
v_Params.h_agregate_BR = [];
v_Params.Firm_percentile = 0;
v_Params.Banks_percentile = 0;

v_Hist.Output = 0;
v_Hist.Firm_Profit = 0;
v_Hist.Firm_Capital = 0;
v_Hist.Firm_NetWorth = 0;
v_Hist.Firm_Loans = 0;
v_Hist.Bank_NetWorth = 0;
v_Hist.Bank_Profit = 0;
v_Hist.Bank_Deposits = 0;
v_Hist.Bank_Loans = 0;
v_Hist.Bank_Loans_Revenue = 0;
v_Hist.Bank_Bad_Loans = 0;
v_Hist.elapsed = [];
v_Hist.new_firms = 0;
v_Hist.new_banks = 0;



%->Random Seed
v_Params.seed = 50;
v_Params.aleat = RandStream('mt19937ar','Seed',v_Params.seed);
RandStream.setGlobalStream(v_Params.aleat);


%% [Start Firms]
tic; disp('[Step...: 01] - Start Firms');
for n = 1:v_Params.f_qtt
    v_Firms(n) = Firms(n, v_Params);
end
toc;

%% [Start Banks]
tic; disp('[Step...: 02] - Start Banks');
 for n = 1:v_Params.b_qtt
     v_Banks(n) = Banks(n, v_Params);
 end
toc;

%% [Time Loop]
tic; disp('[Step...: 03] - Iterations');
for t = 1:v_Params.time
    v_Params.t = t;

    %% [Replace dead Banks]
    Active_Banks = (Property_List(v_Banks, 'Id','List'))';
    new_banks = (v_Params.b_qtt-length(Active_Banks));
    v_Hist.new_banks = cat(1,v_Hist.new_banks,new_banks);
    if new_banks > 0
        v_Banks = Replace_Bank(v_Banks,v_Params,new_banks);
    end
```

```
%% [Replace Dead Firms]
Active_Firms = (Property_List(v_Firms, 'Id','List'))';
new_firms = (v_Params.f_qtt-length(Active_Firms));
v_Hist.new_firms = cat(1,v_Hist.new_firms,new_firms);
if new_firms > 0
    v_Firms = Replace_Firm(v_Firms,v_Params,new_firms);
end

%% [List of Active Banks/Firms]
Active_Banks = (Property_List(v_Banks, 'Id','List'))';
Active_Firms = (Property_List(v_Firms, 'Id','List'))';

%% [Scramble active Firms]
Active_Firms_Scramble=Active_Firms(randperm(length(Active_Firms)));

%% [Bigger Net Worth at time t]
v_Params.NWmax = max((Property_List(v_Firms, 't0_NetWorth','List')));

%% [Banks propensity to be selected]
Banks_Propensity = b_Comp_Propensity(Active_Banks,v_Banks, v_Params);

%% [Firms Loop]
for n = 1:length(Active_Firms);

    % Select one Firm
    Order = Active_Firms_Scramble(n,1);
    %Order = Active_Firms(n,1);

    % Take price at time t
    f_Take_Price(v_Firms(Order), v_Params);

    % Compute price expectation - by smooth process
    f_Take_Price_Smooth(v_Firms(Order), v_Params);

    % Compute leverage target
    f_Comp_Leverage_Target(v_Firms(Order), v_Params);

    % Compute Loans target
    f_Comp_Loan_Target(v_Firms(Order),v_Params);

    % Take an Loan
    f_Take_Loan(v_Firms(Order), v_Banks, Active_Banks, v_Params, Banks_Propensity);

    % Compute firms capital at time t (NetWorth + Loans)
    f_Comp_Capital(v_Firms(Order),v_Params);

    % Firms Output
    f_Comp_Output(v_Firms(Order), v_Params);

    % Firms Profit
    f_Comp_Profit(v_Firms(Order),v_Params);

    %Firms NetWorth
    f_Comp_NetWorth(v_Firms(Order), v_Params);

