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Capital and Reserve Requirements to Control Liquidity Shocks: an Agent Based Perspective

Facultat de Ciències Jurídiques i Econòmiques

UNIVERSITAT JAUME I

Student: Jesus Moliner Moliner

Email: al081512@uji.es

Tutor: Andrea Teglio

Abstract

In this paper, we present an agent based model of the banking system, including banks households and a central bank. The model is able to address some relevant economic issues regarding liquidity shocks, shocks on assets, inequality wealth distributions and herding effects. By analyzing the effects that different policy configurations have on the system, we show that capital requirements are more effective than cash reserve restrictions in order to guarantee the robustness of the banking system. However, in case of high economic instability, liquidity requirements become ineffective. Also, we find that when the central bank is acting as a lender of last resource, capital requirement regulation becomes irrelevant, or even negative for economic growth. We also show that inequality among households wealth has a negative effect in both stability and growth. Finally, the model confirms that panic and herding among households accelerates the banking system breakdown.

Jel classification: E44, E47, E58

Key words: Liquidity Shock, Agent Based Model, Central Bank, Macroeconomic Policy

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1 Introduction

Economic literature regarding the banking system has increased considerably in the last decade. The financial crisis of 2007 has been a natural experiment on a global scale that scientists and researchers around the world have not missed, and whose results and evidences have undermined the foundations of economic analysis.

The causal origin of the crisis is difficult to determine, however, most economists coincide in pointing out some factors such as $i)$the underestimation of risk arising from the sale of hard to value assets (most of them derived from the sub prime mortgages), $ii)$the increasing interconnectedness of global financial markets and $iii)$ the growing degree of banks leverage in the years before the crisis,(read Gorton 2008, Blanchard 2009, and Brunnermeier 2008, for an exhaustive revision)

Although in many circles the bankruptcy of Lehman Brothers in 2008 is considered to be the official beginning of the crisis, first clear evidences were presented in August 2007, with the bankruptcy of some smaller US investment banks; a consequence of a contraction of a housing market deeply affected by the sub-prime mortgages. The proportion between cause and effect revealed a financial system more fragile than previously thought (Krishnamurthy 2009). In numbers, a relatively small reduction on assets, which is estimated to be 250$ Billions according to International Monetary Found (FMI), unleashed a diminution of global output and wealth approximately 100 times bigger, reaching valuation of $26.400 billion in November 2008 (Blanchard 2009).

But the relevance of these facts has a scope that goes beyond the numerical approach. In recent years, a debate on the state of macroeconomic theory itself has been opened. In the words of Krugman (2011), macroeconomics has entered a Dark Age. This way, the general consensus between society, policy makers and researchers advocated by some authors (Galí & Gertler 2007; Goodfriend & McCallum 2007; Taylor 2007) concerning the contingency rules recommended for each possible scenario has been broken.

Before the Recession, most economists defended that "the practice of monetary policy reflects the application of a core set of scientific principles"(Mishkin 2010). With the advent of the crisis, these principles of the New Neoclassical theory (Goodfriend & McCallum 2007; Woodford 2009) have been questioned, and thus the models that are built on them, the so called current Dynamic Stochastic General Equilibrium (DSGE) models. The basic postulates of mainstream DSGE models, which include perfect rationality, complete markets, perfect competition, etc. as well as the representative agent (RA) approach, have shown unable to construct models capable of explaining the basic phenomena underlying the systemic crisis. Moreover, the possibility of such event is even ignored. As a consequence there is a growing number of front line economists claiming that the "economic crisis is a crisis for economic theory"(Kirman 2010, Colander et al. 2009, Krugman 2009, 2011, Caballero 2010, Stiglitz 2011, Kay 2011, Dosi 2012, DeLong 2011).

Regarding the financial system and its regulation, it is common to find strong differences of opinion among authors answering questions such as whether the system should be regulated and what the optimal regulation might be. Once again, these discrepancies are strongly related with the mainstream axioms that each researcher wants to give as valid. Regulation only makes sense in environments with market failures such as externalities, non perfect competition or information asymmetries. Therefore, it stands to reason that authors basing their researches on hypothesis on the line of the seminal paper of Arrow & Debreu, consider the "laisezz-faire" the best policy (see Dowd 1996, Benston & Kaufman 1996).

For the rest, even assuming the existence of imperfections in the financial market that justify its regulation, there is no consensus about the nature of these market failures. However there are two arguments that are usually present in order to defend bank regulation: the risk of a systemic crisis and the asymmetry of information.

The role of liquidity providers leave Banks exposed to runs (Diamond & Dybvig 1983).The reason is that banks are forced to manage a balance sheet where the net value of their assets (after discounting the liquidation costs) is less than the potential liquidity requirements by the depositors. In this scenario, the expected value of a subject's deposit depends on his position in the bank line at the time of withdrawal because of the first come, first served rule. Under these circumstances a run can occur even when there is perfect information about the bank's balance sheet. For instance, in a panic situation, depositors will try to withdraw their founds just in case other depositors might do so first, thus forcing a reliable bank into bankruptcy (Santos 2001).

Asymmetry of information opens the door to an additional source of runs: the filtration of information on the value of banks' assets (Jacklin & Bhattacharya 1988). In this sense, a release of information proving the bad quality of assets owned by a bank could be positive since it is a source of discipline that shall encourage a careful treatment of assets. As opposed, if the trigger of the run is the panic or the existence of asymmetrical information, the effects will be negative because bank will be forced to liquidate the assets prematurely being forced to take both the opportunity and the fire-sell cost.

In order to shed some light over those complex situations this paper presents a basic Agent Based Model (ABM) and its computational implementation focused on the analysis of the effects of liquidity shocks. The model is built around families, banks and a central bank.

Households act via deposits or withdraws in their banks as petitioners or suppliers of liquidity on the system. The banks for their part, are able to capitalize their assets at an exogenous growth rate and have to manage their balance sheet structure. Structures with too much liquidity will mean lower profits as a consequence of having less profitable assets. On the contrary, structures which are too much leveraged will certainly be more profitable but will lead banks into bankruptcy more often. In any case they must comply with the balance sheet composition rules determined by the financial policies represented in the system.

In short, this simple artificial economy allows us to experiment with different sets of policies through capital and cash requirement in different characterizations of the economy. We propose to study the effects on the fundamental variables of the model of some key features as the distribution of wealth of families, the implementation of herding mechanisms or the introduction of a central bank (CB) in the system that performs the role of Lender of Last Resource (LOLR).

It is worth noting that simulations provide a double value: First, experiments could be used as a data generating process. Through different set-ups we can generate large amount of data in order to study a particular aspect of our interest, applying appropriate statistical techniques to the output of the simulation. This can be useful if we have few empirical data on the phenomenon we are interested in or if we want to generate specific scenarios in order to isolate a particular set of variables to study.

Second, real-time executed and monitored experiments allow an intuitive understanding of the dynamics regarding the studied phenomena. On the one hand, this gives the researcher a certain instant feedback when designing the experiments. On the other hand, the possibility to interact with the model in a simple and intuitive way confers a great explanatory power, which makes it suitable for educational purposes. Appendix B shows the appearance of the graphical interface.

Conclusions drawn from this work aim to serve as validation of the model opening the door to future extensions and applications in the field of analysis of the financial system through ABMs.

2 State of the Art

Much of the literature on the role of banks as liquidity providers rest on the seminal papers of Bryant (1980) and Diamond & Dybvig (1983). In their work, they present a model where depositors must choose between withdrawing money or leaving their deposits in the bank. In this research framework there is only one short-term asset that provides liquidity and another illiquid long-term asset that provides greater profitability. The model presents a dual Nash equilibrium, either depositors withdraw according to their needs of liquidity trying to exploit the higher return of the long-term assets, or fear seizes the system and depositors decide to withdraw money regardless their needs, the so called Bank Runs. As a result the bank is forced to liquidate their long-term assets facing a fire-sell cost and paradoxically the situation becomes a self-fulfilling prophecy that justifies the initial distrust. This conceptual framework is commonly used to justify tools such as deposit insurance or total or partial suspension of the convertibility. These regulation tools are used to tip the balance towards the efficient Nash equilibrium (see Wallace et al. 1990, Chari et al. 1989, Selgin 1993, Cooper & Ross 1998, Goldstein & Pauzner 2005 for a deeper treatment).

It is only necessary a brief review to realize that within the IMF, there is only a minority of countries that have not undergone profound financial problems in recent decades (Lindgren et al. 1996). So, given the importance of the problem, a well-nourished line of research has been developed following the theoretical approach proposed by Diamond & Dybvig. Based on their findings, some authors have pointed the deposit guarantee scheme as a preventive tool against pure-panic runs (Bryant 1980, Jacklin & Bhattacharya 1988, Alonso 1996, Bougheas 1999, Chen 1999), while others have defended the partial suspension of convertibility as a more effective practice (Gorton 1985*a*, Chari & Jagannathan 1988).

In parallel of these investigations, other works based on the historical analysis of the crisis have been developed to try to understand the origin of liquidity crisis and how to prevent them. Again, many authors focus their attention on two particular formulas: either a partial or total suspension of the convertibility complemented with the implementation of a clearing house or deposit insurances (see Gorton 1985*b*, Gorton & Mullineaux 1987, Calomiris 1989, 1990, Calomiris & Gorton 1991 etc.).

Moreover, recent studies are being developed in more modern lines of investigation like network analysis and experimental economics.

