Journal of Economic Interaction and Coordination (2021) 16:675–703
https://doi.org/10.1007/s11403-021-00325-6

REGULAR ARTICLE

Dynamic bank runs: an agent-based approach

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Received: 7 May 2018 / Accepted: 26 February 2021 / Published online: 19 March 2021

Abstract

This paper simulates bank runs by using an agent-based approach to assess the depositors' behavior under various scenarios in a Diamond-Dybvig model framework to answer the following question: What happens if several depositors and banks play in multiple rounds of a Diamond-Dybvig economy? The main contribution to the literature is that we consider a sequential service restriction and the influence of the neighborhood in the decision of patient depositors to withdraw earlier or later. Our simulations show that the number of bank failures goes to zero if the amount that banks pay to those who need liquidity is under a certain value. If this amount is above this value, the bank runs continue to occur after a long period and the market concentration is higher than in the former scenario. When wealth accumulation is allowed in the benchmark formulation, bank runs reduce and market concentration increases.

Keywords Bank run · Liquidity · Banking

JEL Classification C63 · G21 · D83

1 Introduction

The main role of commercial banks is to serve as financial intermediaries between depositors and borrowers. One of the reasons for the existence of commercial banks is the presence of asymmetric information, which is the fact that the borrower has more knowledge about his own situation than the lender. In the presence of asymmetric information, it pays the lender to monitor the borrower. However, the monitoring cost may be high for any particular borrower. When many agents perform this monitoring

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activity, they may find worthwhile to delegate it to a specialized entity to save on monitoring costs. This is one possible theory explaining the origins of banks, according to Diamond (1984).

In a fractional reserve bank system, banks are subject to runs. If a significant number of depositors decide to withdraw their resources from the bank, the bank will run out of its reserves, which may trigger liquidity or solvency problems.

We define bank runs as withdrawals over and above the expected demand for liquidity. When this happens, bank insolvencies may arise. Such withdrawals may occur due to random shocks (Diamond and Dybvig 1983) or may be a result of depositors' perceptions that the bank is facing some difficulties (Gorton 1985; Chari and Jagannathan 1988; Jacklin and Bhattacharya 1988; Allen and Gale 1998)[1].

Apart from its historical lessons, the study of bank runs is relevant because banks with good fundamentals may go bust due to a panic crisis triggered by bank runs. The social cost of bank failures may be relevant, and policymakers may benefit from a better understanding of how bank runs work.

In this paper, we simulate a bank run triggered by depositors' strategic decisions in a coordination game based on Diamond and Dybvig (1983). In this framework, some bank depositors are subject to a negative liquidity shock that leads them to withdraw their funds from a bank. Other depositors who are not hit by the adverse shock may be compelled to withdraw their resources from the bank as well, anticipating that the bank may not be solvent if they wait to withdraw later. Such panic behavior may lead to a bank run.

Our model is part of the literature on complex adaptive systems, where agents react to the environment through signals and its internal rules. They have memory and can choose which rule provides a better response, so agents adapt in such a way that they optimize their utility functions in the long term. For details about complex adaptive systems, see Holland (2014).

In particular, we use an agent-based model (ABM) as our approach. ABMs are computational methods to study the overall evolution of economies as complex adaptive systems emerging from the interaction of many autonomous agents following a given set of behavioral rules[2].

The original Diamond-Dybvig economy lasts for three periods. We embed this economy in a dynamic simulation so that the three periods of this model repeat in cycles. Each agent uses data from his memory to estimate what might happen and act to maximize his expected returns. In addition, banks arise endogenously in the model; any agent can become a banker if proper conditions arise.

Our paper extends Grasselli and Ismail (2013)'s model of bank failure into a context of bank runs. Grasselli and Ismail's model has a multibank environment to study financial contagion. As in Diamond and Dybvig (1983), bank depositors face liquidity shocks that lead them to withdraw their funds from the bank. However, unlike Diamond

[1] For the role of fundamentals in explaining bank runs, see the empirical evidence in Saunders and Wilson (1996) and Calomiris and Mason (2003) who study bank distress during the 1930's Depression in the USA, as well as Schumacher (2000) and Samartín (2003) who study bank runs in Argentina in 1994, and 2001, respectively.

[2] The volume edited by Gallegati et al. (2017) provides a good introduction to the ABM approach to economics.

and Dybvig, their model does not allow for bank runs due to coordination problems. Bank failures arise when the adverse liquidity shock is strong enough and banks run out of reserves to cover the withdrawals.

Our paper follows the bank run literature in the Diamond and Dybvig (1983) tradition and we introduce coordination problems into the Grasselli and Ismail (2013) framework. We also consider two elements that feature prominently in the bank run literature and are absent in Grasselli and Ismail's model. The first element is the sequential service constraint and the second is the consideration of neighborhood influence on the patient agent's decision. Our model is therefore capable of generating bank failures due to bank runs. Our results show that the evolution of the considered economy leads to a long-term stability when there is more liquidity, and to instability in a highly concentrated market when there is less liquidity. Grasselli and Ismail (2013) also arrived at the result that there are few established banks in the long run; however, the authors do not relate liquidity to market concentration.

Our most important result is that the number of bank runs decreases with the size of the banks' reserves and with the value of the threshold that leads a patient agent to withdraw early. Temzelides (1997) reaches similar conclusions. We do not impose any deposit insurance. The only elements we have in our model are the sequential service constraint and the agent's punishment when he does not receive the amount promised by the bank and decides not to be a customer anymore.

Davison and Ramirez (2014) provide some empirical support for the relation between bank size and bank runs. They study bank panics in the USA in the 1920s and show that such episodes were less likely to occur in states with relatively larger banks.

There is a long-lasting debate about possible trade-offs between financial stability and bank competition (Allen and Gale 2004). Our paper is not on bank competition, but our results indicate that possible trade-offs between financial stability and a more concentrated banking industry are indeed important, associated with enough reserves to face withdrawals above the predictions. The price to pay for a more stable banking sector may be an increase in concentration.

The structure of the paper is as follows. In Sect. 2, we review the literature. Section 3 presents the model, Sect. 4 shows the results, and Sect. 5 concludes the paper.

2 Literature

Diamond and Dybvig (1983) model a bank as a mechanism that allows investors to finance illiquid but profitable projects, protecting them from unforeseen shocks that result in anticipated consumption. There are two types of agents—patient and impatient—and three periods. In the initial period, zero, agents do not know their type and deposit their endowment of one unit of currency in the bank. In period one, the agent learns his type through a random draw. Impatient agents do not derive utility from period two and therefore decide to withdraw in period one. Patient agents derive utility in both periods (one and two) and therefore they decide whether to withdraw in period one or in period two. The bank does not know the type of each depositor. Diamond and Dybvig (1983) show that there may be bank runs even for banks with sound finances. The authors study how banks pay the depositors when the amount they wish to withdraw exceeds the bank reserves, and they come up with the idea of sequential service constraint: the depositors withdraw sequentially until the bank reserves run out. In addition, they propose that deposit insurance mechanisms inhibit bank runs and the suspension of convertibility leaves agents with liquidity needs without money.

Sequential service constraint is an assumption often adopted in the bank run literature. According to Diamond and Dybvig (1983), the demand deposit contract satisfies the sequential service constraint when the amount owed to the depositor depends on his position in the queue and is independent of the state of the agents who are after him in line. Therefore, if many of the patient agents decide to anticipate the withdrawal, the bank will serve the depositors until its cash is exhausted, leaving the agents that are behind the last to receive nothing. Some authors show that such a measure guarantees the payment promised to patient depositors in the last period; however, it might happen that people in need of liquidity end up out of cash. That is, the solution does not necessarily optimize utility.

Wallace (1988) points out that the hypothesis that people do not communicate in period 1 implies the sequential service constraint. The result is that the returns of early withdrawals depend on the random order of withdraws. Calomiris and Kahn (1991) treat the sequential service constraint on a theoretical model, in which bankers can divert customer resources away, and propose a contract to avoid such a situation. Romero (2009) makes explicit this restriction in his agent-based model simulations.

Does the sequential service constraint always involve a bank run? Green and Lin (2000) say that the answer to this question is no. They construct a theoretical environment in which there is no bank run, even with the sequential service constraint. To achieve this equilibrium, depositors would be encouraged to tell the truth. That is, there is no asymmetric information featuring a coordination game. Peck and Shell (2003) criticize the work of Green and Lin because bank runs are historical facts. To explain the reason for the existence of this phenomenon, they relax two hypotheses of the Green and Lin model. The first is to allow each depositor to have different utility. The second hypothesis is the elimination of the knowledge that the agent would have about their position in the queue to withdraw. Peck and Shell then conclude that in these cases there is the possibility of bank runs.

The assumption of this restriction may be implicit. The experimental work of Garratt and Keister (2009) does not impose the sequential service constraint to participants. If a bank fails, it splits the available amount of cash among depositors. However, if this restriction is placed, the expected value that a depositor receives is the same as was imposed by Garratt and Keister. Deng et al. (2010)'s simulation, on the other hand, makes this constraint implicit on the decision of patient depositors to withdraw or not in the first period.

At the empirical level, Kelly and Ó-Gráda (2000) and Ó-Gráda and White (2003) show that the 1854 bank run in New York was triggered by some depositors' fear of not receiving the promised amount from the bank for arriving too late for a possible run.