    % Store previously interest rate
    v_Firms(Order).t1_Interest = v_Firms(Order).t0_Interest;
end

%% [Banks Loop]
```

```
    for n = 1:length(Active_Banks)
        % Select one Bank
        Order = Active_Banks(n,1);

        % Compute Loans portfolio
        b_Comp_Loans(v_Banks(Order), v_Firms, Active_Firms, v_Params);

        % Compute bank profit
        b_Comp_Profit(v_Banks(Order), v_Params);

        % Compute NetWorth
        b_Comp_NetWorth(v_Banks(Order), v_Params);

        % Store previously variables
        b_Ends_t(v_Banks(Order), v_Params);
    end

    %% [Compute the agregate bad loans]
    v_Params.agregate_BR = b_Comp_Agregate_BR(v_Banks);
    v_Params.h_agregate_BR = cat(1,v_Params.h_agregate_BR,v_Params.agregate_BR);

    v_Params.Firm_percentile = prctile(Property_List(v_Firms, 't0_NetWorth','List'),25);
    v_Params.Banks_percentile = prctile(Property_List(v_Banks, 't0_NetWorth','List'),25);

    %% [Consolidate Variables]
    v_Hist.Output          = cat(1,v_Hist.Output,        Property_Sum(v_Firms, 't0_Output'));
    v_Hist.Firm_Profit     = cat(1,v_Hist.Firm_Profit,   Property_Sum(v_Firms, 't0_Profit'));
    v_Hist.Firm_Capital    = cat(1,v_Hist.Firm_Capital,  Property_Sum(v_Firms, 't0_Capital'));
    v_Hist.Firm_NetWorth   = cat(1,v_Hist.Firm_NetWorth, Property_Sum(v_Firms, 't0_NetWorth'));
    v_Hist.Firm_Loans      = cat(1,v_Hist.Firm_Loans,    Property_Sum(v_Firms, 't0_Loan'));

    v_Hist.Bank_Profit     = cat(1,v_Hist.Bank_Profit,   Property_Sum(v_Banks, 't0_Profit'));
    v_Hist.Bank_NetWorth   = cat(1,v_Hist.Bank_NetWorth, Property_Sum(v_Banks, 't0_NetWorth'));
    v_Hist.Bank_Deposits   = cat(1,v_Hist.Bank_Deposits, Property_Sum(v_Banks, 't0_Deposits'));
    v_Hist.Bank_Loans      = cat(1,v_Hist.Bank_Loans,    Property_Sum(v_Banks, 't1_Loans'));
    v_Hist.Bank_Bad_Loans = cat(1,v_Hist.Bank_Bad_Loans,Property_Sum(v_Banks, ...
        't0_Bad_Loans'));
    v_Hist.Bank_Loans_Revenue    = cat(1,v_Hist.Bank_Loans_Revenue,  Property_Sum(v_Banks, ...
        't0_Loans_Revenue'));

    %% [Time Counter]
    elapsed = toc;
    v_Hist.elapsed = cat(1, v_Hist.elapsed, elapsed);
    fprintf('Iteraction: %5.0f of %5.0f (%5.2f%%) = Elapsed - %8.7f sec = Remaining: %6.2f ...
        sec \n', v_Params.t, v_Params.time, 100*(v_Params.t/v_Params.time) , elapsed, ...
        (mean(v_Hist.elapsed)*(v_Params.time-v_Params.t))); tic
end

%% [Results]
%Export_Full
%Export_Graficos
%Export_Gephi
```

6.1.2 Firms Class Code

```
%% ------------------------------------------------------------------------%
%  Bank networks and firm credit: an agent based model approach
```

```
%  Henrique Teixeira
%  Jun/2015
%-------------------------------------------------------------------------%
classdef Firms < handle

    %% [Properties]
    properties (SetAccess = public)
        %t0 = Current
        %t1 = Previously
        % h = Historic
        %-- Control Variables / General --
        Id;
        Status = 1; %.Firm Status (1=Active, 2=Bankruptcy)
        Birth = 0;  %.Time of Birth
        Death = 0;  %.Time of Death
        Price_Alpha = 0; %Specific Price Alpha