In the one hand, the goal of social network analysis applied to financial networks is to investigate these structures through the use of network and graph theories. This approach represents networked structures in terms of nodes (banks, households, or other agents involved in the network) and the relationships that connect them. Many investigators applying these techniques coincide in the existence of a trade-off between two opposing effects: risk sharing, which is decreasing with network connectivity and systemic risk, which oppositely increases with interconnections (See Allen & Gale 2000, Thurner et al. 2003, Iori et al. 2006, Battiston et al. 2007, 2012, Tedeschi et al. 2014).

On the other hand, bank runs have been studied following experimental methods.The nature of this branch of the economy, rather focused on understanding the behaviour of the subjects, explainse the fact that most of the papers develop models with a single bank, in the line of the original approach of Diamond & Dybvig (see Duffy et al. 2008, for an exahustive review on laboratory research). Nevertheless some researchers have also developed models with more than one bank in order to investigate the determinants of financial contagion (see for exaple Chakravarty et al. 2014). This work is part of a third way that is being developed in parallel with the ones mentioned above: the so called agent-based models. The iteration between these three disciplines, expands the boundaries of economic study and offers alternatives able to model phenomena that are not contemplated in DSGE models. As regards bank runs and the different instruments that could help to prevent them, the flexibility of ABM allows policy makers to test the consequences that different regulations could have on the economy.

For example Ashraf et al. (2011) have developed an ABM adjusted to American reality where heterogeneous firms interact with banks. At the same time, banks are subject to different capital and loan regulations. The Simulations show that banks behaviour is clearly related with the possibilities of the economy to get hit by occasional crisis. But on the other side, banks are presented as economic stabilizers facilitating the integration of new companies thus minimizing inconveniences of bankruptcies. Hence, it is concluded from this work that laxer regulations may favour faster recoveries from crisis. Notwithstanding that, Raberto et al. (2011) through the EURACE model supports the fact that lower capital adequacy ratios could generate short-term growth but also points that in return, increased stocks of private debt endanger the long-run economic stability.

Due to the shortcomings of DSGE models, many economists argue that some economic aspects should be attacked from other angles different to those provided by the neoclassical theory. In this sense, ABM strive to characterize more realistic models borrowing frameworks of interaction between agents from the network analysis, but also microeconomic and behavioural evidence from empirical and experimental economics. In these models, the assumptions of perfectly rational expectations are replaced by bounded rationality and behavioural adaptation, assumptions that best fit the scientific evidence derived from the work of cognitive psychologists (See for example Kahneman & Tversky 2000). Findings from network theory[1] as well as the profound heterogeneity that characterizes real economic agents involved in financial markets invites us to abandon too simplified theoretical frameworks as the representative agent assumption or the idea that economic systems are in equilibrium. Focusing this way on the study of out-of-equilibrium dynamics resulting from interactions between heterogeneous agents. Summarizing, ACE is a multidisciplinary science that studies economies thought as complex evolving systems computationally modelled(Tesfatsion 2006).

Compared with standard DSGE models, ABMs represent "a very powerful device to address policy questions in more realistic,flexible and modular networks" (Fagiolo & Roventini 2012). Thus, ABMs present some advantages in both, theoretical and empirical frameworks.

[1] See for example Albert & Barabási 2002

At a theoretical level, ABMs do not have to be configured as models mathematically solvable, hence too strict consistency requirements are not necessary. This feature, allows researchers to abandon the assumptions of equilibrium or rational expectations and in their place, empirically plausible assumptions could be implemented in a modular way. This modularity makes possible to completely modify or partially retouch these hypothesis easily if the model does not conform expectations. This characteristic supposes a clear difference from DSGE models where the replacement of a hypothesis such as rational expectations leads to a new model that could not even have analytical solution.

Empirically, as pointed above, ABMs could be used as generators of alternative universes. Moreover, their modular structure makes easier to make them fit the data via: input and output validation. Through input validation we could modify assumptions about behaviours or interactions to make them resemble the observed ones. Through output validation, it is possible to restrict the space of parameters and specifications of the model to those that better explain the stylized facts of interest.

Summing up, in order to retain analytical resolvability, DSGE are traditionally constructed to explain a few stylized facts[2] while ABMs can account for many empirical evidence at the same time. Thus, we can point out among the many advantages of the ABMs, their flexibility and modularity as well as a wider explanatory potential and a higher capacity of reproducing empirical data.

This overview would not be complete without mentioning some issues often attributed to ABMs. One of the main criticisms of these models is the loss of control over what is really happening in the simulations. But this is somehow natural, since the ABMs are conceived to explain really complex phenomena. Under the assumption that it is feasible to approximate the problem in a mathematical and more analytical way, computational economy would not be necessary.

A second very controversial downside among the community of experts is that ABMs are frequently over-parametrized, in order to imitate as much as possible the described reality. In this sense, some authors argue that many times ABMs rely on agents whose behaviour depends on many free parameters. Others downplay the issue by stating that the over-parametrization problem can be solved through input calibration processes that might reduce the free parameters of the model.

A third problem that we can label as the "initial conditions problem" appears when trying to represent non ergodic processes through ABM. It is important to understand that the ABMs could be interpreted as artificial stochastic data generation processes (DGP) that should be able to mimic the real one generating empirical observations. In this sense, and supposing

[2]See Aoki 2006, for a detailed discussion

non ergodic models, the initial conditions take a relevant role, and it arises the question of how far back in time one has to go to identify the correct initial set-up for the main variables. A last but not least issue is the problems found when trying to compare simulated and real-world data. Using ABMs as DGPs allows us to obtain as many artificial realizations as we like, but frequently we will only have a few empirical realizations, which makes it difficult to compare the natural DGP with our artificial one. As a counterargument it is worth mentioning that when we try to model a fact it is possible to expand our empirical observations using data from different sources, territories, moments of time, etc.

In general, these problems are far from solved and represent the source of many discussions among the specialized community. The intensity of these debates shows that behind this new paradigm there is a passionate community that has no doubt of the great potential of these new models.

3 The model

This paper investigates a partial model of the economy consisting of M banks and N households. Initially, households hold a fraction of his wealth in cash and the rest as a deposit according with their preferences. In each period families choose to withdraw or deposit money from the banks. Banks are represented by a basic balance sheet structure and are forced to fulfil certain capital and liquidity restrictions.

3.1 Households

Families are the engine of the model as they are responsible of the the endogenous liquidity shocks. Deciding between deposit or withdrawal, households force banks to restructure their balance sheets to meet their demands of liquidity. High levels of demand may push banks to suffer liquidity crisis, or even lead them to bankruptcy.

3.1.1 Households Characterization

As the model is focused on banks performance, households are mainly characterized in function of the exogenous parameters of their banks. Other household specific features that are considered, are the distribution of wealth among families and their preferences between cash and deposits. The wealth (W_{it}) of each family at certain time t = 1, $\cdots$,T consists of two parts: cash (C_{it}) and deposits (D_{it}) that household has at a particular time.

The percentage of wealth that households prefer to hold in cash form is represented by the parameter c, which could be interpreted as the models' version of the Keynesian liquidity preference.

$$W_{it} = C_{it} + D_{it} \tag{1}$$

$$D_{it} = (1-c)W_{it} \tag{2}$$

$$C_{it} = c\,W_{it} \tag{3}$$

As there are N_j households at bank j, the average deposit of each household is an Nth part of the bank deposits.

$$\bar{D}_{jt} = \frac{D_j}{N_j} \tag{4}$$

Initial average wealth of households is obtained combining equations (2) and (4)

$$\bar{W}_{j0} = \frac{\bar{D}_j}{(1-c)N_j} \tag{5}$$

In order to analyse the impact of different distributions of wealth, the initial endowment of each household is distributed as a normal[3] with mean $\bar{W}_{j0}$ and σ times the mean, standard deviation.

$$W_{ij} \sim N(\bar{W}_{jt}, \sigma\,\bar{W}_{jt}) \tag{6}$$

Thus, with $\sigma = 0$ wealth is distributed uniformly or what is the same, initial endowments of all households are equal to average wealth. Higher values of σ allow us to represent scenarios with deeper inequalities. For instance with $\sigma = 0.5$ wealth is initially distributed as a normal distribution which mean is the average wealth and which standard deviation is half this value.

3.1.2 Households Behaviour

The specifications concerning dynamics of demand for liquidity by families have been modelled trying to avoid too restrictive assumptions. Two parameters characterize this behaviour: p which is the probability a household has to choose to withdraw in this period and α, the percentage of their current wealth that families deposit or withdraw. Due to restrictions imposed by equations (1),(2) and (3), this simplified behaviour is summarized by the following rule: Each period, with probability p households choose to withdraw $min(W_{it}, D_{it})$ and with probability $(1-p)$ deposit $min(W_{it}, C_{it})$. In plain words, if a family chooses to ask for liquidity, it will withdraw a percentage α of his wealth as long as it has deposits to withdraw. If it has not got enough deposits, then it will withdraw all the remaining founds. In the same line,

[3] To describe inequality in a more realistic way a fat-tailed function would be more appropriate. However, this first approach enables the model to represent different initial endowments of wealth which allows us to draw some qualitative conclusions about the effect of inequality.

when households choose to deposit and αW_{it} is higher than the remaining cash, they will just deposit all the remaining effective. To model trends when deciding whether to withdraw funds, which are a characteristic feature of the bank-runs, it has been implemented a basic herding mechanism where withdraw probability in a period (p_t) depends on how much households deposit or withdraw founds on the previous period.

3.2 Banks

Banks are the key element of the model, their decisions concerning balance sheet composition can have a relevant impact on their financial robustness. Also, the capability of banks to meet capital and liquidity constraints play an important role: on the one hand these restrictions impose minimum cash and equity levels that have important effects, as it will be shown in this paper and, on the other hand, compliance with these requirements will open the door to liquidity injections from the lender of last resort (Central Bank).