One possible element to trigger bank runs is the influence of the depositor's social network on decision-making. Kiss et al. (2014) and Kiss et al. (2018) present experimental evidence for the effect that observing other depositors' actions has in preventing or leading to bank runs. If depositors who decide first and have their actions observed by other depositors along the line keep their money in the bank, they help to prevent bank runs. By contrast, if they decide to withdraw their deposits, they help to trigger panic bank runs.

Kelly and Ó-Gráda (2000) discovered that during the panics of 1854 and 1857 in New York, the social network to which these depositors belonged was the most active factor in the withdrawal decision. Hong et al. (2004) point out that Kelly and Ó-Gráda (2000) did not consider "anti-social" agents. Hong et al. (2004) develop a model for the stock purchase decision and conclude that sociable people are more susceptible to invest in stock markets compared to those who are "anti-social".

Iyer and Puri (2012) also observed the importance of social networks by studying an episode of bank run in India in 2001. The authors report that the likelihood of a depositor running increases with the fraction of running depositors in his neighborhood. Moreover, in India, a common requirement for opening a bank account is for the new client to be introduced by an incumbent. Another possible measure of social network is therefore given by the network of a depositor's introducer. Iyer and Puri (2012) confirm the positive effect of runners in a depositors' introducer network on the likelihood of a depositor running.

The complexity ABM literature makes the hypothesis that social networking matters for bank runs. For example, the simulations of Romero (2009), Deng et al. (2010), and Grasselli and Ismail (2013) consider the influence of the depositor's network of contacts in their decision-making. According to Deng et al. (2010), a bank run may occur only by imitation among depositors, even in the absence of exogenous shocks.

Bank runs can have high social costs and it is, therefore, desirable to design policies to prevent them. Diamond and Dybvig (1983) exploit the suspension of convertibility and deposit insurance as alternatives. In the first choice, no one in the line can withdraw in the first period after a pre-established ratio of depositors is reached.

Under the assumption of sequential service constraint, the authors show that when the proportion of impatient agents is random, bank contracts fail to achieve optimal risk sharing, i.e., to serve all impatient agents in the second period and all patients in the third one. The use of convertibility suspension in the 1857 bank run is cited by Kelly and Ó-Gráda (2000) and by Ó-Gráda and White (2003). Ennis and Keister (2009) focus on policies that are *ex post* efficient, once the run is underway. The authors show how the anticipation of such intervention can create the necessary conditions for a self-fulfilling run to occur in the paradigm of Diamond and Dybvig (1983).

Diamond and Dybvig (1983) propose that contracts of deposit insurance provided by governments achieve a unique Nash equilibrium if the ruler imposes an optimal rate to fund the deposit insurance. Diamond and Dybvig (1983)'s statement is contested by Wallace (1988), who concluded that the deposit insurance proposed by them is not feasible, but he leaves open the feasibility of other arrangements. Another drawback, according to Ennis and Keister (2009), is that it is not always feasible for the government to guarantee payment of the full amount of deposits in the advent of a widespread run. Calomiris and Kahn (1991) argue that the bank run is a disciplinary mechanism of the market, because if depositors realize that the bank is diverting money, they withdraw and may start a bank run. Therefore, deposit insurance encourages moral hazard, because depositors can invest in banks taking more risks.

From an empirical perspective, Iyer and Puri (2012) show the importance of deposit insurance to prevent bank runs. Iyer and Puri (2012) use micro-level data at the depositor level to study a bank run in India in 2001, and report that insured depositors are less likely to withdraw their funds during a bank run. Nevertheless, deposit insurance is only partially effective in preventing runs. Iyer and Puri (2012) also found that insured depositors with higher account balances increase the likelihood of running.

Our modelling approach is to develop an agent-based version of the Diamond-Dybvig economy. There is some considerable ABM literature on bank crisis. However, most of this literature concentrate on contagious effects spreading from networks of banks which are interconnected through the interbank market (Georg 2013; Grilli et al. 2015; Dias et al. 2015; Bardoscia 2017; Chan-Lau 2017 to quote a few) following the seminal work of Allen and Gale (2000) on banking networks. Neveu (2018) provides a recent comprehensive survey of this literature.

There are not many ABM models of bank runs triggered by coordination problems as in the Diamond-Dybvig approach. Arifovic (2019) and Deng et al. (2010) are some examples.

Arifovic (2019) study how the 'withdraw (run)' and 'wait (no run)' equilibria are affected by extrinsic random variable announcements in an economy with agents that adapt using individual evolutionary algorithms. The results of the model simulation depend on the levels of strategic uncertainty. 'No-run' and 'run' outcomes are observed for low levels of strategic uncertainty. For high levels of strategic uncertainty, however, the adaptive agents evolve strategies that follow sunspot announcements.

Deng et al. (2010) consider depositors interacting with neighbors and receiving signals about their withdrawal behavior. Depositors decide whether to wait or to withdraw comparing the signals with activation thresholds. The authors show that the 'no-run' equilibrium is more likely to be observed for larger shares of patient deposits, larger activation thresholds and larger interaction neighborhoods.

These previous studies do not consider a multibank environment. Romero (2009) and Grasselli and Ismail (2013) embed the Diamond-Dybvig structure into a multibank environment. Following the network literature, these papers study contagious effects from the interbank market.

Our approach considers multibanks in a Diamond-Dybvig economy, but we do not model bank contagion. Our main question is the stabilizing mechanism arising from the size of bank reserves through the behavior of depositors and their social interactions repeated across time.

3 Model

Our model combines elements of the original Diamond and Dybvig (1983) bank run setup with elements of Grasselli and Ismail (2013)'s dynamic bank failure model alongside a consideration of the social network of the depositor to influence his decision-making.

3.1 Agents, preferences, banks

There are three periods, 0, 1, and 2, as in Diamond and Dybvig (1983). We follow Grasselli and Ismail (2013) and allow banks to arise endogenously. In period zero, before banks are formed, each agent i has a random preference parameter from a uniform distribution U_i in [0, 1]. Agents with $U_i \leq 1/2$[3] are the impatient ones, whereas those with $U_i > 1/2$ are the patient ones.

Each agent is endowed with one monetary unit and he has access to asset markets that gives him the choice of receiving back his unit monetary investment in period one, if he decides to invest in liquid assets. In the case of investing in illiquid assets, he may receive $r < 1$ if he withdraws in period one or $R > 1$ if he waits until period two. Impatient agents will choose the liquid asset while patient ones will choose the illiquid asset. Alternatively, an agent can choose to deposit his monetary endowment in a bank according to the rules that we will describe briefly.

Let $\bar{U}_i$ be the actual preference endowment in period 0. There is then an exogenous liquidity preference shock such that his preference in period 1 becomes:

$$\rho_i = \bar{U}_i + (-1)^{b_i} \frac{\epsilon_i}{2}$$

where b_i is a random variable with Bernoulli distribution taking values in the set $\{0, 1\}$, with equal probability, and $\epsilon_i \in [0, 1]$ has a uniform distribution. In other words, agents can change their liquidity preference depending on the size of the shock in $\bar{U}_i$. As before, agents are impatient if $\rho_i \leq 1/2$, and patient otherwise.

The preference shock in period one opens the possibility for agents to search for partners to trade their assets and improve their consumption possibilities when they choose to invest in asset markets in period 0. For those agents who decided to become bank depositors, they have the choice to withdraw in period one or to wait and withdraw in period two.

The model allows for cycles to repeat several times. Therefore, given a cycle k, the draw to determine the initial preference $\bar{U}_i$ of each agent and consequently the assets in which he invests is done in period zero; in period one the preference shock ρ_i occurs as well as the search for partners to trade, and in period two agents with illiquid assets receive R.

Banks arise endogenously. A bank is defined as an agent who owns a contract that pays r_1 in period one, such that $1 < r_1 < R$, and pays r_2 in period two, with $r_1 < r_2 < R$. All the rates r_1, r_2, r, and R are public and known to everybody. This assumption distances our model from the global game framework in which depositors receive noise private signals about the banks' fundamentals (Morris and Shin 2003; Goldstein and Pauzner 2005).

When there is a bank, agents may or may not adhere to this contract according to the rules described below.

[3] Romero (2009) and Grasselli and Ismail (2013) used 1/2 also as a threshold to discriminate who are patient or impatient.

Table 1 Moore neighborhood of agent A_0.

A_1	A_2	A_3
A_4	A_0	A_5
A_6	A_7	A_8

The other agents A_i, $1 \leq i \leq 8$, are its neighbors in the lattice.

3.2 Transition rules

The structure we consider follows the ABM tradition and allows for memory and learning. Based on their predictions, the agents decide whether or not to become customers of a bank.

The transition rules for agents are as follows:

Bargain $B(\rho, v)$: agents who have a positive preference shock in period one look for a neighbor that was hit by a negative preference shock to trade assets.

In this rule, after the shock preferences, ρ, those agents who had decided not to become a bank's client, who have liquid assets, and now want to wait to receive R can trade with someone in their social network v who has illiquid assets and needs money immediately. This change improves the situation to both; however, it is not always possible to find a partner in his social network, v.

If there is a bank in his neighborhood, the agent does not consider starting a new one. However, if there is none, the agent may consider becoming a banker.

Become a bank $BK(r_1, r_2, R, v)$: at time 0, the agent estimates the proportion of impatient agents in his social network v. Given the parameters r_1, r_2 and R, the agent decides whether to open or not a bank.