        %-- Loans Book, register all variables relative of Loans --
        Book_Loans;

        %-- Firm NetWorth --
        t1_NetWorth = 0
        t0_NetWorth = 0
        h_NetWorth;

        %-- Firm Output, Firm's Production --
        t1_Output = 0;
        t0_Output = 0;
        h_Output;

        %-- Firm Capital, sum of NetWorth and Loans --
        t1_Capital = 0;
        t0_Capital = 0;
        h_Capital;

        %-- Firm Target Leverage --
        t1_Leverage_Target = 0;
        t0_Leverage_Target = 0;
        h_Leverage_Target;

         %-- Loans Target--
        t1_Loan_Target = 0;
        t0_Loan_Target = 0;
        h_Loan_Target;

        %-- Loans --
        t1_Loan = 0;
        t0_Loan = 0;
        h_Loan;

        %-- Lender --
        t1_Lender = 0;
        t0_Lender = 0;
        h_Lender;

        %-- Firm Profit, Revenues minus Costs --
        t1_Cost = 0;
        t0_Cost = 0;
        h_Cost;
```

```
        %-- Firm Profit, Revenues minus Costs --
        t1_Profit = 0;
        t0_Profit = 0;
        h_Profit;

        %-- Firm Price, exogenous and stochastic--
        t1_Price = 0;
        t0_Price = 0;
        h_Price;

        %-- Firm Price, exogenous and stochastic--
        t1_Price_Smooth = 0;
        t0_Price_Smooth = 0;
        h_Price_Smooth;

        %-- Firm Interest Rate--
        t1_Interest = 0;
        t0_Interest = 0;
        h_Interest;
    end

    %% [Methods]
    methods

        %% [Firms]
        %Objective..: Create Firms Instances
        function Obj = Firms(Id, v_Params)
            Obj.Id = Id;
            Obj.Birth = v_Params.t;

            % In the begining, firms will start with the same NetWorth
            if v_Params.t == 0
                Obj.t0_NetWorth = v_Params.f_start_networth;
            else
                % In the middle of simulation, firms will start with a
                % NetWorth with uniform distribution (0,1)
                Obj.t0_NetWorth = v_Params.Firm_percentile;
            end
            Obj.Price_Alpha = (v_Params.price_alpha_max - v_Params.price_alpha_min)*...
                              rand + v_Params.price_alpha_min;
            Obj.t0_Leverage_Target = 1;
            Obj.t0_Capital = Obj.t0_NetWorth + Obj.t0_Loan + Obj.t1_Loan;
            Obj.t0_Output = v_Params.f_productivity*(Obj.t0_Capital^v_Params.f_elasticity);
        end

        %% [f_Comp_Capital]
        %Objective..: Compute Firm's Capital
        function f_Comp_Capital(Obj, v_Params)
            %[1] Save the previoysly value
            Obj.t1_Capital = Obj.t0_Capital;

            %[2] Compute the new one
            Obj.t0_Capital = Obj.t0_NetWorth + Obj.t0_Loan + Obj.t1_Loan;

            a(1,1) = Obj.t0_Capital;
            a(1,2) = v_Params.t;
            %[3] Store the new value
            Obj.h_Capital = cat(1,Obj.h_Capital,a);
        end
```

```
%% [f_Comp_Output]
%Objective..: Compute Firm's Output
function f_Comp_Output(Obj, v_Params)
    %[1] Save the previoysly value
    Obj.t1_Output = Obj.t0_Output;

    %[2] Compute the new one
    Obj.t0_Output = v_Params.f_productivity*(Obj.t0_Capital^v_Params.f_elasticity);

    a(1,1) = Obj.t0_Output;
    a(1,2) = v_Params.t;
    %[3] Store the new value
    Obj.h_Output = cat(1,Obj.h_Output,a);
end