3.2.1 Balance sheet structure

Banks are represented by a basic balance sheet structure divided in Assets and Liabilities. On the left side of the balance, we have non liquid Assets (A) and Liquidity (L), the right side is represented by households Deposits (D) and bank Equity (E) as shown in Figure 1

Assets	Liabilities
A	D
L	E

Figure 1: Balance sheet structure

Each period, bank j faces an aggregate net withdrawal demand ($\omega_{j,t}$), consisting on the present sum of net withdrawal requests ($w_{i,j,t}$) of their clients. If a household presents a negative $w_{i,t}$ it means that in this period this family is depositing cash in the bank, while positive values mean that families are retiring deposits.

$$\omega_{t,j} = \sum_{i=1}^{N} w_{i,j,t} \tag{7}$$

Banks can only satisfy the demands of families with the available reserves, so it is necessary to compare demanded with available liquidity. We define[4] K_t as the difference between available liquidity (L_t) and the aggregate withdrawal demand(ω_t).

$$K_t = L_t - \omega_t \tag{8}$$

[4]As the dynamics are repeated for each bank, we will focus on the characterization of the single agent. In this way we facilitate the understanding by eliminating the subscript j of all equations.

This way, if in a period the aggregate withdrawal demand (ω_t) exceeds the available Liquidity (L_t), banks will not be able to handle households' requests and will be forced to sell as many assets as necessary to cover the difference. As opposed, if L_t is higher than ω_t, cash demand can be normally attended. Therefore, it seems clear that banks will need no liquidity if $L_t > \omega_t$ and if not, the liquidity shortage will be equal to the difference $L_t - \omega_t$ or what is the same K_t. Thus, the need for liquidity can be modelled as a function $\delta(K_t)$:

$$\delta(x) = \begin{cases} 0 \quad if \quad x \geq 0 \\ \\ x \quad if \quad x < 0 \end{cases} \tag{9}$$

To cover this lack of liquidity , banks are forced to sell illiquid assets facing a fire-sell cost (l) represented in the model as a percentage of the book value of the sold assets. Hence, the asset variation in each period due to liquidity shocks is represented by the expression:

$$\Delta A_t^l = \frac{\delta(K_t)}{1-l}$$

If liquidity is enough to cover demand then $\delta(K_t) = 0$ and no assets are sold. In shortage situations $\delta(K_t) > 0$ and represents the demand that bank could not cover with actual liquidity so ΔA_t^l assets must be sold to cover the shortage.

The dynamic equations that define the balance sheet model for each bank in function of their liquidity demands is:

$$\begin{aligned} A_{t+1} &= A_t + \frac{\delta(K_t)}{1-l} && (10) \\ D_{t+1} &= D_t + K_t - L_t && (11) \\ E_{t+1} &= E_t + \delta(K_t)\frac{l}{1-l} && (12) \\ L_{t+1} &= K_t - \delta(K_t) && (13) \end{aligned}$$

As banks can only monetize a fraction $(1-l)$ of their assets condition

$$\frac{K_t}{1-l} < A_t^l$$

must be fulfilled to assure that banks do not reach negative assets. The interpretation is simple, banks cannot sell assets that they do not own hence the liquid value of their illiquid assets is constrained for this condition.

3.2.2 Characterizing Banks

In order to simplify bank characterization, the balance sheet components that define bank typology are determined through three parameters. The first one is the initial Equity over Assets ratio $\epsilon_0 = E_0/A_0$, which is the level of capital requirements accomplished in $t = 0$. The second determinant is the initial cash reserve ratio defined as $\gamma_0 = L_0/D_0$ that defines the fraction of deposits that the bank is keeping as liquidity reserve in $t = 0$. The last initial parameter is banks' total assets (TA), which is a measure of their size. Basic relationship between balance sheet endogenous variables is:

$$TA_t = E_t + D_t = A_t + L_t \tag{14}$$

Operating on the last equation on $t = 0$ we could obtain the following initialization equations for our endogenous variables:

$$A_0 = TA\,\frac{\gamma - 1}{\epsilon\gamma - 1} \tag{15}$$

$$D_0 = TA\,\frac{\epsilon - 1}{\epsilon\gamma - 1} \tag{16}$$

$$L_0 = TA\,\frac{\gamma(\epsilon - 1)}{\epsilon\gamma - 1} \tag{17}$$

$$E_0 = TA\,\frac{\epsilon(\gamma - 1)}{\epsilon\gamma - 1} \tag{18}$$

3.2.3 Banks Behaviour

Bank revenues are determined each period depending on the return on assets(ROA) which is represented in the model by the exogenous parameter r. Once banks get their income, they will use some part of this income to remunerate deposits and the remainder to increase their equity. We model this allocation using another exogenous parameter η which characterize the proportion of revenues that are capitalized. Consequently, in normal conditions the remaining $(1 - \eta)$ is used to pay off deposits. In situations less favourable, in which banks are unable to accomplish equity requirements, they will not remunerate depositors and will transform all the income to equity. Or what is the same, they will switch to a new state where $\eta = 1$.

To calculate interest rate paid to depositors (R_t) we need to subtract the retained earnings from the obtained revenue, and distribute it among all deposits, as shown in equation (19). Therefore, household i receives a pay-off (P_{it}) on time t which is R_t times its deposits (D_{it}) as shown in equation (20).

$$R_t = r\frac{A_t}{D_t}(1-\eta) \quad (19)$$

$$P_{it} = R_t D_{it} \quad (20)$$

In addition, this remuneration is paid in accordance with the liquidity preferences of depositors. So, a percentage c of their remuneration is paid in cash, resulting in a reduction of liquidity. While the remaining $(1-c)$ is deposited in their accounts, thus increasing bank deposits and leaving liquidity intact.

Another two determinant factors that define how banks behave are equity and reserve ratio:

Equity ratio(ϵ) is the relative proportion of equity that banks use to finance their assets. This ratio indicates how much leveraged a bank is since it represents the proportion of assets financed with own resources as opposed to those purchased through debt. So, less leveraged banks will present higher ϵ values, as opposed a $\epsilon = 0$ situation would mean that assets are fully financed with liabilities. Moving on to liquidity, reserve ratio (γ) is defined as the fraction of deposits that a bank holds as cash reserves. It represents the fraction of deposits that households have to demand in order to exhaust bank liquidity reserves.

At a legislative level, trying to ensure some robustness, policy makers establish minimum thresholds for these ratios that banks may accomplish. In our model we characterize those minimum levels (ϵ_{min} and γ_{min}) as exogenous parameters. Playing with these values, the model will allow us to reproduce different stylized legislative frameworks.

Given the policy rules and their actual balance sheet, once banks obtain their financial revenue they follow a simple rule in order to maximize their profits: buy as many assets as system conditions allow them. In plain words, if a certain period a bank does not accomplish capital or liquidity restrictions, it will not buy assets, trying to improve their situation. If on the contrary, both restrictions are met, it will buy as many assets as it can under the condition that the balance sheet structure resulting of these operations must continue fulfilling the established policy requirements. Analytically, at the end of each period banks have to decide how much liquidity are going to transform in assets. Through this relationship $-\Delta L_t = \Delta At$ and subject to:

$$\frac{L_t + \Delta L_t}{D_t} = \frac{L_{t+1}}{D_{t+1}} = \epsilon_{t+1} \geq \epsilon_{min} \quad (21)$$

$$\frac{E_t}{E_t + \Delta A_t} = \frac{E_{t+1}}{A_{t+1}} = \gamma_{t+1} \geq \gamma_{min} \quad (22)$$

Is possible to conclude that the maximum amount of dispensable liquidity is defined by the following inequation:

$$(-\Delta L_t)^{max} \leq L_t - \gamma_{min} D_t \tag{23}$$

So, if $(-\Delta L_t)^{max}$ is a positive number, it means that it is possible for the bank to spend that amount of liquidity (or less) on buying assets while still respecting the cash reserve rule. If it is a negative number, it indicates that the bank is under the threshold and that it will be needed that amount of liquidity to accomplish cash requirements again.

Performing the same analysis on the equity over assets restriction, it can be proved that maximum allowed asset variation given the endogenous variables is:

$$(\Delta A_t)^{max} \leq \frac{E_t}{\epsilon_{min}} - A_t \tag{24}$$

There, a positive $(\Delta A_t)^{max}$ represent the quantity of assets that can be bought without braking the minimum capital requirements rule. As before, a negative number represents that the bank is not accomplishing the requirements and indicates the "exceed of assets" for the given equity.

Summing up, the asset variation due to bank purchases could be expressed as the following equation:

$$\Delta A_t^p = \begin{cases} min((-\Delta L_t)^{max}, (\Delta A_t)^{max}) & if \quad (-\Delta L_t)^{max} > 0 \; and \; (\Delta A_t)^{max} > 0 \\ \\ 0 & if \quad (-\Delta L_t)^{max} \leq 0 \; or \; (\Delta A_t)^{max} \leq 0 \end{cases} \tag{25}$$

Therefore, if requirements permit it, banks will buy as many assets as they were allowed by the strictest restriction ie $min((-\Delta L_t)^{max}, (\Delta A_t)^{max})$. On the contrary, in a situation where $(-\Delta L_t)^{max} > 0$ but $(\Delta A_t)^{max} \leq 0$ capital requirements prevent the purchase of any assets no matter that it is possible to buy more assets without crossing the cash ratio threshold. In the same way, asset acquisition is prevented when capital requirements allow it but cash reserve ratio does not. Obviously if both $((-\Delta L_t)^{max}$ and $(\Delta A_t)^{max}$ are negative — so neither capital nor reserve ratios are fulfilled— any asset will be also bought.

