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Simulating the Fractional Reserve Banking using Agent-based Modelling with NetLogo

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***Abstract*—This work presents a multi-agent-based computational model of an artificial fractional reserve banking system. The model is implemented in NetLogo. The computational experiments and simulations we performed to analyse the proposed model show that different scenarios can lead to bank insolvency. We show that both the minimum reserve rate and the loss of confidence have large contributions to the insolvency of a bank, suggesting them as likely destabilizing economic forces driving the dynamics of the model.**

***Index Terms*—agent-based model, agent-based simulation, BDI agents, fractional reserve banking, NetLogo.**

I. Introduction

AGENT-BASED models (ABMs) are computational models consisting of a set of autonomous, self-driven agents that exhibit complex behaviours emerging from their interactions rather than from the complexity of the individual agents. ABMs are usually simulated in frameworks specially developed for these purposes [1]. They have already been applied to the study of emergent phenomena in a variety of domains that include social, political, and economic sciences.

ABMs have several interesting properties. Among them are the following: they are relatively easy to implement, are very practical for analysing the evolution of the simulations step by step, and can show emergent properties that could be difficult to predict. By stepping the simulations, it is possible to analyse the emergence of stylised facts and new equilibrium states, as well as the conditions under which they occur. For example, it is possible to analyse the emergence of pernicious domino effects, which may be achieved by increasing the degree of interdependence between the agents. The domino effects are of special interest to the analysis of financial fragility, in particular bankruptcies cascades, due to the intricate structures of liabilities among heterogeneous agents.

One of the goals of the ABM we present in this paper is to describe a methodological tool that can reproduce some of the stylised facts in fractional reserve banking (FRB) systems. *Fractional reserve banking*[1] is a banking system "in which banks hold only a fraction of their deposits in reserves, so that the reserve-deposit ratio is less than 1" [2]. In other words, some of the deposits are further used by the banks to be loaned out at interest-earning rates to other parties. Yet FRB has received a lot of criticism. For example, there are studies that show the viability of ending fractional reserve banking, as is the case of the FRB in Iceland [3].

Why then a computational agent-based model to simulate FRB? We believe that understanding FRB better could be one of the most important outcomes. Simulating artificial scenarios could help suggesting possible improvements or new policies. This is especially important for scenarios that could eventually be avoided if anticipated by a computational economic model for FRB. The FRB agent-based model presented in this paper can then be used to analyse possible scenarios that arise from evaluating different initial parameter settings of the model. The major purpose of the model is to provide artificial ways to represent and to simulate the impact of the fractional reserve banking system on a time period. It defines a very simple modern banking world that is, by no means, an example of real bank operations or of federal restrictions or monetary exchanges. Instead, it could serve as a basic playground setting, for example, to drive the policies and behaviours of banks before testing their validity in the real world. It could also be useful to find out the sufficient conditions for a banking system to become fragile and unstable.

II. Related Work

Traditional simulation approaches mainly use historical data [4] to analyse the interbank payment interactions. For example, Bedford, Millard, and Yang apply some stochasticity to test different bank behaviours under different hypotheses on the operational rules [5]. They propose a simulation-based framework to analyse large-value payment systems for a variety of worst-case scenarios. The framework shows many similarities to the stress-testing methods that are used to evaluate the robustness of banking systems to financial shocks.

Other researchers have used computer simulations to analyse interbank lending for scenarios with homogeneous and heterogeneous agents. Iori, Jafarey, and Padilla [6] show that, if the banks are homogeneous in size and risk exposure, then the interbank market has strong effects to avoid cascades and stabilise the system. However, if the agents are heterogeneous, then the system may present some cascade effects.

Modern simulation approaches like ABM have also been used to study economic and social systems, where the main

[1] Also known as *fractional deposit lending*.

idea is to describe the behaviour of the agents in the system and to reconstruct the aggregate behaviour by simulating their interactions. Also, some works allow behaviour adaptation based on changes in the different scenarios [7]. By this means, ABM is a methodology bringing together verbal descriptions of component systems and equation-based models [8]. In particular for our investigations, we are interested in ABM for analysing the credit, liquidity, and operational risks of settlement systems. In this type of system, banks are modelled as software agents that follow some behavioural rules and act independently, which leads to stylised facts that result from their interactions in the simulated world.