In the ABM tradition, agents lack full knowledge and have instead limited information about the environment and other agents. We introduce this feature in our model by considering Moore neighborhoods, that is, a two-dimensional square lattice composed of a central cell and the eight cells that surround it (see Table 1). Romero (2009) and Grasselli and Ismail (2013) also consider Moore neighborhoods. By contrast, Deng et al. (2010) consider the diamond-shaped von Neumann neighborhoods of different ranges.

By assumption, the first candidates to become bank clients are the bank's eight neighbors in its Moore neighborhood and the banker himself, so there are nine potential depositors.

The decision to become or not a bank depends on an unknown proportion of impatient agents; for this reason, it is necessary to estimate this number through a random variable w such that:

$$w \in \left\{0, \frac{1}{9}, \frac{2}{9}, \frac{3}{9}, \frac{4}{9}, \frac{5}{9}, \frac{6}{9}, \frac{7}{9}, \frac{8}{9}, 1\right\}$$

The potential bank computes y_i and x_i according to $y_i = w_i r_1$, and $Rx_i = (1 - w_i) r_2$, and check whether the condition $y_i + x_i \leq 1$ holds or not. When this condition is met it is worth establishing himself as a banker. In this case, the bank

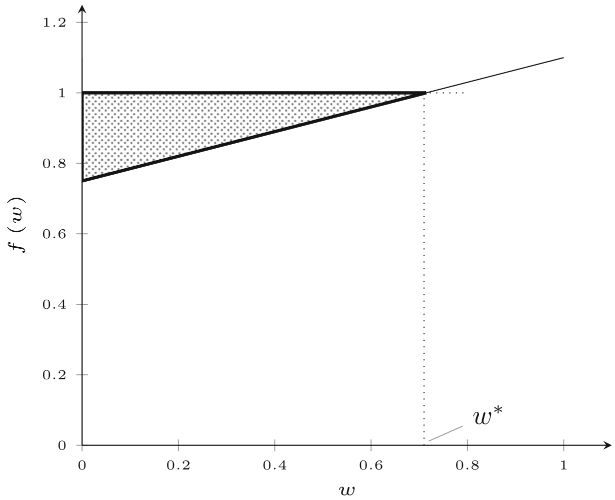

Fig. 1 Amount needed to support withdrawals as function of the proportion of impatient depositors

invests the fraction x_i in the illiquid asset, the fraction y_i in the liquid asset, and the remaining $(1 - x_i - y_i)$ is kept as reserves. Manipulating the inequality, it follows that, for a bank to be established, the fraction of impatient depositors should be subject to the following upper limit:

$$w_i \leq \frac{R - r_2}{Rr_1 - r_2}$$

We can write the per capita present value amount that the bank must provide for paying customers in periods one and two as:

$$f(w) = r_1 w + \frac{r_2 (1 - w)}{R}$$

If $w \in [0, 1]$ then $f(w) \in [r_2/R, r_1]$. According to Bolzano's theorem,[4] for each value $Q \in (r_2/R, r_1)$ there exists $\omega \in \left[w^*, 1\right]$ such that $f(\omega) = Q$, where $f(w^*) = 1$. In other words, there are realizations of w which discourage the creation of a bank or, if it already exists, the amount collected from customers in a cycle may not be enough to honor the contract.

Figure 1 exemplifies the graph of the $f(w)$ function with the following parameters: $r_1 = 1.1$, $r_2 = 1.5$ and $R = 2$. Note that when w is above a certain threshold w^*, the deposits are insufficient to honor the contract between the bank and its customers. The shaded area is when a bank is viable, where $1 - (x + y) \geq 0$. This surplus is added to the bank reserves.

Up to now, we mostly followed Grasselli and Ismail (2013)'s model development. We start to depart from them by considering a role for the agent's social network.

[4] Bolzano's theorem states that if a function f is continuous in a closed interval $[a, b]$ then $\forall S \in (f(a), f(b))$, $\exists c \in (a, b)$ such that $f(c) = S$.

3.3 Clients' behaviour

The rule for opening a bank account is:

> Become a client of next-door bank or next-door neighbor's bank $T(v, pyf)$: If the agent evaluates that is advantageous, he opens an account in a bank in the immediate neighborhood; if there is no one in this condition, he becomes a client of the same bank of one of her/his neighbors.

The result of the comparison of payoffs for an agent to decide to join a bank or not is denoted pyf. Following ABM convention, we incorporate the idea that agents have limited knowledge and information processing capacity. They rely on heuristic behavior constructed from their memories to dictate their actions.

We use the same mechanism of agent's decision of Grasselli and Ismail (2013). Each agent uses seven potential predictors constructed from his memory, which is limited to five cycles. This memory contains information on three items: one, if the budget constraint remains unchanged after the shock, N; two, if there was a change but no partner was found, B; and, three, if there was a change and someone to bargain with was found, G.

The forecast of each situation is compared to the actual realization and an array of forces of the predictors, Φ is updated as follows: if the prediction turns out to be correct, one is added to the appropriate element in Φ; otherwise, one is subtracted. The stated predictors are:

1. Next period will be the same as the previous cycle
2. Next period will be the same as two cycles ago
3. Next period will be the same as three cycles ago
4. Next period will be the same as four cycles ago
5. Next period will be the same as five cycles ago
6. Next period will be equal to the mode of the last three previous cycles
7. Next period will be equal to the mode of the last five previous cycles

In the decision to become a bank customer, the agent can map the return of each predictor to a situation in which he deposits or not his cash in a bank, obtaining, respectively, the vectors Π_d and Π_n. We use the vector of forces of the predictors, Φ, as weights. Thus, the respective expected returns are $\Pi_d^T \cdot \Phi$ and $\Pi_n^T \cdot \Phi$ and he chooses the option that gives the highest expected return.

The rationale for the next-door rule $T(v, pyf)$ is to become a client of the same bank with someone from his own social network, a feature that was found to be relevant in Iyer and Puri (2012).

Withdrawals follow the order in a queue where closer clients have priority to withdraw. If there is more than one client at the same distance from the bank, we choose randomly who will receive first. This queue represents the sequential service constraint described by Diamond and Dybvig (1983) and is a key element discussed in the bank run literature.

The final rule defines the withdrawal behavior:

Withdraw in period one $R(\rho, d)$: if $\rho \leq 1/2$ the agent withdraws in period one. If the agent is not a bank customer, he can receive one monetary unit if he has liquid assets or he can receive r if he has the illiquid asset. If he is a bank customer, the returns are r_1 or zero in period one depending on the distance to his bank, d.

Everyone who has the preference parameter ρ below the assumed threshold, 1/2 in this case, will withdraw at time 1 of the cycle. Bank runs can occur at time 1 if patient clients believe that banks will not afford their demands at time 2. We also introduce an imitation rule for patient depositors[5]:

Imitation rule $M(\rho, v, n)$: If $\rho > \frac{1}{2}$ and more than n neighbors in his social network v intend to withdraw now, the client decides to withdraw too.

The agents in our formulation learn about behavior through imitation observing and interacting with neighbors (local interaction). The local interaction and imitation structure is standard in the agent-based bank run literature and is also used by Deng et al. (2010) and Grasselli and Ismail (2013).

3.4 Banks' behaviour

We extend Grasselli and Ismail (2013) model in another dimension through the introduction of sequential service constraints:

Sequential service $SS(d)$: Closest bank clients withdraw first.

Banks consider the distance d from their clients and start to pay for those who live closest.

It may be the case that the amount estimated for the bank to face withdraws in period one is not enough. The bank then uses its reserves to serve the customers. If the reserves run out, the bank sells the illiquid assets. If the bank exhausts all resources, the last clients in line do not receive anything and the link between them and the bank is broken.

Fail F: if a bank has five or fewer clients, it fails. The remaining clients are released.

After the bank liquidation, the remaining customers return to their original state and decide whether to join another bank at the start of the next cycle.

If bank i survives, it updates its expected proportion at cycle k, w_i^k, of liquid assets to face withdraws in period one by the following adaptive rule:

$$w_i^k = w_i^{k-1} + \alpha \left(\bar{w}_i - w_i^{k-1} \right)$$

where $\bar{w}_i$ is the actual proportion of clients who withdrew in period 1 at cyle k-1.

[5] Kiss et al. (2014) have done an experiment with humans, and found that imitation can trigger a bank run. Ó-Gráda and White (2003) using econometric methods reached the same conclusion.

3.5 Simulation's dynamics

Before we present the results in the next section, we summarize the sequence of events for each cycle:

- Agents who are not banks
  1. Period 0:
     - Agent receives a unit endowment and U preference shock.
     - Agent decides whether or not to be a bank if he is neither a bank client nor a bank already.
     - Agent decides whether or not to be a bank client provided that he is neither a bank nor a bank client already.
     - Agents who decided to be neither banks nor bank clients choose to invest in the liquid or in the illiquid asset.
  2. Period 1:
     - Agent receives ρ preference shock.
     - If agent is not a bank or a bank client, he tries to find some other agent to trade with.
     - Impatient depositors start to queue to withdraw.
     - Patient depositors join the queue if a certain proportion of their neighbors, who are clients of the same bank, show intention to withdraw.
  3. Period 2:
     - Patient depositors that did not withdraw in period 1 receive the minimum between r_2 and the remaining per capita amount of funds available at the bank.
     - If each client receives less than r_1, then they break the link with the bank.
- Banks:
  1. Period 0:
     - Each bank counts how many clients they have from the end of the previous cycle. If a bank has five or fewer clients, then it is liquidated.
     - Banks receive deposits from their clients and allocate these deposits among liquid assets, illiquid assets, and reserves.
  2. Period 1:
     - Banks serve their clients in order of distance:
       - Banks use their investment in liquid assets first to pay their clients;
       - If the resources invested in liquid assets finish, then banks use their reserves to face the withdraws;
       - If bank reserves are not enough, banks liquidate their investment in illiquid assets to pay the remaining clients in the line;
       - Bank depositors that were not served break the link with the bank. If bank has five or fewer clients remaining, then it fails.
  3. Period 2:
     - If the sum of x and reserves is not enough to pay r_2 to every client, then the bank pays a share fewer than r_2.