So, dynamic equations that represent bank capitalization, deposit remuneration and asset purchasing decisions are:

$$\begin{aligned} A_{t+1} &= A_t + \Delta A_t^p && (26) \\ L_{t+1} &= L_t + (1-c) r A_t - A_t^p && (27) \\ D_{t+1} &= (1-c)(1-\eta) r A_t && (28) \\ E_{t+1} &= E_t + \eta r \; A_t && (29) \end{aligned}$$

Examining the equations, we can observe how these variables interact:

First and obviously, assets on next period depend on how many assets are bought on the current one as shown in equation (26).

Second, according with equation (27), liquidity variation has a negative relationship with c and A_t^p. Higher values of households liquidity preference increases the amount of dividends paid in cash hence it implies less liquidity accumulation. The other relationship is more simple, the more assets a bank purchases in a period the less remaining liquidity it will hold at the beginning of the next one.

Third, as shown in equation (28) deposit evolution depends negatively on c, because higher liquidity preferences imply that less profits are paid through deposits. And η which represents that the more earnings a bank retain the less profits are distributed among depositors.

Fourth, equity accumulation, described in equation (29), is directly proportional to η. Logically higher capitalization of revenue implies higher equity accumulation.

In last place, it is worth mentioning that the return on assets ratio r has a positive and direct relationship with liquidity, deposits and equity evolution but its relation with assets evolution is not so direct. Logically, higher returns expand banks purchasing capability but legislative requirements also play an important role.

3.3 Agents Interaction

3.3.1 Households-Households Interaction

With the intention to analyse the effect of widespread panic situations in the main variables of the model a simple herding mechanism has been implemented as follows:

$$p_t^w = p_0^w + \rho\, m_t \tag{30}$$

In order to avoid ad-hoc assumptions, we establish that the probability of deciding to withdraw (p_t^w) money depends on how many withdrawals have been in the previous period, on the basic withdrawal probability parameter (p_0^w) and in an exogenous parameter ρ. This allows us to exogenously adjust the impact that general feeling has in each individual decisions. The endogenous variable $m \in [-1, 1]$ can be understood as a "panic level" indicator. And it is calculated as follows:

$$m_t = \frac{deposits_{t-1} - witdraws_{t-1}}{deposits_{t-1} + witdraws_{t-1}}$$

Thus, $m = -1$ ($m = 1$) indicates the more optimistic (pessimistic) scenario where the probability that a household decide to withdraw is ρ times smaller (higher) than the initial probability.

3.3.2 Central Bank-Banks Interaction

The last interaction we found in the model is the one that takes place between the central bank and the other banks. If there is central bank acting as a lender of last resort, a bank that suffers a shock of liquidity will not be forced to fire-sell assets. Instead, if cash reserve and equity requirements are fulfilled, central bank will provide enough liquidity to cover the shortage. This condition acts as an incentive for banks to meet the requirements. At the current stage of the model, we focus our attention on the implications that a LOLR could have in our fundamental variables but forthcoming amendments could broaden the spectrum of possibilities.

We would like to propose to introduce debt dynamics in the model. This would enable it to analyse the consequences of debt in the system as well as its relationship with our fundamental variables. The possibility of implementing this improvement in upcoming works remains open.

In the same way, we propose to increase the complexity of the system implementing an interbank market. In our opinion, this is the next step to follow if we intend to fully understand the problem of liquidity shocks and how policy decisions could help us to prevent them.

However, some interesting conclusions have been drown from the actual model.

3.3.3 Households-Banks Interaction

As we have seen so far, most important interaction happens between households and banks. Most of the components of this interaction have been explained above but summarizing, it could be said that the aggregate demand of liquidity is constructed adding individual household demands. So, this net withdrawal demand, forces banks to readjust their balances to attend petitions as well as to accomplish capital and liquidity requirements.

4 Simulation Results

The agent-based computational model described in previous sections enables us to study some qualitative features of the relationship between banks, households and central-bank. Depending on the characteristics to study we have launched four general typologies of experiments. First experiments are designed in order to study the relationship between the system robustness and capital (ϵ) and liquidity (γ) requirements. On the next experiment, we focus our attention on the effect that inequality has on the robustness of the financial system and by extension over all the artificial economy. The third configuration replicates a crisis situation where banks receive a shock on their assets value at the same time that the growth rate falls drastically. The simulations also allow us to compare two different scenarios: one with a CB acting as a lender of last resource and another one with a CB acting via regulation. In the last experimental framework a stylized herding effect has been implemented. We analysed the effects of these coordination failures on system stability measuring the variations on the defaulting time of the banks and as well as the impact on the growth rate.

4.1 Comparing the Impact of Capital and Liquidity Requirements

This first experiment models an extreme situation which pushes banks to bankruptcy. Each bank is connected to 10 households. Each family deposits or withdraws 2% of its wealth each period($\alpha = 0.02$). Banks are initialized in a standard[5] parametrization where $\epsilon_0 = 0.1$ and $\gamma_0 = 0.01$. In each run a particular regulation framework is modelled varying parameters $\gamma = 0.01, 0.02, \cdots, 1$ and $\epsilon = 0.06, 0.08, \cdots, 0.16$.. Thus, the parameters grid is representing situations with lax regulations ($\gamma = 0.01, \epsilon = 0.06$ on the more permissive extreme) and others more restrictive ($\gamma = 0.1, \epsilon = 0.16$ on the more restrictive extreme) as well as situations where one policy tool is being used more restrictively than the other. To determine the capacity to avoid bankruptcy of each set-up, we measure the average time[6] it takes banks[7] to default. As shown in Figure 2.

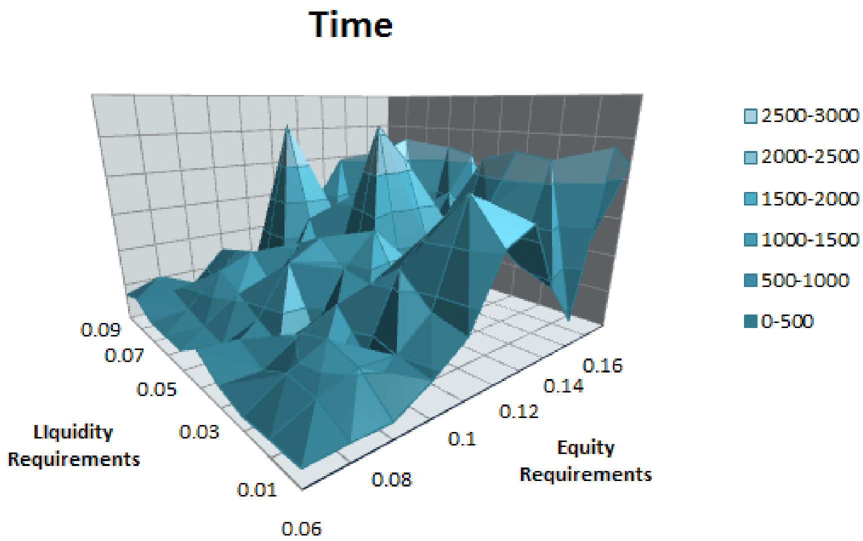


Figure 2: Mean of Defaulting time for each (γ, ϵ)

[5]Standard in the sense that in each execution is initialized with the same parameters. We should understand the model as a first qualitative approach. The empirical validation remains open for new work.

[6]Measured in simulation steps

[7]At this preliminary version, the model have not interactions among banks. In addition, each household have its deposits in a single bank

As it can be appreciated, the slope of the graphic is oriented, roughly, parallel to capital requirements axis. So, ϵ affects the robustness of the system in a clearly greater way than γ. From the results of the simulations we can conclude that limiting banks leverage through capital requirements in order to avoid bankruptcies is more effective than forcing them to keep liquidity reserves. In order to quantify this difference we construct a performance indicator(ϕ) that represents the share of the best performance that a particular set-up has. For each pair (γ, ϵ) the average bankruptcy time $(\bar{T}^b_{\epsilon,\gamma})$ is divided by the average default time of the best parameter combination $(Max(\bar{T}^b)$ as shown in Equation 31.

$$\phi_{\epsilon,\gamma} = \frac{\bar{T}^b_{\epsilon,\gamma}}{Max(\bar{T}^b)} \tag{31}$$

Results are shown in Figure 3. Colours have been added for an easier visual understanding. Red tones represent worst performances while green ones indicate the best ones. It is easy to see that poor (good) results predominate in the firsts (last) columns, which represent low (high) ϵ values. As opposed, performance variation between rows is not clear. It can be concluded that our model presents major robustness improvements with ϵ than with γ variations.