Simulation tools like StartLogo have also been used to simulate behavioural rules for banks in Real Time Gross Settlement systems. Arciero and co-authors present a model with a money market [9] which, after a critical event, either blocks or limits the activity of the bank. In their model, banks are perfectly informed on all payment requests. Thus, when delays in payments start accumulating, some banks start adjusting their expectations accordingly until the turbulence spills over in the market, needing the intervention of the central bank.

III. An Agent-based Computational Model for Fractional Reserve Banking

A computational model that describes an FRB system using ABM was introduced in a previous work [10]. The model basically consists of three main groups of artificial entities that are simulated by three types of agents, i.e., depositors or investors, debtors or borrowers, and banks, which interact through communication in a multi-agent system. When compared to the approach of Mallet of simply managing a list of accounts with deposits and loans [11], our model differs in that it simulates not only the bank behaviour, but also other parties and the interactions involved. In this paper, we focus on initial experiments with our model rather on extending it.

Each agent in our model pursues different interests. They are modelled in NetLogo,[2] a multi-agent programmable modelling environment [12], by following the BDI paradigm [13]. In other words, they are artificial agents with *beliefs* (B), *desires* (D), and *intentions* (I) that are defined using the NetLogo BDI add-on [14].

All agents follow a deliberation process that determines their subsequent actions and interactions with other agents. For example, depositors aim to create as much capital as possible without running the risk of losing their assets due to insolvency of the bank. They can retrieve the entire deposit or a specific, lower amount. They can also deposit money or do nothing. Figure 1 shows the deliberation process of a depositor agent. After updating her knowledge about the world and depending on both her preferences and trust in the bank, a depositor decides on whether to deposit money or to retrieve it, partially or totally.

[2]Jonathan Wiens implemented the first version of the NetLogo model. Eric Faustmann and Damian Rhein extended it.

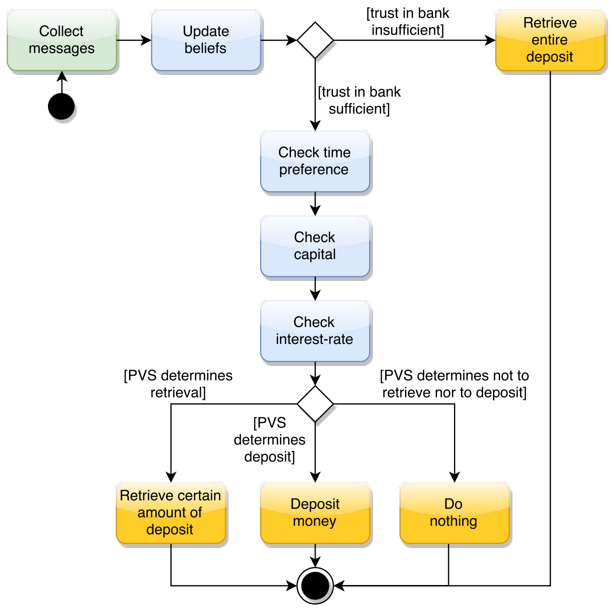

Fig. 1. Deliberation process of the depositor agent. PVS: personal value scale.

Depositors act depending on their own personal value scale. It would not be reasonable for a depositor to deposit 80% of her on-hand cash into a bank she has 10% of trust in, for instance. Other variables influence the decision process, too, like the time preference p, the current capital C, the deposit interest rate β, and the trust t in the bank. Algorithm 1 shows the pseudo-code that drives the depositors' actions, where D is the amount to deposit, W is the amount to withdraw, and S is the current deposits or savings in the bank. If confidence in the bank is lost, i.e., the trust in the bank is less than 30%, then a depositor might withdraw her entire deposits. She might deposit money, however, if the trust has a greater value and depending on both the time preference (a random parameter to simulate the possibly non-deterministic character of each agent's operations) and the interest rate.

Debtors or borrowers behave similarly, only that they have other local variables as well as actions in their repertoire, like borrowing a specific amount of money from the bank. The bank agent serves as a contact partner for depositors and debtors. It accepts or rejects requests from the agents depending on its own state. For example, a bank would award no credit to debtors if its reserves fall below the minimum permissible reserve amount because otherwise it could lead to insolvency. All agents update their information and knowledge about the world, i.e., their beliefs, iteratively, which determines the construction of new desires and intentions that are transformed in later actions.