%% [f_Comp_Leverage_Target]
%Objective..: Compute Firm's Leverage
function f_Comp_Leverage_Target(Obj,v_Params)
    %[1] Save the previoysly value
    Obj.t1_Leverage_Target = Obj.t0_Leverage_Target;

    %[2] Compute the new one
    % If price expectation is greather then interest, then the firm
    % increase their leverage, else decrease
    if Obj.t0_Price_Smooth >= Obj.t1_Interest
        Obj.t0_Leverage_Target = Obj.t1_Leverage_Target*...
                                 (1+v_Params.f_leverage_adjust*rand);
    else
        Obj.t0_Leverage_Target = Obj.t1_Leverage_Target*...
                                 (1-v_Params.f_leverage_adjust*rand);
    end

    a(1,1) = Obj.t0_Leverage_Target;
    a(1,2) = v_Params.t;
    %[3] Store the new value
    Obj.h_Leverage_Target = cat(1,Obj.h_Leverage_Target,a);
end

%% [f_Comp_Loan_Target]
%Objective..: Compute Firm's Loan Target
function f_Comp_Loan_Target(Obj,v_Params)
    %[1] Save the previoysly value
    Obj.t1_Loan_Target = Obj.t0_Loan_Target;

    %[2] Compute the new one
    Obj.t0_Loan_Target = Obj.t0_NetWorth * Obj.t0_Leverage_Target;

    a(1,1) = Obj.t0_Loan_Target;
    a(1,2) = v_Params.t;
    %[3] Store the new value
    Obj.h_Loan_Target = cat(1,Obj.h_Loan_Target,a);
end

%% [f_Take_Loan]
%Objective..: Firm's taking loan in the credit market
function f_Take_Loan(Obj, Banks, Active_Banks, v_Params, Banks_Propensity)
    %[1] Save the previoysly value
    Obj.t1_Loan = Obj.t0_Loan;
    Obj.t1_Interest = Obj.t0_Interest;
    Obj.t1_Lender = Obj.t0_Lender;
```

```
%Compute the Loan value
Obj.t0_Loan = max(0, Obj.t0_Loan_Target - Obj.t1_Loan);

%If the Firms need a new Loan
if Obj.t0_Loan > 0

    %Number of banks to consult, cannot be less then 1.
    Number_Banks = max(floor(length(Active_Banks)*v_Params.f_assimetry_banks), 1);

    %Random weighted sample with size "Number_Banks"
    Set_Banks = datasample(Active_Banks, ...
                           Number_Banks, ...
                           'Replace',false,...
                           'Weights',Banks_Propensity(:,2));

    %Return the Interest rate for the consulted banks.
    for i = 1:Number_Banks;
        Set_Banks(i,2) = b_Return_Interest_Rate(Banks(Set_Banks(i,1)),...
                                                 Obj,...
                                                 v_Params);
    end;

    %Consult the interest rate from the previously lender,
    %if he still alive
    if Obj.t1_Lender ~= 0 && Banks(Obj.t1_Lender).Status == 1
        Old_Int = b_Return_Interest_Rate(Banks(Obj.t1_Lender),...
                                          Obj,...
                                          v_Params);
    else
        Old_Int = 999;
    end

    %Propensity to change.
    for i = 1:Number_Banks;
        %If the interest rate from the consulted bank is
        %less then the interest from the last lender, then
        %has a probability to change to the new one.
        if Set_Banks(i,2) < Old_Int
            Set_Banks(i,3) = 1 - exp((Set_Banks(i,2)-Old_Int)/Set_Banks(i,2));
            Set_Banks(i,4) = rand;
        else
            Set_Banks(i,3) = 999;
            Set_Banks(i,4) = 0;
        end
    end;

    %Flag if Propensity greater then random number
    Set_Banks(:,5) = (Set_Banks(:,3) > Set_Banks(:,4)) &...
                     Set_Banks(:,3) ~= 999;