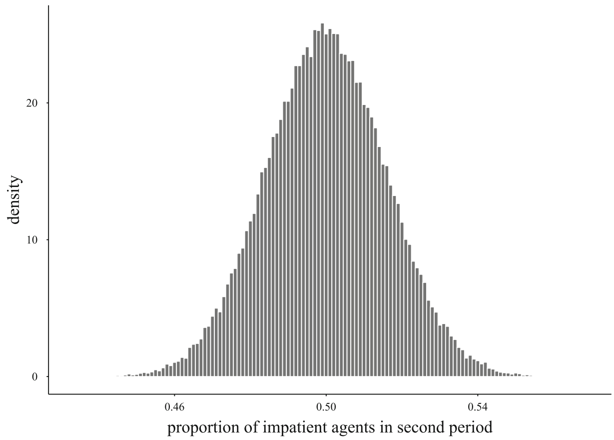

Fig. 2 Histogram of impatient agents in second period

- If the sum of x and reserves is enough to pay r_2 to every client, then the bank pays r_2 and it adds the surplus to its reserves.

4 Results

In this section, we present some simulations of our model[6]. The benchmark simulations' parameters are $r_1 \in \{1.001, 1.003, 1.005, 1.007, 1.009\}$, $r_2 = 1.03$, $r = 0.8$ and $R = 1.05$ with a patient depositors' threshold to imitate its neighbors in the following set of proportions $\{0.4, 0.6, 0.8\}$. The preference shock U is randomly selected from a uniform distribution in the interval $[0, 1]$.

The preference shock ρ was simulated 100.000 times in R with a seed parameter of 4242. Figure 2 shows the distribution of agents that need liquidity. Thus, the minimum proportion of agents that needed liquidity was 0.434 and the maximum was 0.568. Note that while the proportion of impatient agents in Samartín (2003) can take only two values, in our model such proportion can take values in a continuous interval, as in Grasselli and Ismail (2013).

Figure 3 describes how many bank runs occur in 100 simulations from 100 cycles in a world with $99 \times 99 = 9{,}801$ agents in an unbounded lattice, that is, the neighbors of an agent on the edge of the world are on the opposite edge. The vertical axis is the average number of bank runs and the abscissa is the number of Diamond and Dybvig like cycles. The bank serves the customers in the queue in period 1 of each cycle, while the remaining resources are still enough to pay the customers in period 2. Thus, customers receive r_2 in period 2. This rule would prevent withdrawal from patient agents; the simulation, however, allows them to follow the imitation rule.

Bank runs are rare events even when banks are still small at the initial cycles. The average number of bank runs is never above 2.0 and it converges towards zero after

[6] The simulations were implemented using Netlogo. Netlogo was developed by Wilensky (1999). Our written Netlogo code is available upon request.

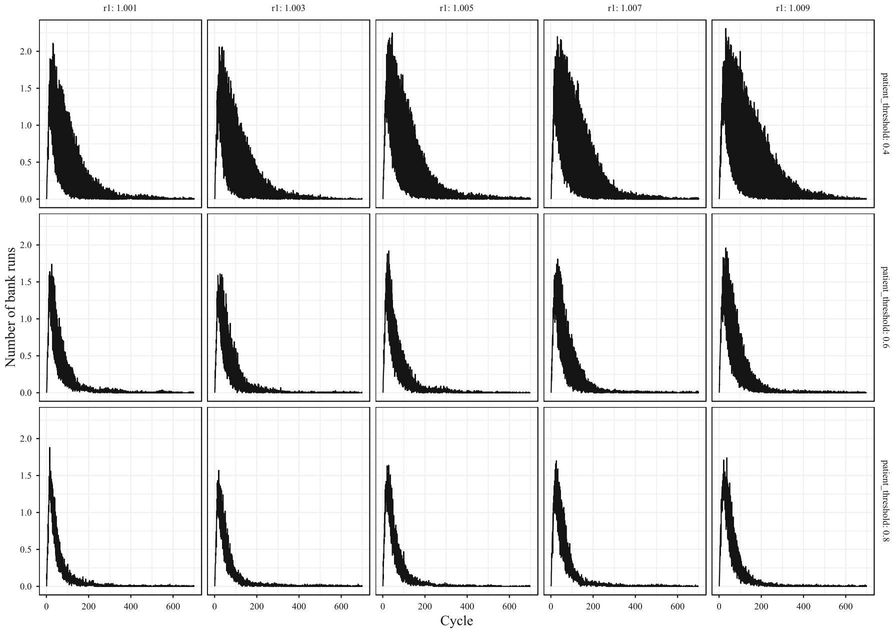

Fig. 3 Average number of bank runs by cycle. Each row represents a different proportion threshold to patient agents that run by imitating their neighbors. This proportion is 0.4 in the first row, 0.6 in the second, and 0.8 in the third. Each column represents a different r_1. They are, from left to right: 1.001, 1.003, 1.005, 1.007 and 1.009

cycle 300. Smaller banks lose depositors during the process. These lost clients end up joining a larger financial institution until the presence of small banks becomes unfeasible. Due to this feature, the patterns in the simulations show the survival of a few large banks after a long time.

The decay of bank runs in Fig. 3 is correlated to the increase in banking concentration; at the end of the simulations, there are only big banks. Temzelides (1997) shows similar results in a repeated Diamond-Dybvig economy with learning and local interactions (in a circular city).

We also measured the number of customers who cannot withdraw in period 1 and therefore get nothing. In Fig. 4 we depict the evolution of this metric, where the ordinate represents the average number of customers who stood in the queue and did not get money.

Figure 5 shows the average number of banks by cycle. Banks start to appear very early, and their number increases quickly until reaching an average of around 5 by cycle 30. However, when the patient's threshold to run by imitating neighbours is low, the volatility is higher, and the number of banks varies between 3 and 5. There are more bank runs at first, possibly because banks have few customers.

Bank's reserves grow linearly as can be seen in Fig. 6. Bank runs decrease with the size of reserves, as is seen in Fig. 8. Since there could be the question whether a run in a larger bank could hurt more customers, Figs. 4 and 7 show that a greater bank concentration also means a smaller number of clients harmed by a possible run.

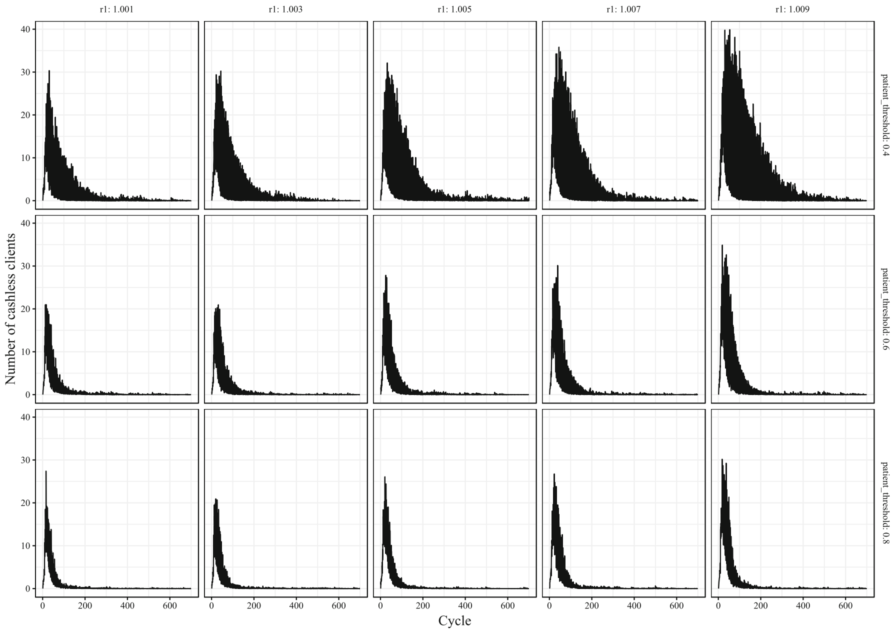

Fig. 4 Average number of clients without cash by cycle. Each row represents a different proportion threshold to patient agents that run by imitating their neighbors. This proportion is 0.4 in the first row, 0.6 in the second, and 0.8 in the third. Each column represents a different r_1. They are, from left to right: 1.001, 1.003, 1.005, 1.007 and 1.009

The more frequent runs at the beginning of the simulations may be due to the law of small numbers cited by Kahneman (2011)[7]. According to the author, people tend to generalize from small samples; for example, assume that the likelihood of being impatient is 40%. A patient agent considers only the behavior of his eight immediate neighbors so that if four or more are impatient, he decides to withdraw earlier. The probability of misinterpretation becomes:

$$\sum_{k=4}^{8} \binom{8}{k} \cdot 0.4^k \cdot 0.6^{(8-k)} = 40.59\%$$

That is, due to a small sample size, the probability that half or more of his neighbors are impatient is 40.59%.