IV. Experimental Settings

We are interested in finding which parameter values lead to either bank insolvency or to a stationary scenario with no insolvency of the bank, over iterations.

```
input  : Incoming messages IM
output: Action a
begin
    process messages IM;
    update beliefs;
    update desires;
    if 0.5 ≤ t ≤ 1 then
        D = C · (p + β);
    else if 0.3 ≤ t < 0.5 then
        W = S · (1 − p);
    else
        W = S;
    end
    update intentions;
    a = selectBestOption();
    return a;
end
```

Algorithm 1: Depositor agent: Pseudo-code of the deliberation process at every iteration.

A bank becomes insolvent when its reserves are lower than the money one or more depositors want to withdraw back from their deposits. Such illiquid state scenarios are reached when both the trust of the depositors decreases, leading to withdrawals, and the reserves of the bank are lower than the withdrawals. Intuitively, the following three scenarios could lead to an illiquid state: (i) the bank does not invest at least some part of the deposits and converts them into profits from the loan interests to at least cover the deposit interests; (ii) the trust of the debtors decreases so that they do not want to get a loan. Thus, the profits of the bank would decrease and the bank will not be able to pay the deposit interests back; (iii) the bank uses a large part of the reserves but even a small withdrawal from a depositor can lead to an insolvency of the bank.

In order to analyse these scenarios, we first perform three computer experiments, i.e., *E1*, *E2*, and *E3*, where we change the values of both the minimum reserve rate and the average loss of confidence rate parameters, while leaving the rest of the parameter fixed, which are: number of depositors (5), number of debtors (5), average income (2000), start capital (5000), starting loan (credit) interest (10%), starting deposit interest (0.2%), and average win of confidence rate (30%). See Table I for those parameter values that differ among the experiments.

TABLE I
PARAMETER VALUES DIFFERING IN ALL EXPERIMENTS *E1*, *E2*, AND *E3*.

Experiment	minimum reserve rate	average loss of confidence rate
E1	1%	30%
E2	1%	50%
E3	5%	30%

V. Results and Discussion

Different experimental results lead to the insolvency of the bank because of the scenarios mentioned in Section IV. We start by investigating the role of the average loss of confidence rate in the dynamics of the model. Figures 2 and 3 show an example of the evolution of the money warehouse receipts and the reserves over some iterations for an average loss of confidence rate of 30% and 50%, respectively. Note that in Figure 2 both the average loss of confidence rate and the average win of confidence rate are equal, whereas in Figure 3 the average loss of confidence rate is greater than the one depicted in Figure 2.

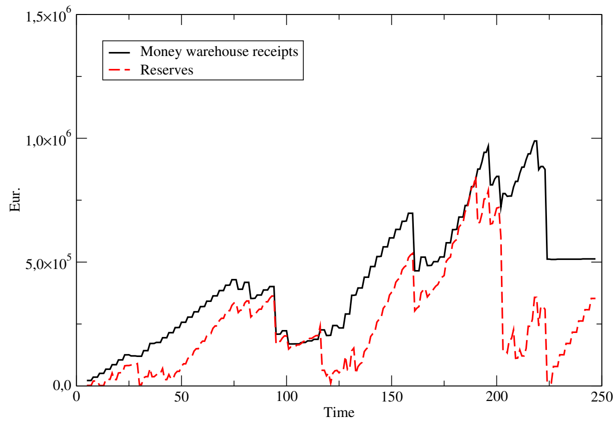

Fig. 2. Experiment *E1* with an average loss of confidence rate of 30% and a minimum reserve rate of 1%.

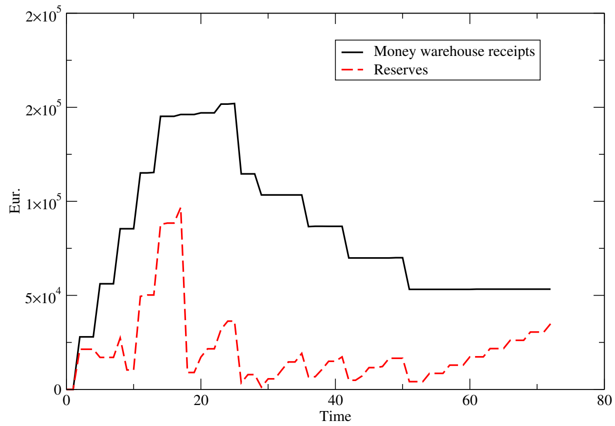

Fig. 3. Experiment *E2* with an average loss of confidence rate of 50% and a minimum reserve rate of 1%.