    %Sort by banks with greather propensity to change and less
    %interest rate
    Set_Banks = sortrows(Set_Banks,[-5 2]);

    %If any bank has a greater interest rate, then take the
    %older one, if he still alive. Else, take the bank that
    %passed by the propensity to change.
    if max(Set_Banks(:,5)) == 0 && Banks(Obj.t1_Lender).Status == 1
```

```
            Selected = Obj.t1_Lender;
            Int = Old_Int;
        else
            Selected = Set_Banks(1,1);
            Int = Set_Banks(1,2);
        end

        %Set Banks Sample
        % 38 0.15184 0.28056 0.24650 1
        % 28 0.15184 0.28056 0.46639 0
        % 10 0.15184 999     0.00000 0
        % 1  0.15184 999     0.00000 0
        % 2  0.15184 999     0.00000 0

        %Take Loan from the selected bank
        Obj.t0_Lender = Selected;
        Obj.t0_Interest = Int;
        b_Return_Loan(Banks(Selected), ...
                      Obj, ...
                      Obj.t0_Loan, ...
                      Int, ...
                      v_Params)

        %Store values at firms book loans
        Row = size(Obj.Book_Loans,1)+1;
        Obj.Book_Loans(Row,1) = v_Params.t;
        Obj.Book_Loans(Row,2) = Selected;
        Obj.Book_Loans(Row,3) = Obj.t0_Loan;
        Obj.Book_Loans(Row,4) = Int;
    end

    a(1,1) = Obj.t0_Loan;
    a(1,2) = v_Params.t;

    b(1,1) = Obj.t0_Interest;
    b(1,2) = v_Params.t;

    c(1,1) = Obj.t0_Lender;
    c(1,2) = v_Params.t;
    %[3] Store the new value
    Obj.h_Loan = cat(1,Obj.h_Loan,a);
    Obj.h_Interest = cat(1,Obj.h_Interest,b);
    Obj.h_Lender = cat(1,Obj.h_Lender,c);
end

%% [f_Take_Price]
%Objective..: Firm's current price
function f_Take_Price(Obj, v_Params)
    %[1] Save the previoysly value
    Obj.t1_Price = Obj.t0_Price;

    %[2] Compute the new one
    Obj.t0_Price =  max(0,Obj.Price_Alpha + ...
                      normrnd(v_Params.price_mu, v_Params.price_sigma));

    a(1,1) = Obj.t0_Price;
    a(1,2) = v_Params.t;
    %[3] Store the value
    Obj.h_Price = cat(1,Obj.h_Price,a);
end
```

```
%% [f_Take_Price_Smooth]
%Objective..: Firm's current price
function f_Take_Price_Smooth(Obj, v_Params)
    %[1] Save the previoysly value
    Obj.t1_Price_Smooth = Obj.t0_Price_Smooth;

    %[2] Compute the new one
    if v_Params.t == 1
        Obj.t0_Price_Smooth = Obj.t0_Price;
    else
        Obj.t0_Price_Smooth =  v_Params.price_smooth*Obj.t1_Price + ...
                               (1 - v_Params.price_smooth)*Obj.t1_Price_Smooth;
    end

    a(1,1) = Obj.t0_Price_Smooth;
    a(1,2) = v_Params.t;
    %[3] Store the value
    Obj.h_Price_Smooth = cat(1,Obj.h_Price_Smooth,a);
end

%% [f_Comp_Profit]
%Objective..: Compute firm's current profit
function f_Comp_Profit(Obj,v_Params)
    %[1] Save the previoysly value
    Obj.t1_Profit = Obj.t0_Profit;
    Obj.t1_Cost = Obj.t0_Cost;

    %[2] Compute the new one
    Obj.t0_Profit =  Obj.t0_Price*Obj.t0_Output - ...
                     Obj.t0_Interest*Obj.t0_Loan - ...
                     Obj.t1_Interest*Obj.t1_Loan;