Figure 8 relates the size of banks' reserves and the number of runs. The negative correlation between runs and banks' reserves can be explained by the fact that banks with enough reserves can face a bank run using its reserves to pay the excess withdraws.

The most important policy instrument used by bank regulators around the world to prevent bank runs is the implementation of deposit insurance mechanisms. We do not consider deposit insurance in our modelling and our framework could therefore

7 Horváth and Kiss (2016) developed a formal model making a connection between bank runs and the law of small numbers.

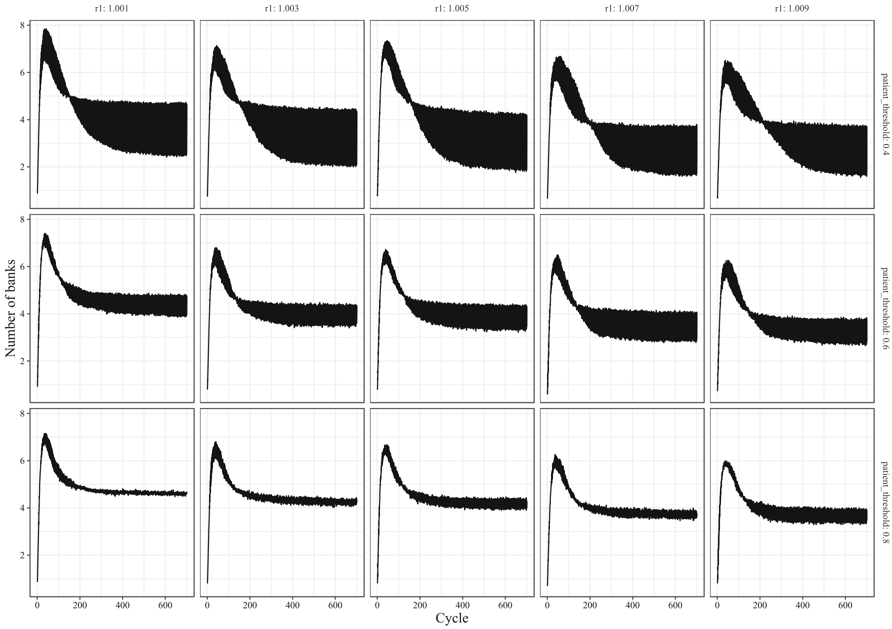

Fig. 5 Average number of banks by cycle. Each row represents a different proportion threshold to patient agents that run by imitating their neighbors. This proportion is 0.4 in the first row, 0.6 in the second, and 0.8 in the third. Each column represents a different r_1. They are, from left to right: 1.001, 1.003, 1.005, 1.007 and 1.009

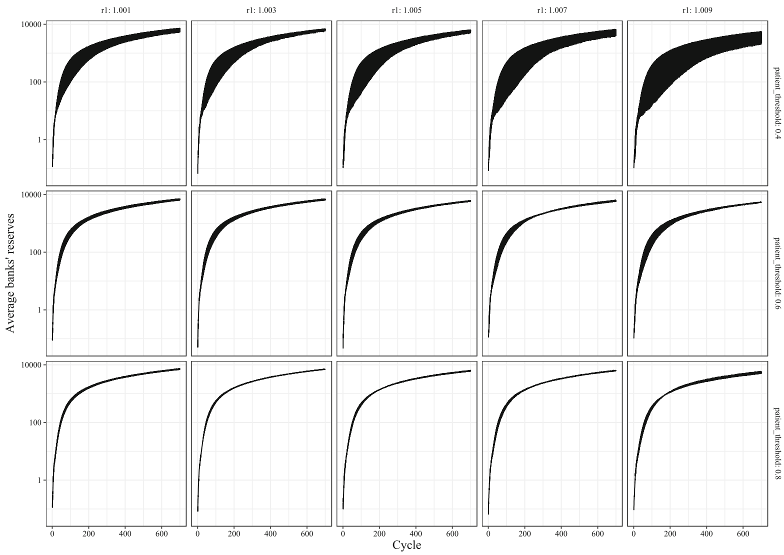

Fig. 6 Average banks' reserves by cycle. Each row represents a different proportion threshold to patient agents that run by imitating their neighbors. This proportion is 0.4 in the first row, 0.6 in the second, and 0.8 in the third. Each column represents a different r_1. They are, from left to right: 1.001, 1.003, 1.005, 1.007 and 1.009

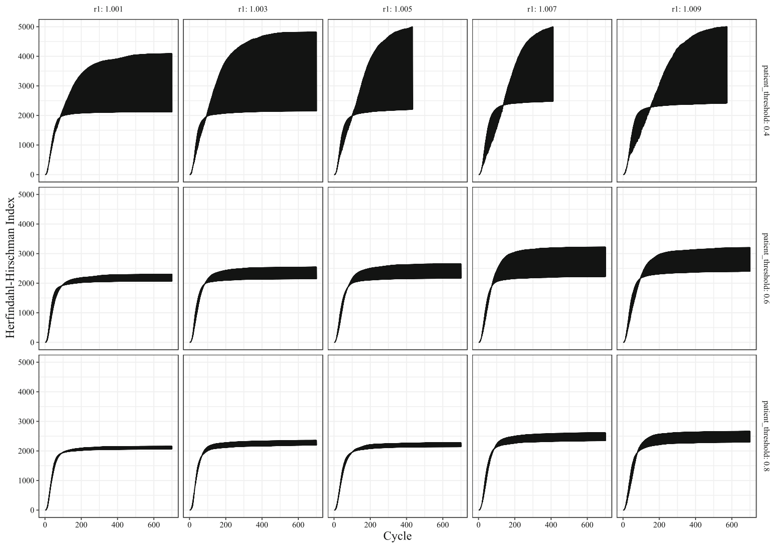

Fig. 7 Average Herfindahl-Hirschman Index by cycle. Each row represents a different proportion threshold to patient agents that run by imitating their neighbors. This proportion is 0.4 in the first row, 0.6 in the second, and 0.8 in the third. Each column represents a different r_1. They are, from left to right: 1.001, 1.003, 1.005, 1.007 and 1.009

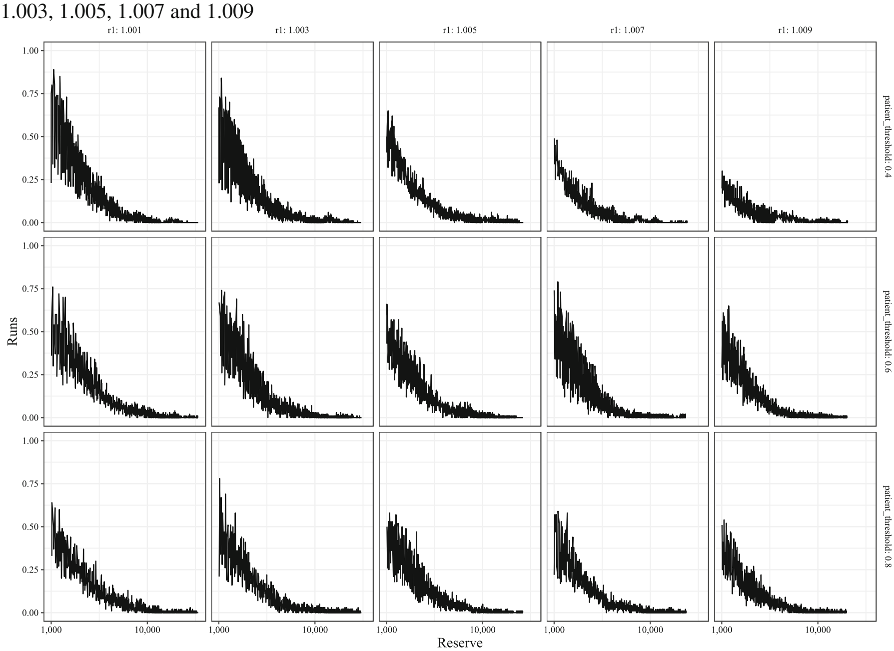

Fig. 8 Banks' reserves versus Number of runs. Each row represents a different proportion threshold to patient agents that run by imitating their neighbors. This proportion is 0.4 in the first row, 0.6 in the second, and 0.8 in the third. Each column represents a different r_1. They are, from left to right: 1.001, 1.003, 1.005, 1.007 and 1.009

be thought as the investigation of bank run episodes previous to the launching of such regulations. In such an environment, our model highlights the relevance of social interactive mechanisms that lead to the emergence of a concentrated banking sector combined with an elevated level of banks' reserves that reduces the number of bank runs significantly. In a sense, our results indicate an alternative development that could have happened in history if deposit insurance had not been implemented. It is not clear whether the welfare implications would be more favorable in our alternative world of few but stable banks, relative to a world with deposit insurance.

4.1 Robustness

We test the combinations of $r_1 \in \{1.1, 1.2\}$ and patient threshold to run of 0.5 and 0.6 as robustness check of our model, keeping $r_2 = 1.5$, $r = 0.8$ and $R = 2$[8]. In our benchmark setting, we used the combination $r_1 \in \{1.001, 1.003, 1.005, 1.007, 1.009\}$ and thresholds in the set $\{0.4, 0.6, 0.8\}$ for patient depositors to run.