It can be seen that an insolvency is more probable when the loss of confidence increases, leading to a lesser number of iterations needed for a bank to become insolvent. Thus, when the average loss of confidence is greater than the average win of confidence, then both the depositors and the debtors lose their trust in the bank. Furthermore, if the reserves are low because of a large loan and the bank is not able to pay a deposit back, then all depositors start trying to withdraw their deposits, leading to an insolvency of the bank. This can be seen in Figures 2 and 3 at the end of the simulations starting at iteration 220 and 50, respectively.

Furthermore, the larger the difference between the average loss and the win of confidence, the faster the depositors start to withdraw their deposits and the faster the debtors stop asking for loans from the bank. Note also that if the average loss of confidence is too great, then the difference between the deposits and the reserves can be so small that the bank may reach a state in which it does not become insolvent but neither does it have any depositors or debtors any more.

Figure 4 shows an example of the evolution of both the money warehouse receipts and the reserves for some iterations for the computer experiment *E3* with a minimum reserve rate of 5%. When comparing this result with the one from the computer experiment shown in Figure 2 where the minimum reserve rate is 1%, we can observe that the amount in Euros is greater in the computer experiment with higher minimum reserves (i.e., the one from Figure 4). It can be seen that the reason for the bank insolvency was the loss of confidence of a single depositor, which led to a cascade of confidence loss and withdrawals from all other depositors.

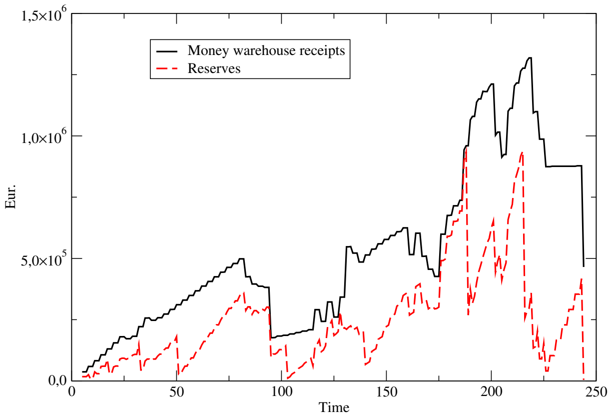

Fig. 4. Experiment *E3* with minimum reserve rate of 5% and an average loss of confidence rate of 30%.

We performed more computer experiments with larger minimum reserve values leading to fewer bank insolvency scenarios. The larger the minimum reserves are, the fewer the cases where the bank is not able to pay the withdrawals of the depositors. Therefore, it is not probable that a bank becomes insolvent unless a large number of depositors decide to withdraw their deposits at the same time.

These computer experiments also show that the minimum reserves do not have a great influence in the model. The reason for this is that there are not so many depositors. Thus, each agent has a large influence in the dynamics of the model. In this context, the loss of confidence of a single depositor can only lead to a withdrawal of 10 to 20% of the deposits in the bank. Furthermore, it was observed that the bank rarely becomes insolvent when the confidence loss has values between 30 and 60% and the re-utilised percentage of money is between 10 and 40%. It was also observed that, for a confidence loss between 30 and 40%, the bank becomes insolvent when a depositor withdraws her deposits just after a loan was granted.

VI. Conclusions

The results of the computer experiments show that the variable that has the greatest influence in the dynamics of the model is the average loss of confidence. This variable is determined randomly in the current version of the model. Further work is to consider different trust reputation mechanisms to make it adaptable, together with the average win of confidence, according to the number of deposits and loans over time.

Moreover, it would be of interest to further investigate the influence of the number of depositor and debtor agents in the model, i.e., whether the dynamics of the model scale in size or not. With respect to the bank agent, it would be interesting to analyse the impact of excluding external sources that would help a bank to pay to the depositors and keep it solvent.

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