		ε										
		0.06	0.07	0.08	0.09	0.1	0.11	0.12	0.13	0.14	0.15	0.16
γ	0.01	0.08	0.08	0.07	0.16	0.28	0.59	0.66	0.34	0.13	0.92	0.83
	0.02	0.07	0.15	0.21	0.19	0.32	0.78	0.56	0.41	0.87	0.46	0.29
	0.03	0.06	0.17	0.25	0.11	0.46	0.60	0.61	0.64	0.89	0.30	0.47
	0.04	0.10	0.10	0.20	0.28	0.34	0.27	0.29	0.34	0.84	0.44	0.59
	0.05	0.18	0.17	0.08	0.10	0.36	0.52	0.25	0.40	0.45	0.49	0.52
	0.06	0.10	0.06	0.14	0.38	0.48	0.23	1.00	0.82	0.34	0.60	0.81
	0.07	0.10	0.09	0.22	0.23	0.41	0.13	0.63	0.15	0.47	0.23	0.84
	0.08	0.10	0.12	0.29	0.36	0.22	0.49	0.48	0.20	0.83	0.89	0.83
	0.09	0.17	0.17	0.16	0.32	0.24	0.99	0.54	0.78	0.66	0.46	0.39
	0.1	0.13	0.20	0.12	0.29	0.10	0.63	0.25	0.32	0.26	0.65	0.66

Figure 3: Performance score $\phi_{\gamma,\epsilon}$

4.2 Cash Reserve Requirements in Presence of Higher Liquidity hocks

The experiment above has shown that cash requirements are relatively less determinant than capital requirements in order to prevent bankruptcies. Another interesting finding is that if we expand the scale of liquidity shocks enough, cash requirements become irrelevant in determining default times. To show this, we set-up an experiment similar to the one above but in which three levels of demand (α= 0.02, α=0.03 and α=0.04) have been simulated. Concretely, this simulation is composed by the same parameter ranges than the first experiment (γ between 0.01 and 1, and ϵ between 0.06 and 0.16) but in order to lighten the computational effort we have reduced the number of banks of each parametrization to 20.

Conceptually, higher levels of α represent more turbulent environments, where households deposits and withdraws are more pronounced and therefore more stress is created on the financial system. Our model suggests that in this kind of scenarios regulations through capital requirements may be more appropriated.

The prevailing dynamics behind this phenomenon is as follows: having more equity in relation to their assets puts banks in a stronger position to resist assets fire-selling before defaulting. In addition, with low cash fluctuations, it is possible to partially prevent the fire-selling of assets by increasing the available liquidity buffer. As the only equity reducing mechanism are those sales, if banks succeed in avoiding them, they could improve their defaulting times. However, if cash fluctuations are high enough, cash reserves lose their effectiveness and capital requirements become the only relevant default prevention mechanism.

The output of this experiment is analysed in Table 1. It shows 4 regressions where the explained variable (Steps) measures the steps it takes banks to default and the explicative ones are the studied parameters: α,ϵ,γ. Parameter α represent the percentage of their wealth that households withdraw each period and parameters ϵ and γ represent the regulatory levels of capital and liquidity requirements.

Regresion (1) includes all the observations while the other three regressions only include one alpha level each one. Qualitatively speaking, all relevant variables present the expected signs i.e, higher requirements imply higher defaulting times and in regression (1) higher turbulences have a negative effect on the system robustness. In regressions (3) and (4) it is possible to see evidences of the phenomenon previously described. Coefficients of parameter γ become non significant presenting p-values far higher than 5%. Thus, we find that liquidity requirements have a limited capacity to stabilize this economy, especially when fluctuations are higher. Epsilon coefficients decrease in the measure that liquidity shocks become more pronounced. In this sense, the economic interpretation is straight forward, even more efficient tools, as equity over assets limitations, become less effective when the system is exposed to higher fluctuations.

Table 1: Time it takes banks to default depending on regulation variables

	(1)	(2)	(3)	(4)
		$\alpha = 0.02$	$\alpha = 0.03$	$\alpha = 0.04$
	Steps	Steps	Steps	Steps
α	-274382.5^{***}			
	(12936.6)			
ϵ *(Capital Requirements)*	55062.7^{***}	107025.0^{***}	68730.5^{***}	29621.4^{***}
	(3207.9)	(9058.3)	(5478.0)	(3673.2)
γ *(Cash Reserve Requirements)*	8348.1^{*}	39389.3^{***}	-2839.0	861.9
	(3518.7)	(8066.5)	(6054.3)	(4348.9)
Constant	5625.1^{***}	-5572.1^{***}	-3955.6^{***}	-2003.4^{***}
	(497.3)	(908.1)	(663.4)	(468.3)
Observations	1427	343	508	576

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.3 Inequality Matters

Our model treats inequality through an exogenous parameter that allows us to compare different distributions of wealth among families. As already mentioned, our approach aims to stylize the phenomenon of inequality in a qualitative way. Simulations confirm that inequality affects negatively both default probability and growth rate of the economy. We run 80 different set-ups where wealth share is represented as a normal distribution centred on the initial average wealth ($\bar{W}_{i0}$) and with different standard deviations.The most unequal scenario presents a standard deviation equal to its mean, and the most equal distribution presents a standard error 0.2 times this value. There are $M = 50$ banks each one connected to $N_j = 10$ households. The growth rate of the economy is $r = 0.005$ and the fire-sell cost is $l = 0.25$. Regulation parameters are adjusted as follows: $\gamma = 0.01$, $\epsilon = 0.1$.

In order to understand the impact of inequality on the main variables, two OLS regressions are presented in Table 2. In the first regression (1) we focus our attention on how sigma affects the time it takes banks to default (Step). As it can be seen, both effects — lineal and quadratic — are relevant at a 1% level of significance. The existence of a quadratic effect could be graphically appreciated in Figure 4. The appearance of this exponential relationship points that the effects over the default probability of a growing inequality are worse in initially less unequal populations.

Looking at regression (2), where the total wealth generated in the simulation (tw) is regressed over our inequality parameters, it is possible to observe that conclusions are roughly similar. The graphical representation of the effect of inequality on growth is shown in the Figure 5.

Thus, the effects observed in this section are consistent with the stylized facts we intend to describe, which could be interpreted as a qualitative validation of the model.

Table 2: Effects of Inequality on robustness and growth

	(1) [step]	(2) tw
σ^2	5122.7^{**}	1275659.6^{***}
	(1834.6)	(124865.3)
σ	-9685.9^{***}	-1173859.0^{***}
	(2273.7)	(141227.7)
Constant	8786.0^{***}	228887.7^{***}
	(640.3)	(34133.6)
Observations	3505	595

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

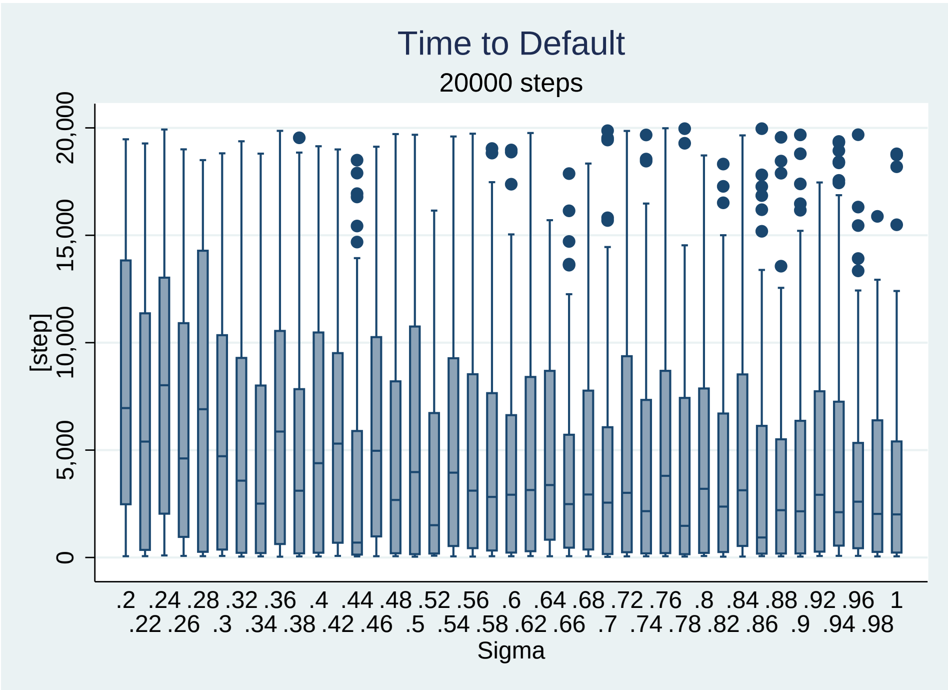


Figure 4: Time it takes banks to default depending on inequality levels

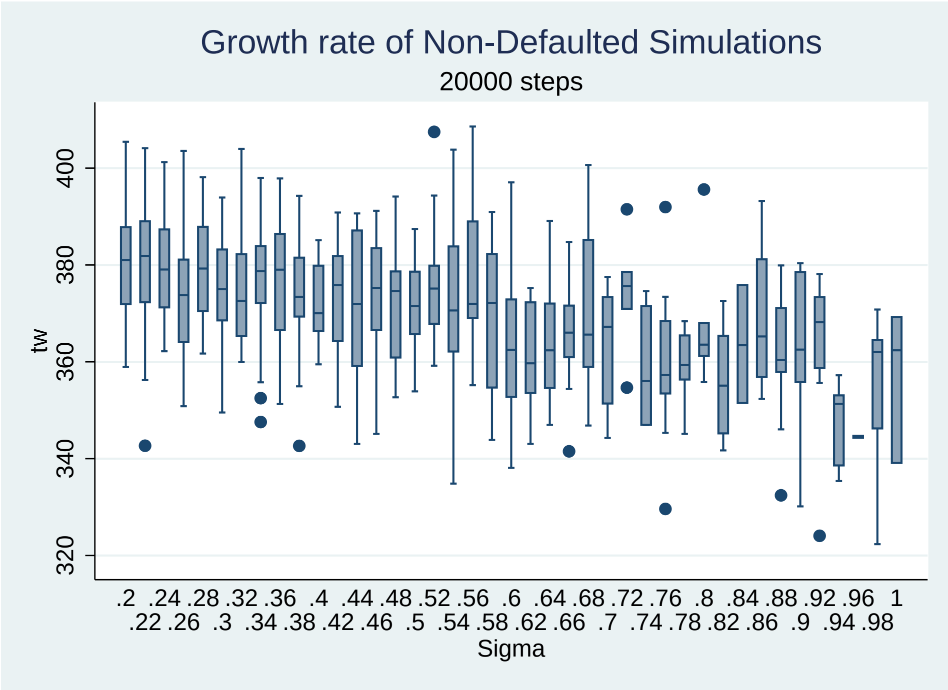


Figure 5: Growth levels achieved by surviving banks depending on inequality levels

4.4 The Central Bank as a Lender of Last Resource

In this analysis, we pretend to simulate a crisis situation where banks face at the same time a decrease of growth rate that places their return on assets close to 0 and a shock on the value of their assets. Starting from the same pre-crisis regulation, we pretend to describe the effects on economic growth of different policies adopted on crisis periods. Runs are composed by $M = 100$ banks each one connected to $N_j = 10$ households. Initial capital and cash ratios are characterized by $\gamma = 0.01$ and $\epsilon = 0.1$. In addition there is a central bank that can act as lender of last resource. The crisis begins on period 1200, and the output of the model is the total growth of economy after 5000 periods (tw). This could be interpreted as a proxy of the capacity of the system to recover from a punctual crisis and return to its growth path. We experiment with different capital requirements levels (ϵ) and with the existence of a LOLR that covers liquidity shortage during the crisis period.