    Obj.t0_Cost = Obj.t0_Interest*Obj.t0_Loan + ...
                  Obj.t1_Interest*Obj.t1_Loan;

    a(1,1) = Obj.t0_Profit;
    a(1,2) = v_Params.t;

    b(1,1) = Obj.t0_Cost;
    b(1,2) = v_Params.t;
    %[3] Store the value
    Obj.h_Profit = cat(1,Obj.h_Profit,a);
    Obj.h_Cost = cat(1,Obj.h_Cost,b);
end

%% [f_Comp_NetWorth]
%Objective..: Compute firm's current NetWorth
function f_Comp_NetWorth(Obj, v_Params)
    %[1] Save the previoysly value
    Obj.t1_NetWorth = Obj.t0_NetWorth;

    %[2] Compute the new one
    Obj.t0_NetWorth = Obj.t1_NetWorth + Obj.t0_Profit;

    a(1,1) = Obj.t0_NetWorth;
    a(1,2) = v_Params.t;

    %[3] Store the value
    Obj.h_NetWorth = cat(1,Obj.h_NetWorth,a);
```

```
            if Obj.t0_NetWorth < 0.001
                Obj.Status = 0;
                Obj.Death = v_Params.t;
            end
        end

    end %.Methods
end %.Class
```

6.1.3 Banks Class Code

```
%-------------------------------------------------------------------------%
%  Bank networks and firm credit: an agent based model approach
%  Henrique Teixeira
%  Jun/2015
%-------------------------------------------------------------------------%
classdef Banks < handle

    %% [Properties]
    properties (SetAccess = public)
        %t0 = Current
        %t1 = Previously
        % h = Historic
        Id;
        Status = 1; %.Firm Status (1=Active, 2=Bankruptcy)
        Birth = 0;  %.Time of Birthf
        Death = 0;  %.Time of Death

        %-- Loans Book, register all variables relative of Loans --
        Book_Loans_Out;
        Book_Consults;

        %-- Bank Equity --
        t1_NetWorth = 0
        t0_NetWorth = 0
        h_NetWorth;

        %-- Bank Deposits --
        t0_Deposits = 0
        t1_Deposits = 0;
        h_Deposits;

        %-- Bank Sum_Loans_Revenue --
        t0_Loans_Revenue = 0
        t1_Loans_Revenue = 0;
        h_Loans_Revenue;

        %-- Bank Sum_Loans_Revenue --
        t0_Loans = 0
        t1_Loans = 0;
        h_Loans;
        t0_Sum_Loans;

        %-- Bank Sum_Loans --
        t0_Bad_Loans = 0
        t1_Bad_Loans = 0;
```

```
        h_Bad_Loans;

        %-- Bank Cash --
        t0_Profit = 0
        t1_Profit = 0;
        h_Profit;
    end

    %% [Methods]
    methods
        %% [Banks]
        %Objective..: Create Banks Instances
        function Obj = Banks(Id,v_Params)
            Obj.Id = Id;
            Obj.Birth = v_Params.t;
            if v_Params.t == 0
                Obj.t0_NetWorth = v_Params.b_start_networth;
            else
                Obj.t0_NetWorth = v_Params.Banks_percentile;
            end
            Obj.t0_Deposits = 0;
        end

        %% [b_Return_Interest_Rate]
        %Objective..: Return Interest Rate to firm
        function Interest = b_Return_Interest_Rate(Obj, Firm, v_Params)

            %[1] Compute the new one
            %[f1] - Bank specific component
            f1 = v_Params.b_risk_premium*(Obj.t0_NetWorth^(v_Params.b_risk_premium*(-1)));

            %[f2] - Firms specific component
            if ~isempty(Firm.Book_Loans)
                k = nnz(Firm.Book_Loans(:,2)==Obj.Id);
            else
                k = 0;
            end

            %f2 = ...
                v_Params.b_risk_premium*(Firm.t0_Leverage_Target/(1+(Firm.t0_NetWorth/v_Params.NWmax)));
            f2 = v_Params.b_risk_premium*(...
                Firm.t0_Leverage_Target*(1+(1/(v_Params.h+v_Params.h_bar*k)))/...
                (1+(Firm.t0_NetWorth/v_Params.NWmax)));