We find that greater r_1 leads to lower banks' reserves, more bank runs, and more market concentration. These results are compatible with the findings of Arifovic et al. (2013) and Arifovic (2019) that an r_1 above a certain limit makes the state of their experimental economy change from the no-run equilibrium, to an indeterminacy region and, for even larger values of r_1, to a run equilibrium. r_1 and r_2 values relate to their coordination parameter associated to the proportion of patient agents who choose to wait to withdraw in the last period to receive the higher r_2 payoff compared to those who choose to withdraw early.[9] Our benchmark corresponds to a coordination parameter that leads to no-run equilibrium while the raise to $r_1 = 1.2$ corresponds to a coordination parameter in the indeterminacy region.

We also find that the value of patient threshold to run changes the intensity of the results, which agree with the agent-based Deng et al. (2010) model of bank run.

Figure 9 shows that when $r_1 = 1.1$ the number of runs goes to zero after two thousand cycles. However, when $r_1 = 1.2$ the number of runs decreases with time, but does not go to zero and the worst case is the combination with patient threshold equal to 0.5. This pattern repeats in Fig. 10, which shows the average number of depositors who fail to withdraw their funds.

When r_1 increases form 1.1 to 1.2, the result is a situation with fewer banks (Fig. 11), and higher concentration (Fig. 12). Again, the combination $r_1 = 1.2$ and patient threshold equal to 0.5 is the worst scenario.

The combination of r_1 and patient threshold affects the amount of banks' reserves (Fig. 13). When banks take more risk, offering a higher r_1, the reserves either remain constant in a low level—as in the combination of $r_1 = 1.2$ and patient threshold of 0.6—or the financial system does not have reserves at all as in the combination of $r_1 = 1.2$ and patient threshold of 0.5. The low level of reserves makes the banks more vulnerable to runs, and it is more difficult to survive in a riskier environment, inducing a higher concentration eventually.

[8] Romero (2009) and Grasselli and Ismail (2013) used these same set of parameters.

[9] Arifovic et al. (2013) and Arifovic (2019) show that this coordination parameter is given by $\frac{r_1(r_2-1)}{r_2(r_1-1)}$.

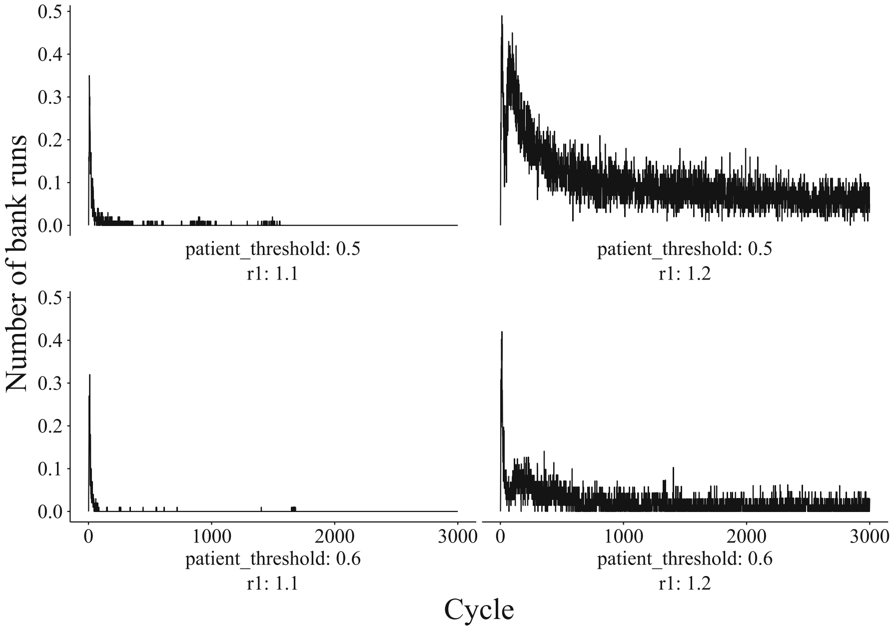

Fig. 9 Average number of bank runs by cycle varying r_1 and patient threshold

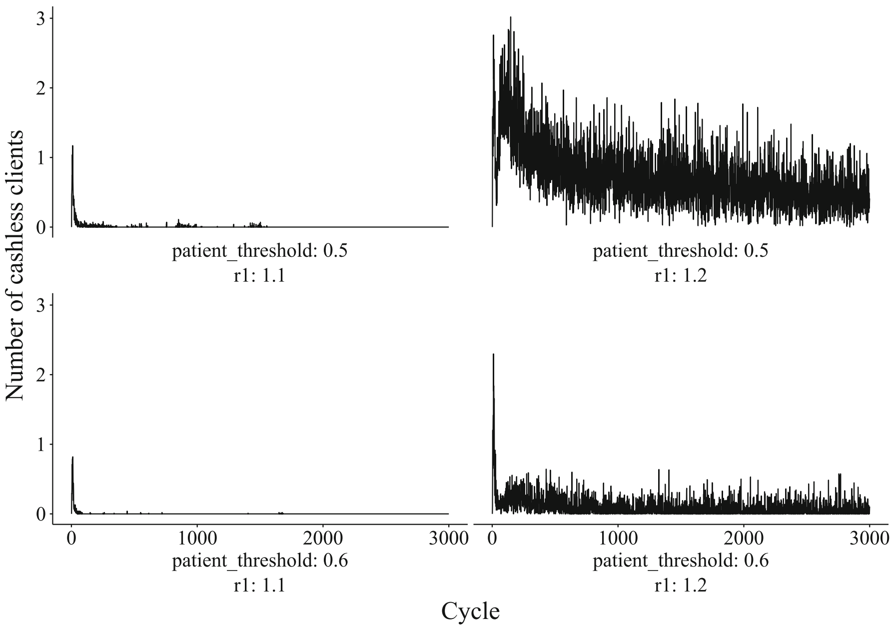

Fig. 10 Average number of clients without cash by cycle varying r_1 and patient threshold

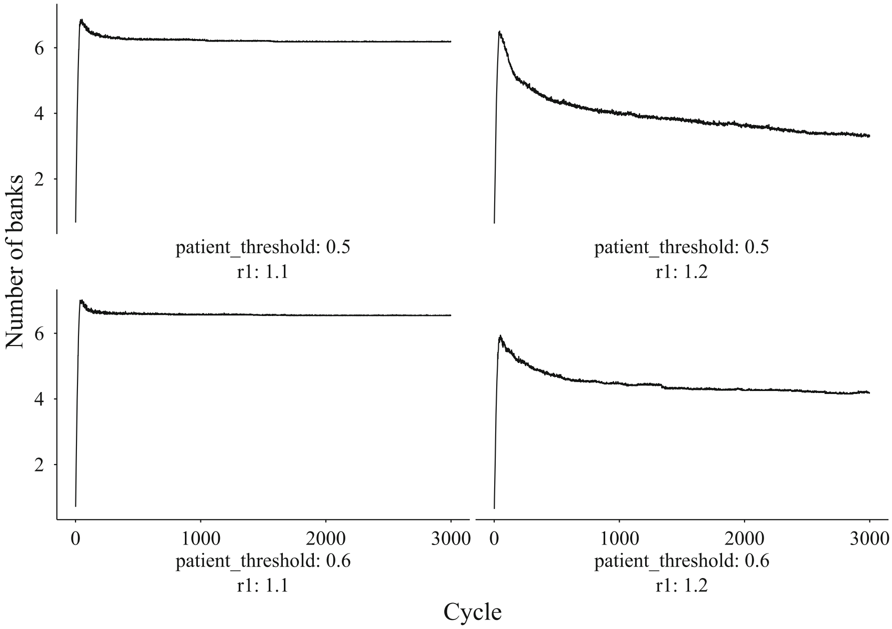

Fig. 11 Average number of banks by cycle varying r_1 and patient threshold

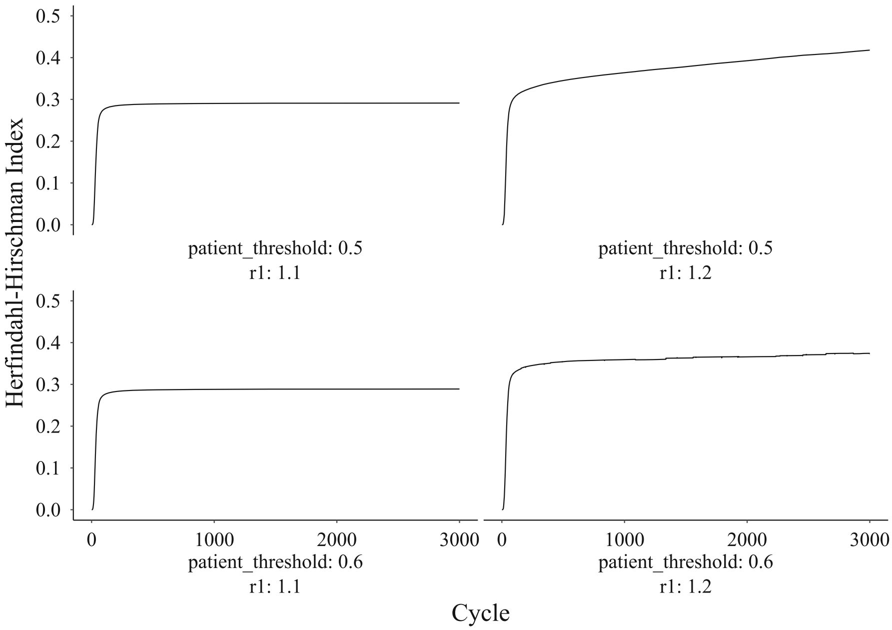

Fig. 12 Average Herfindahl-Hirschman Index by cycle varying r_1 and patient threshold