The experiment described in this section is divided in two stages: pre-crisis and post-crisis. In the pre-crisis one, banks adapt their initial balance sheets — which are equal for all banks and all runs — to the new capital requirements determined by ϵ. In this first 1200 periods stage, the general economy parameters are: $r = 0.005$ and $l = 0.10$.

The crisis is represented by an 8% diminution on the asset value of each bank $\Delta A_j = -0.08$ and by a very low return on assets (ROA) ($r = 0.0001$). The next 3800 periods compose the post-crisis stage where central bank plays a determinant role. If a bank accomplishes policy requirements, it could ask for liquidity to CB. Thus, given the case that the bank could not attend households liquidity demands, fire-selling dynamics are avoided facilitating the economy to continue its growth path. At the end of these 5000 periods, the total wealth generated by the economy is stored in our tw variable.

Our model does not include inflation dynamics to describe the effects on prices of this expansion of the money supply but this analysis is beyond the objective of this work although it could be implemented in future versions.

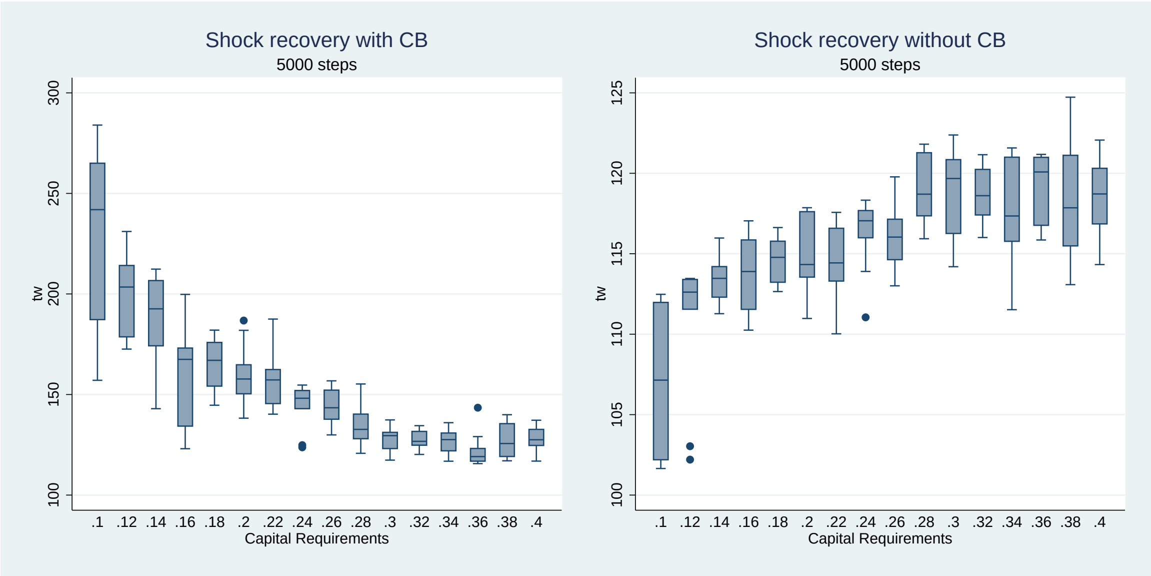


Figure 6: Total Wealth on crisis scenarios with and without LOLR depending on ϵ

Looking at the results of the simulations, represented in Figure 4.4, it is clear that the action of a CB as a lender of last resource changes the direction of the effect that capital requirements present on the economy growth. If banks can borrow from the CB in case of liquidity shortages, they become able to construct successfully more leveraged portfolios. And this allows them to take advantage of the economy growth more efficiently. As opposed, if the CB only acts by the regulatory way the effect of rising capital requirements works on the other way. If banks cannot borrow money from the CB, having higher capital requirements help them to absorb the shock on their balances. In other words, the loss of equity due to a reduction of assets value is proportionally smaller in less leveraged banks. What is clear is that the presence of a lender of last resort makes it more profitable for banks to get more leveraged. This can suggest a potential danger in performing long-standing money supply expansions by a lender of last resource.

4.5 Panic and Bank Runs

The latter phenomenon studied in this paper is the effect of systemic panic on the economy. Our model reproduces this stylized effect on the line of Diamond & Dybvig as a coordination failure among depositors. This experiment reproduces the effects that different coordination parameter values ($\rho \in [0, 50]$) have on the system. Technically ρ is the percentage points that are added to the basic withdraw probability of each family when the system is affected by panic. As the basic probability is 50%, with $\rho = 50$, each household has a 100% probability to perform a withdraw. On the contrary, $\rho = 0$ means that no herding effects among households are present.

In order to isolate this effect, the rest of the parameters remain in a neutral position where $\epsilon = 0.1, \gamma = 0.01, r = 0.005$ and $l = 0.05$. The simulation lasts for 20000 periods and the variables of interest are: $Step$, which is the time it takes banks to default, measured in simulation periods, and rtw, which is the wealth level of the economy as a fraction of the initial one.

As Figure 7 shows, the observed effect coincides with the expected ones. Higher ρ values imply that liquidity fluctuations in the economy become more abrupt forcing banks to use fire-sell mechanisms more often. With enough coordination levels, banks are simply unable to attend households liquidity petitions even fire-selling all their assets[8] which leads them to bankruptcy.

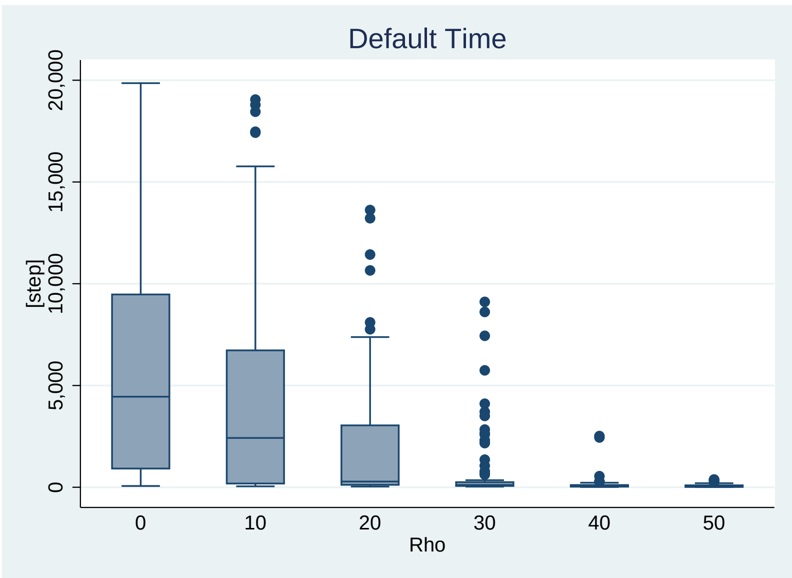


Figure 7: Time it takes banks to default depending on coordination level

[8]The maximum liquidity that a bank could provide selling all its assets is $(1 - l)A_t$

Even when these mechanisms do not suppose banks' default, the effects on growth are also critical. As shown in Figure 8, the relationship between ρ and rtw is highly appreciable. With higher herding effects, households coordinate their behaviours provoking the net aggregate withdrawal to reach higher values. When panic seizes the system, liquidity shortage becomes inevitable. Thus, banks end up paying it with reductions on their equity as a result of the already explained fire-sell mechanisms. On the contrary, when there is a general feeling of confidence and households deposit all their wealth on banks the positive effect are not too generous. Two effects are responsible for this: First fire-sell cost is higher than the return on assets. This implies that the extra return obtained by the banks in the confidence phases is less than the additional penalty suffered in the panic stages. And secondly, much of the generated wealth is accumulated by households in the form of bank deposits. This generates a perverse mechanism where, on confidence phases, balance sheets get oversized and much more leveraged. When the mood changes, and the system enters a panic stage, households have more founds to withdraw in proportion with banks equity forcing them into fire-sell dynamics more often.