            %[2] Store the new value
            Row = size(Obj.Book_Consults,1)+1;
            Obj.Book_Consults(Row,1) = v_Params.t;
            Obj.Book_Consults(Row,2) = Firm.Id;
            Obj.Book_Consults(Row,3) = f1;
            Obj.Book_Consults(Row,4) = f2;
            Obj.Book_Consults(Row,5) = k;

            %[3] Return Value
            Interest = v_Params.central_bank_rate + f1 + f2;
        end

        %% [b_Return_Loan]
        %Objective..: Give Loan to firm
        function b_Return_Loan(Obj, Firm, Value, Interest, v_Params)
            %[3] Compute Loans (Accumule)
```

```
        Obj.t0_Loans = Obj.t0_Loans + Value;

        %[4] Compute Deposits
        Obj.t0_Deposits = max(0,...
                              (Obj.t0_Loans + ...
                               Obj.t1_Loans - ...
                               (1-v_Params.b_capital_coef)*Obj.t0_NetWorth)/ ...
                               (1-v_Params.b_reserve_coef));


        %[2] Store the new value
        Row = size(Obj.Book_Loans_Out,1)+1;
        Obj.Book_Loans_Out(Row,1) = v_Params.t;
        Obj.Book_Loans_Out(Row,2) = Firm.Id;
        Obj.Book_Loans_Out(Row,3) = Value;
        Obj.Book_Loans_Out(Row,4) = Interest;
    end

    %% [b_Comp_Loans]
    %Objective..: Compute loans Portfolio
    function b_Comp_Loans(Obj, Firms, Active_Firms, v_Params)
        %[1] Save the previoysly value
        Obj.t1_Loans_Revenue = Obj.t0_Loans_Revenue;
        Obj.t1_Bad_Loans = Obj.t0_Bad_Loans;
        Obj.t0_Bad_Loans = 0;

        if ~isempty(Obj.Book_Loans_Out)
            % Compute Loans Revenue
            Obj.t0_Loans_Revenue = sum(bsxfun(@times,...
                                                 (Obj.Book_Loans_Out(:,1) == ...
                                                     v_Params.t | ...
                                                     Obj.Book_Loans_Out(:,1) == ...
                                                     (v_Params.t-1)) & ...
                                                     ismember(Obj.Book_Loans_Out(:,2),Active_Firms),...
                                                 bsxfun(@times,...
                                                        Obj.Book_Loans_Out(:,3),...
                                                        Obj.Book_Loans_Out(:,4))));


            % Compute Bad Loans
            %List of lenders
            bad(:,1) = Obj.Book_Loans_Out(:,2);

            %Flag Lenders has a loan from last period and dead now
            bad(:,2) = bsxfun(@times,...
                              Obj.Book_Loans_Out(:,1) == (v_Params.t-1) & ...
                              ~ismember(Obj.Book_Loans_Out(:,2),Active_Firms),...
                              Obj.Book_Loans_Out(:,3));

            %Only where flag not equal 0
            bad = bad((bad(:,2)~=0),:);
            bad(:,3) = 0;
            bad(:,4) = 0;

            %
            bad(length(Obj.t0_Bad_Loans(:,1)),3)=0;
            if max(bad(:,1)) > 0
                for i = 1:length(bad(:,1))
                    %Compute Loss Given Defaults
                    bad(i,3) = max(0, (1-(Firms(bad(i,1)).t1_NetWorth/...
```

```
                                          (Firms(bad(i,1)).t0_Loan + ...
                                              Firms(bad(i,1)).t1_Loan)))*...
                                          (1-v_Params.f_legal_expediture));
                  bad(i,4) = bad(i,2)*bad(i,3);
              end