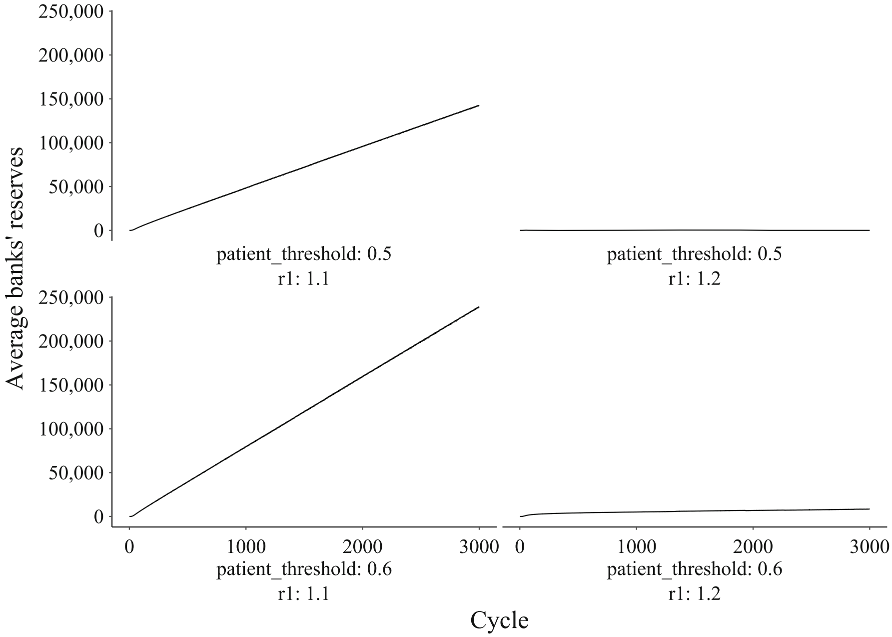

Fig. 13 Average banks' reserves by cycle varying r_1 and patient threshold

As a summary, the results of our simulations indicate that long-term bank runs are rare when the promised payment by the bank in the second period (r_1) is 1.1, even if some clients are locally subject to errors induced by a small sample. However, if r_1 is 1.2, the number of bank runs is low but they do not go to zero, with nonzero occurrences during the whole period of simulations. Moreover, in the latter scenario, the market concentration measured by the Herfindahl-Hirschman index was greater than in the former. When $r_1 = 1.2$ and patient depositors' threshold to imitate is 60% or above, bank reserves were constant. If $r_1 = 1.2$ and patient depositors' threshold to imitate is 50% or above, bank reserves were zero. Bank reserves increase with time when $r_1 = 1.1$. Thus, the patient depositor threshold to imitate influences the growth rate of reserves. Banks calculate the amount to pay in the last period in each cycle, depending on the size of the queue and the number of customers who stay to withdraw.

4.2 Extension: heterogeneous deposits by agents

We have not so far considered the possibility that agents can accumulate wealth between cycles. From one cycle to the next each agent returns to the unit endowment. We now relax this assumption and give the opportunity that agents could accumulate wealth between cycles.

In our benchmark formulation, banks with enough reserves do not face runs. Depositors of such large banks are too small to trigger runs when they decide to withdraw their funds. If we allow depositors to accumulate wealth, they may become big enough

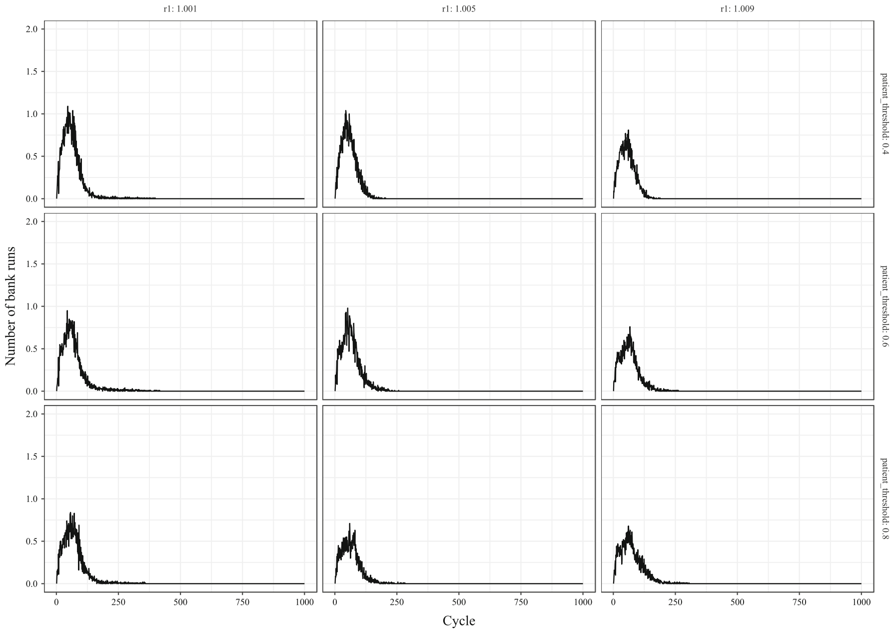

Fig. 14 Average number of bank runs by cycle. Each row represents a different proportion threshold to patient agents that run by imitating their neighbors. This proportion is 0.4 in the first row, 0.6 in the second, and 0.8 in the third. Each column represents a different r_1. They are, from left to right: 1.001, 1.003, 1.005, 1.007 and 1.009

so that their withdrawal decision can trigger a run even for large banks. The aim of the extension we present now is to evaluate if this possibility arises in our setting.

In our model, there are agents which never withdraw in period one. Therefore, we expect that those agents' wealth would follow a geometric progression growth. Otherwise, there are agents which always withdraw in period one, and this kind of agent would end up with no wealth growth.

For each agent i, let ω_i denote his available wealth, which can be allocated in the asset market or deposited in a bank. ω_i is the sum of the wealth at the end of the previous cycle plus one unit of endowment received at the start of each cycle.

The allocation decision of the ω_i wealth at time 0 follows the same rules as in the benchmark formulation with the exception of $\bar{\omega}$, which is now the proportion of wealth withdrawn in period one instead of the proportion of clients who had withdrawn. In period one, after the liquidity shock, the sequence of events depends on whether or not the agent had decided to be a bank client in the previous period.

- Agents who are not clients of a bank:
  - Impatient agents spend their total wealth in period one; in the next cycle, their initial wealth will be zero;
  - Patient agents do not spend anything in period one, receive $R \cdot \omega_i$ in period two, and spend ω_i. Their initial wealth in the next cycle will be $(R - 1)\omega_i$.
- Agents who are the clients of a bank:

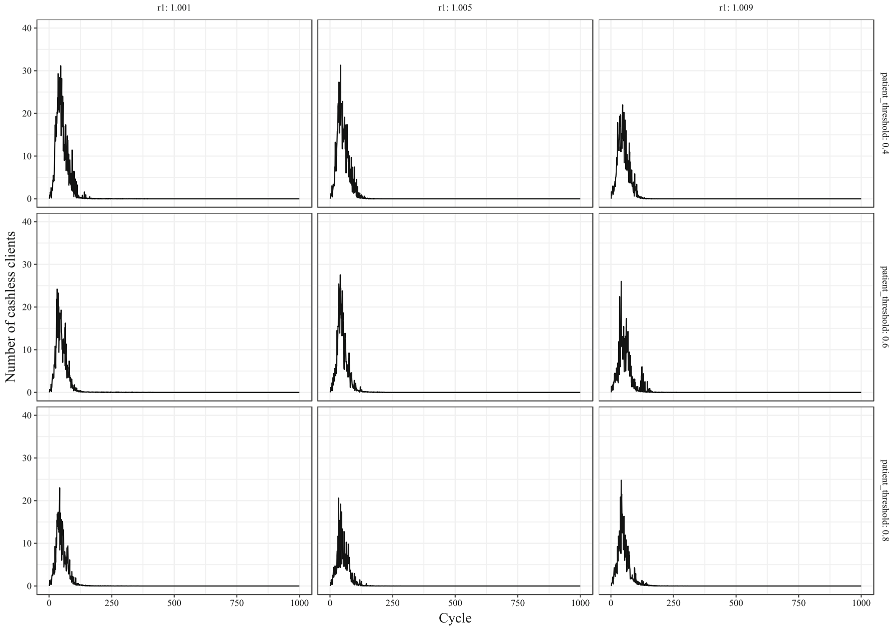

Fig. 15 Average number of clients without cash by cycle. Each row represents a different proportion threshold to patient agents that run by imitating their neighbors. This proportion is 0.4 in the first row, 0.6 in the second, and 0.8 in the third. Each column represents a different r_1. They are, from left to right: 1.001, 1.003, 1.005, 1.007 and 1.009

- Impatient agents receive $r_1 \cdot \omega_i$ and spend ω_i in period one; in the next cycle, their initial wealth will be $(r_1 - 1)\omega_i$;
- Patient agents do not spend anything in period one, receive $r_2 \cdot \omega_i$ in period two, and spend ω_i. Their initial wealth in the next cycle will be $(r_2 - 1)\omega_i$.

On the other hand, banks receive the wealth of each client as deposit. In period one, a line of clients which want to withdraw is formed, sorted by the distance from the bank. Each bank can pay $r_1 \cdot \omega_i$ for its client i if there is enough cash. The bank uses its assets to pay depositors according to the following order:

1. Liquid assets;
2. Reserves;
3. Illiquid assets

If the bank's resources are not enough to pay everyone, some clients will receive nothing, and the bank will fail.