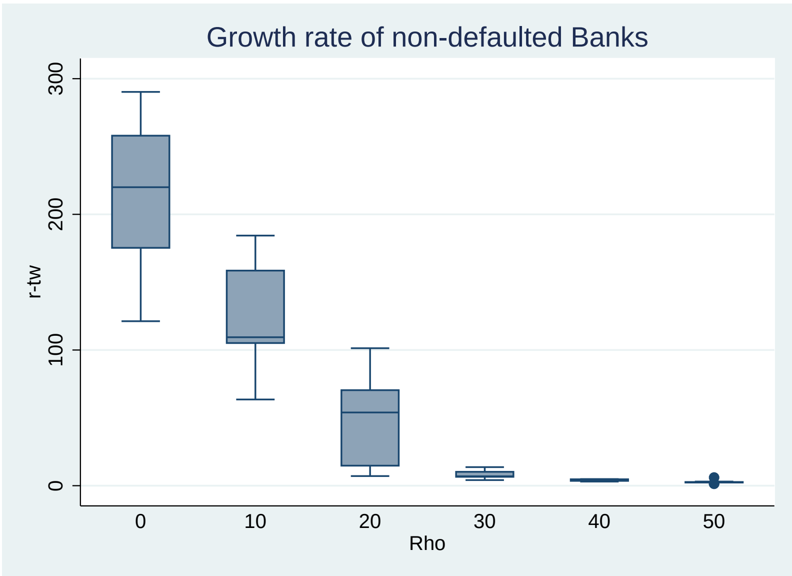


Figure 8: Growth on the economies with non-defaulted banks depending on coordination level

5 Conclusions and Preliminary Policy Implications

In this paper, we introduced an agent based model of the banking system, including banks households and a central bank. The model has shown able to address some relevant economic issues regarding liquidity shocks, shocks on assets, inequality wealth distributions among households and herding effects. By analysing the effects that different policy configurations have on the system, we could affirm that capital requirements are more effective than cash reserve restrictions in order to guarantee system robustness. Also, we find that once a certain threshold of turbulence it exceeded, liquidity requirements become irrelevant. Simulations including a central bank as a lender of last resource have shown that tightening capital requirements affect growth rate on a negative way, as opposed as the positive effect that it has when the lender of last resource is not present. The model has been also capable of simulating scenarios with different wealth distributions showing that inequality has a negative effect in both stability and growth. Finally, bank runs have been studied applying simple herding dynamics. As a result of these simulations, it can be concluded that having a herding effect among households has harmful consequences: it makes financial system more fragile and also it reduces the growing capability of the entire economy.

The Macroeconomic policy implications that emerge from the model should be taken prudentially. The first conclusions that can be drawn from this study is that, in relatively stable periods, liquidity constraints may favour the growth of the economy. In contrast, if a turbulent period is expected, central bank can strengthen the financial system by increasing capital requirements. Once the economy is on a crisis period central bank can stabilize the economy injecting liquidity to the financial system which could avoiding some bankruptcies. But this mechanism generates incentives for the banks to get more leveraged which can put the long-term stability of economy at risk.Finally, the negative effect of inequality suggests that the application of redistributive policies may have a stabilizing effect on the system.

Looking forward, the fact that the results match our expectations could be considered as a first validation step. Some extensions for the model have to be implemented in order to add new features and improve the actual ones. Next steps in developing the model could be introducing inflation mechanisms, interbank markets or more sophisticated herding dynamics. These extensions could convert our partial equilibrium model in a general equilibrium one. This will allow us to represent situations that now we can not examine and also understand the phenomena we have studied with the current version with a more realistic approach.

A Appendix I: NetLogo Code

Program used for generating simulations of interest is listed below.

```
breed [banks bank]
breed [households household]
undirected-link-breed [relationships relationship]
relationships-own [ hh-w bank-money]
banks-own [ A L D Eq K Km P R Cap demanded-w default? distance-from-BP total-w
    death-tick I v-A v-L v-D v-Eq ini-A ini-Eq L-bc Eqt-1]
households-own [ w myBank hh-cash hh-deposit wealth-t]
globals [n-of-defaulted-banks  run-n min-eoa ini-tw cont eta wt-1 mood final-prob I
    -gdp I-wg]
;;;;;;;;;;;;;;;;;;;;;;;;;;; MAIN ACTIONS
    ;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;

to setup
clear-all
reset-ticks
set-default-shape banks "square"
set-default-shape households "house"
set n-of-defaulted-banks 0
setup-banks
setup-links
setup-households
set ini-tw tw
ask banks [set ini-A A set ini-Eq Eq]
set cont 0
end

to go
tick

end-vars

set wt-1 tw
ifelse mood-on [ set final-prob w-prob + ro * mood] [set final-prob w-prob]

launch-households
launch-banks
hh-update
calc-mood
end

;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;SETUPS;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
to setup-banks
set min-eoa ((ini-equity-over-assets * (ini-liquidity-ratio - 1)) / ((ini-liquidity
    -ratio * ini-equity-over-assets) - 1))
```

```
create-banks number-of-banks
ask banks [ setxy random-xcor random-ycor set death-tick "NA"]
ask banks [create-c-network]
ask banks [

set Eq TA * min-eoa
set D TA * (1 - min-eoa)
set A TA * (min-eoa / ini-equity-over-assets)
set L TA * ( 1 - (min-eoa / ini-equity-over-assets))
set R roa * A / D
set default? False
set l-bc 0
set Eqt-1 0

]
end
to setup-links
ask relationships [set hh-w 0]
end

to setup-households
ask households [
let avg-wealth (([D] of myBank / (1 - c )) / hh-per-bank)



set hh-cash c * avg-wealth
set hh-deposit (( 1 - c) * avg-wealth)
]
setup-households-normal
end
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;LAUNCHES;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;

to launch-households
ask households[ ifelse any? my-links
[set w decided-w demand w]
[]
]
end

to launch-banks
ask banks [ifelse default?
[]
[ ifelse (Eq / A) < Equity-over-assets [set eta 1][set eta standard-eta]
set eqt-1 eq
capitalize-distribute
attend-petitions
```

```
ifelse K >= 0 [go-normal][
ifelse cb = "parcial" [
ask-cb]
[time-to-sell]
]

check-default
set Km K
set K 0
]
]
ask banks [set label precision (Eq / A) 2]

end


;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;; HOUSEHOLDS RELATED
    ;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;

to-report decided-w
let _w (alpha) * wealth-t
ifelse random 101 <= final-prob [
ifelse _w <= hh-deposit [report _w][
report hh-deposit]
][

ifelse _w <= hh-cash [
report (-1 * _w)][
report  (-1 * hh-cash)]
]
end

to demand [w-value] ;<---------- cambiar nombre a "withdraw"
ask link-with myBank [set hh-w w-value]

end

to hh-update

ask households[
if any? my-links[
set hh-cash hh-cash + [bank-money] of link-with myBank
set hh-deposit hh-deposit - [bank-money] of link-with myBank
set wealth-t hh-cash + hh-deposit]
]
end
```

```
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;; BANKS RELATED ;;;;;;;;;;;;;;;;;;;;

to create-c-network
let g (360 / hh-per-bank)
let n 0
hatch-households hh-per-bank [
set myBank myself left (g * n) fd 2 + random-float 2 set n n + 1 create-
    relationship-with myself]
end


to attend-petitions
set demanded-w reduce + [hh-w] of my-links
set K L - demanded-w

end

to go-normal
set D D - demanded-w
set L K
ask my-links [set bank-money hh-w]
; A y E permanecen constantes
end

to time-to-sell
set D D + K - L
liquidate-assets
set L 0
set Eq Eq + (liquidation-cost * K)/(1 - liquidation-cost)
ask my-links [set bank-money hh-w]
end
to liquidate-assets ; <--Restringe alcanzar assets negativos
ifelse (A + (K / (1 - liquidation-cost)) <= 0 )[set A 0][set A A + (K / (1 -
    liquidation-cost))
]
end
to ask-cb
set D D - L
set L 0
set l-bc l-bc + (K * -1)
ask my-links [set bank-money hh-w]
end


to check-default
```

```
if Eq <= 0.1[set default? True set n-of-defaulted-banks n-of-defaulted-banks + 1
    set death-tick ticks ask my-relationships [die]]
end


to capitalize-distribute

set I roa * A
let Eq-temp Eq + (eta * I) ; seria lo mismo calcular E = A + L - D (Comprobado en
    excel)
set D D + (1 - eta) * (1 - c) * I
let DeltaL I * (1 + c * (eta - 1)) ; comprobado en excel tambiÃl'n
let L-temp L + DeltaL
let DeltaAmax (Eq / equity-over-assets) - A
let -DeltaLmax ((liquidity-ratio * D) - L-temp) * -1
let Lbc DeltaAmax - -DeltaLmax
let +debt 0

ifelse cb = "total" and (Eq / A) >= equity-over-assets[

ifelse DeltaAmax <= 0[
set color red
set L L-temp

]

[ifelse -DeltaLmax <= DeltaAmax [ set A A + DeltaAMax set L L-temp - -DeltaLmax
    set D D + Lbc set color violet set +debt Lbc]
[
set L L-temp - DeltaAmax
set A A + DeltaAmax set color green]
if -DeltaLmax < 0 [set color black]

]

]

;Cuando el BC no actua
[
ifelse DeltaAmax <= 0 or -DeltaLmax <= 0[
ifelse DeltaAmax <= 0 [set color red][set color cyan]
set L L-temp ]


[ifelse -DeltaLmax <= DeltaAmax [ set A A + -DeltaLMax set L L-temp - -DeltaLmax
    set color blue]
[
```

```
set L L-temp - DeltaAmax
set A A + DeltaAmax set color green]

]
]
ask link-neighbors [ let Payoff (1 - eta) *( [l] of myBank / [D] of myBank) * hh-
    deposit
set hh-deposit hh-deposit + Payoff * (1 - c)
set hh-cash hh-cash + Payoff * c]
set Eq A + L - D
set l-bc l-bc + +debt

end

to distribute
ask link-neighbors [

set hh-deposit hh-deposit * (1 + [R] of myself)
]

set Eq A + L - D
end


to-report endog-roa
;((30*sin(0.1x+2.8)+30)/(2*(x+100)) or (1.5/(0.1x+10))*(sin(0.1x+2.8)+1) or 1.5*(
    sin(0.1x+2.8)+1)/(0.1x+10) EN RADIANES HAY QUE CONVERTIR A GRADOS!!!
report ((1.5 * (sin((18 / pi) * ticks + 2.8) + 1)/ (0.1 * ticks + 14))/ 10)
end

to-report endog-roa2
report ((2.6 * (sin((27 / pi) * ticks + 1) + 1)/ (ticks + 50))/ 100)
end

to-report endog-l
report (roa * -20) + 0.5
end

to-report endog-l2
report (roa * -400) + 0.8
end

to-report death-ticks
report [death-tick] of banks
end

to-report t1
```

```
report min [death-tick] of banks
end
to-report t2

report max [death-tick] of banks
end


to-report end-liquidity-cost
report ((-20 * roa) + 0.5)
end

to-report calc-min-e [liq-r]

report equity-over-assets * ( liq-r - 1) / (( equity-over-assets * liq-r) - 1)
end

to show-e
ask banks [ show Eq / A]
end

to end-vars
if roa-mode = 1 [
set roa endog-roa
set liquidation-cost endog-l]
if roa-mode = 2 [
set roa endog-roa2
set liquidation-cost endog-l2]
if roa-mode = 3 [
set roa  0.001
set liquidation-cost  0.6]
end

to setup-households-normal
ask banks[ setup-wealth ]
ask households [set hh-cash wealth-t * c set hh-deposit wealth-t * (1 - c)]
end


to-report values-vector [n nu sigma]; <- Genera una lista con n valores
    distribuidos como una normal cuya media es exactamente nu. Genera n-1 y fuerza
    el ultimo.
ifelse n > 1 [
let _list n-values (n - 1) [random-normal nu sigma]
let t_nu mean _list

let last-val (nu * n) - ((n - 1) * ( t_nu))
```