               Obj.t0_Bad_Loans = sum(bad(:,2));
          end

          %Bad Table Sample
          %Lender Value   LGD     Loss
          %1473   1.78980 0.07946 0.14223
          %1652   0.61290 0.01968 0.01206
          %1659   0.95223 0.04514 0.04299
          %1672   0.46977 0.07567 0.03555
      else
          Obj.t0_Loans_Revenue = 0;
          Obj.t0_Bad_Loans = 0;
      end

      a(1,1) = Obj.t0_Loans_Revenue;
      a(1,2) = v_Params.t;

      b(1,1) = Obj.t0_Bad_Loans;
      b(1,2) = v_Params.t;
      %[3] Store the value
      Obj.h_Loans_Revenue = cat(1,Obj.h_Loans_Revenue,a);
      Obj.h_Bad_Loans = cat(1,Obj.h_Bad_Loans,b);

  end

  %% [b_Comp_Profit]
  %Objective..: Create Banks Instances
  function b_Comp_Profit(Obj, v_Params)
      %[1] Save the previoysly value
      Obj.t1_Profit = Obj.t0_Profit;

      %[2] Compute the new one
      Obj.t0_Profit = Obj.t0_Loans_Revenue + ...
                      Obj.t1_Loans_Revenue - ...
                      v_Params.central_bank_rate*Obj.t1_Deposits - ...
                      v_Params.b_operational_cost*Obj.t0_NetWorth-...
                      Obj.t0_Bad_Loans;

      a(1,1) = Obj.t0_Profit;
      a(1,2) = v_Params.t;

      %[3] Store the value
      Obj.h_Profit = cat(1,Obj.h_Profit,a);
  end

  %% [b_Comp_NetWorth]
  %Objective..: Create Banks Instances
  function b_Comp_NetWorth(Obj, v_Params)
      %[1] Save the previoysly value
      Obj.t1_NetWorth = Obj.t0_NetWorth;

      %[2] Compute the new one
      Obj.t0_NetWorth = Obj.t1_NetWorth + Obj.t0_Profit;
```

```
            a(1,1) = Obj.t0_NetWorth;
            a(1,2) = v_Params.t;

            %[3] Store the value
            Obj.h_NetWorth = cat(1,Obj.h_NetWorth,a);

            if Obj.t0_NetWorth < 0.01
                Obj.Status = 0;
                Obj.Death = v_Params.t;
            end
        end

        %% [BR]
        %Objective..: Create Banks Instances
        function BR = b_Comp_Agregate_BR(Obj)
            BR = sum((Property_List(Obj, 't0_Bad_Loans','List'))) / ...
                 sum((Property_List(Obj, 't1_Loans','List')));

             if isinf(BR)
                 BR = 0;
             end;
        end

        %% [b_Ends_t]
        %Objective..: Create Banks Instances
        function b_Ends_t(Obj, v_Params)
            %[1] Store Last Positions
            Obj.t1_Deposits = Obj.t0_Deposits;
            Obj.t1_Loans = Obj.t0_Loans;

            a(1,1) = Obj.t0_Loans;
            a(1,2) = v_Params.t;

            b(1,1) = Obj.t0_Deposits;
            b(1,2) = v_Params.t;

            %[3] Store the value
            Obj.h_Loans = cat(1,Obj.h_Loans,a);
            Obj.h_Deposits = cat(1,Obj.h_Deposits,b);

            Obj.t0_Loans = 0;
        end

        %% [b_Comp_Propensity]
        %Objective..: Bank?s propensity to be selected
        function Banks_Propensity = b_Comp_Propensity(Active_Banks,Banks,v_Params)
             Banks_Propensity = Active_Banks;
             for i = 1:length(Banks_Propensity)
                 Banks_Propensity(i,2) = Banks(Banks_Propensity(i,1)).t0_NetWorth;
             end

             big = max(Banks_Propensity(:,2));

             Banks_Propensity(:,2) = (Banks_Propensity(:,2)/big).^v_Params.bank_propensity;
        end

    end %Methods
end %Class
```