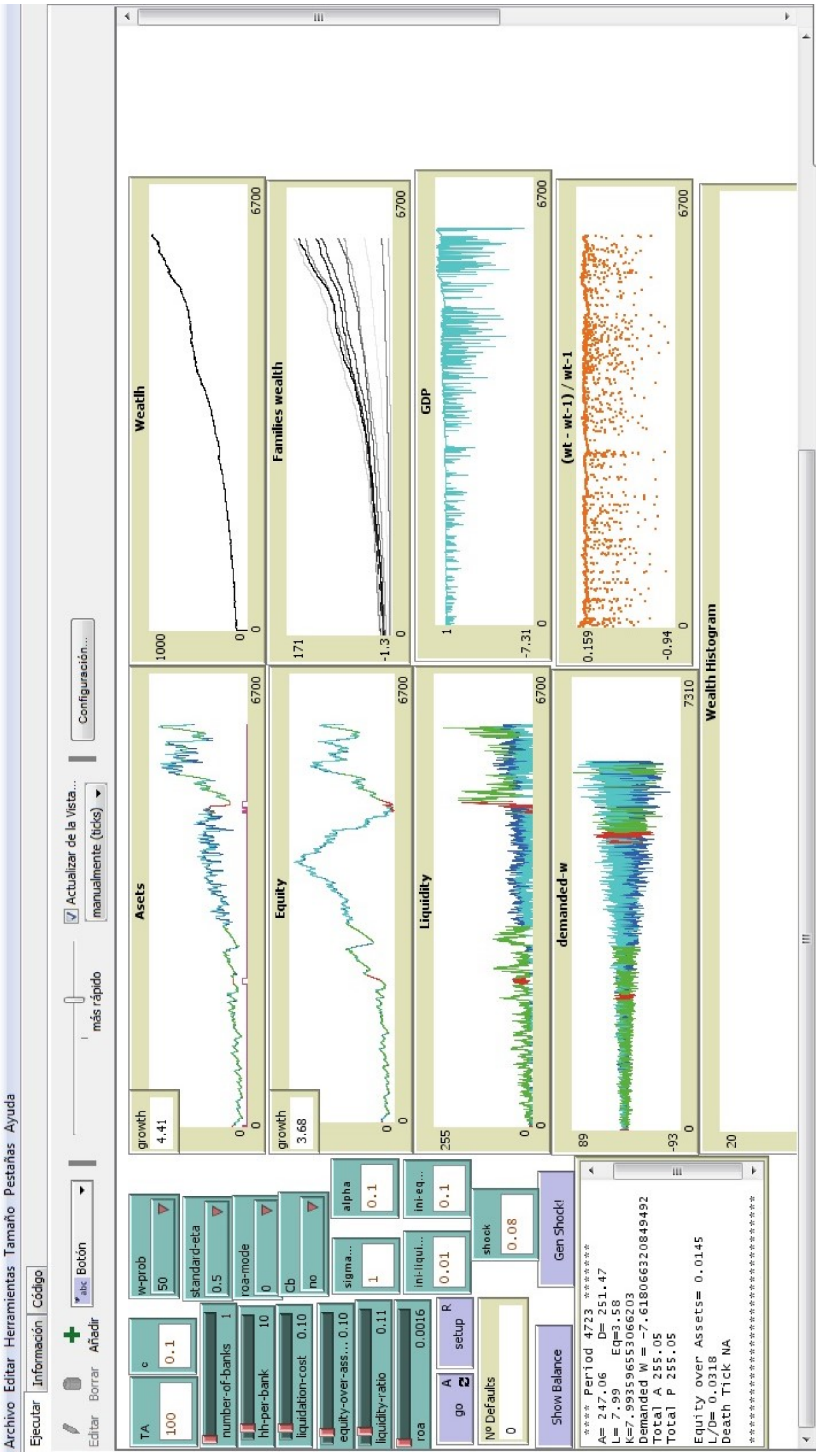
```
set _list lput last-val _list
report _list ]
[ report nu ]
end

to gen-checked-vector [n nu sigma]
let vector values-vector n nu sigma
set vector sort vector

ifelse first vector >= 0 []
[gen-checked-vector n nu sigma]
end
```

```
to setup-wealth ;la riqueza media segun los depositos es ( [D] of myBank / (1 - c )
    ) / n of hh
set cont cont + 1
let pos 0
let avg-b-wealth (D / (1 - c ) ) / hh-per-bank
let sigma avg-b-wealth * sigma-mult

let vector values-vector hh-per-bank avg-b-wealth sigma
set vector sort vector
ifelse cont < 1000
[
ifelse first vector <= 0 [setup-wealth]
[
;print vector
ask link-neighbors [
set wealth-t item pos vector
set pos pos + 1] ]
][print "Error"]
end
to bal
ask banks [print (word "\n"" **** Period " ticks " *********\n"
"A= "precision A 2 "    D= " precision D 2 "\n"
"L= "precision L 2 "    Eq=" precision Eq 2 "\n"
"K=" K "\n""Demanded W = " demanded-w "\n"
"Total A " precision (A + L) 2 "\n"
"Total P " precision (D + Eq) 2 "\n")
ifelse Eq != 0 and A != 0[print word "Equity over Assets= " precision (Eq / A) 4][
   print "cero"]]
end
```

```
to obal
ask banks [output-print (word "\n"" **** Period " ticks " *******\n"
"A= "precision A 2 "    D= " precision D 2 "\n"
"L= "precision L 2 "    Eq=" precision Eq 2 "\n"
"K=" Km "\n""Demanded W = " demanded-w "\n"
"Total A " precision (A + L) 2 "\n"
"Total P " precision (D + Eq) 2 "\n")
ifelse Eq != 0 and A != 0[output-print (word "Equity over Assets= " precision (Eq /
     A) 4 "\n"
"L/D= " precision (L / D) 4)][print "cero"]
output-print word "Death Tick " death-tick
output-print "\n*******************************"]
end
to-report tw
let v 0
ask banks [set v v + (Eq + D)]
ask households [set v v + hh-cash]
report v
end


to-report r-tw
report tw / ini-tw
end

to-report report-aw
let l-wealth []
ask households [ set l-wealth lput wealth-t l-wealth]
report mean l-wealth
end

to-report wg
report (tw - wt-1) / wt-1
end
to-report gdp

report (tw - wt-1)
end
to-report debt
report [l-bc / Eq] of bank 0
end
to-report deltaEq.bank [number]

report ([Eq] of bank number / [Eqt-1] of bank number) - 1
end

to calc-mood
```

```
let vec [w] of households
let dep 0
foreach vec [ if ? <= 0 [set dep dep + 1]]
let ret hh-per-bank - dep

set mood (ret - dep) / hh-per-bank
end



to-report bw-hhw
let bw 0
let hhw 0
ask banks [set bw bw + Eq]
ask households [set hhw hhw + hh-cash + hh-deposit]
report (bw / hhw)
end

to-report pbw
let bw 0
let hhw 0
ask banks [set bw bw + Eq]
ask households [set hhw hhw + hh-cash + hh-deposit]
report bw / (bw + hhw)
end

to-report phhw
let bw 0
let hhw 0
ask banks [set bw bw + Eq]
ask households [set hhw hhw + hh-cash + hh-deposit]
report hhw / (bw + hhw)
end
```

B Appendix II: NetLogo Environment



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