Agents spend ω_i each cycle and save the earnings for the next cycle. Since the return on savings is higher for patient agents, they become richer than impatient ones through time. Patient agents are the strategic ones, that is their behavior is the one that is the key for triggering bank runs. Therefore, by allowing them to be the richest ones, we are given the model more opportunity to generate bank runs triggered by withdraws from rich depositors.

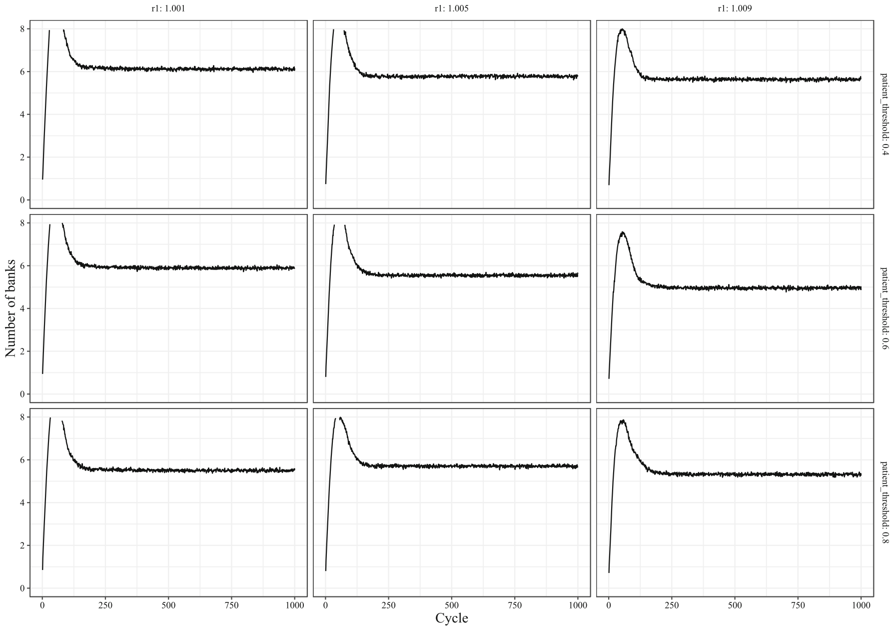

Fig. 16 Average number of banks by cycle. Each row represents a different proportion threshold to patient agents that run by imitating their neighbors. This proportion is 0.4 in the first row, 0.6 in the second, and 0.8 in the third. Each column represents a different r_1. They are, from left to right: 1.001, 1.003, 1.005, 1.007 and 1.009

All other aspects of the economy, including the transition rules used by the agents, are the same as in the benchmark model. We now present the results of this extension. The underlying parameters and the number of simulations are the same as in the benchmark simulations. Figure 14 shows the average number of bank runs for each cycle.

When comparing Figs. 3 and 14, the number of bank runs reduces with wealth accumulation. There is higher volatility in the benchmark case of homogeneous deposits, especially when the threshold for patient agents runs is lower. While in the case of heterogeneous deposits, the volatility is much lower than the corresponding thresholds in the homogeneous case. Also, in the case of heterogeneous deposits, more cycles are needed for the number of runs to fall.

As for the number of customers who lose all their money, Fig. 4 describes the homogeneous case and Fig. 15 the heterogeneous one. Again, there is less volatility in the heterogeneous case, but it is also noted that the maximum number of agents who run out of money is lower in the heterogeneous case.

When analyzing the evolution of the number of banks, under the homogeneous deposit case described in Fig. 5, there is greater volatility in the lower thresholds for the imitation of patient agents. In Fig. 16, which describes the heterogeneous deposit case, the number of banks in the end is practically equal, around 5 banks, to the homogeneous one.

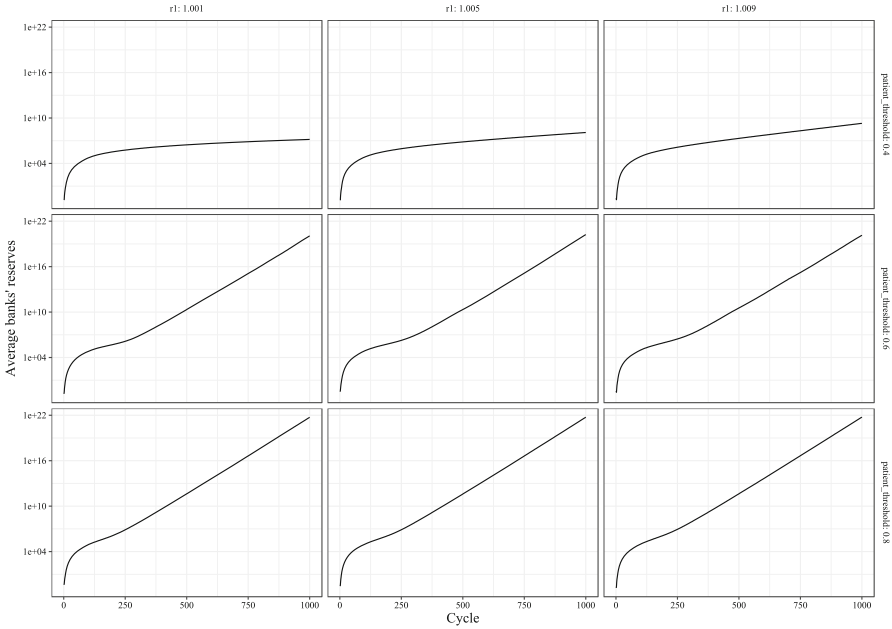

Fig. 17 Average banks' reserves by cycle. Each row represents a different proportion threshold to patient agents that run by imitating their neighbors. This proportion is 0.4 in the first row, 0.6 in the second, and 0.8 in the third. Each column represents a different r_1. They are, from left to right: 1.001, 1.003, 1.005, 1.007 and 1.009

The average bank reserve in the homogeneous deposit case is described in Fig. 6 in a linear scale. While in the heterogeneous case, Fig. 17, the vertical axis is in logarithmic scale. This is due to an exponential increase in the wealth of some agents, which makes banks also have the potential to increase exponentially. Again, the volatility is higher in the case of homogeneous deposits compared to heterogeneous deposits. In the lowest threshold, the growth of reserves is much lower than in the higher thresholds. Possibly, this may be due to the difficulty of accumulating wealth when the patient agents are more likely to imitate their neighbours.

As far as market concentration is concerned, the average Herfindahl-Hirschman index in the homogeneous deposit case, Fig. 7, is more volatile as well as lower than in the heterogeneous deposit case described in Fig. 18. In other words, the market becomes more concentrated as we allow wealth accumulation.

When analyzing the correlation of the number of runs with the average reserve level per bank, both in the homogeneous deposit conditions, Fig. 8, and in the heterogeneous deposit case, Fig. 19, we observe the same pattern of increase of runs when the reserves are still low with decline as the reserves increase. However, in the heterogeneous deposit case, it is noted that this peak happens when the reserves are larger than in the homogeneous deposit conditions.

In summary, when we allow wealth accumulation by depositors, bank runs fall. In response to wealthier depositors banks accumulate more reserves, which make them

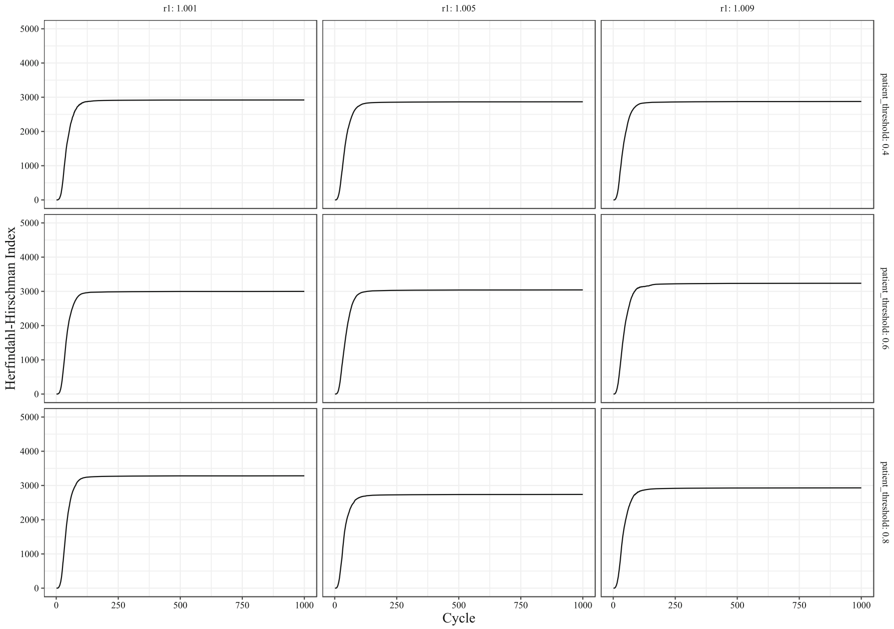

Fig. 18 Average Herfindahl-Hirschman Index by cycle. Each row represents a different proportion threshold to patient agents that run by imitating their neighbors. This proportion is 0.4 in the first row, 0.6 in the second, and 0.8 in the third. Each column represents a different r_1. They are, from left to right: 1.001, 1.003, 1.005, 1.007 and 1.009

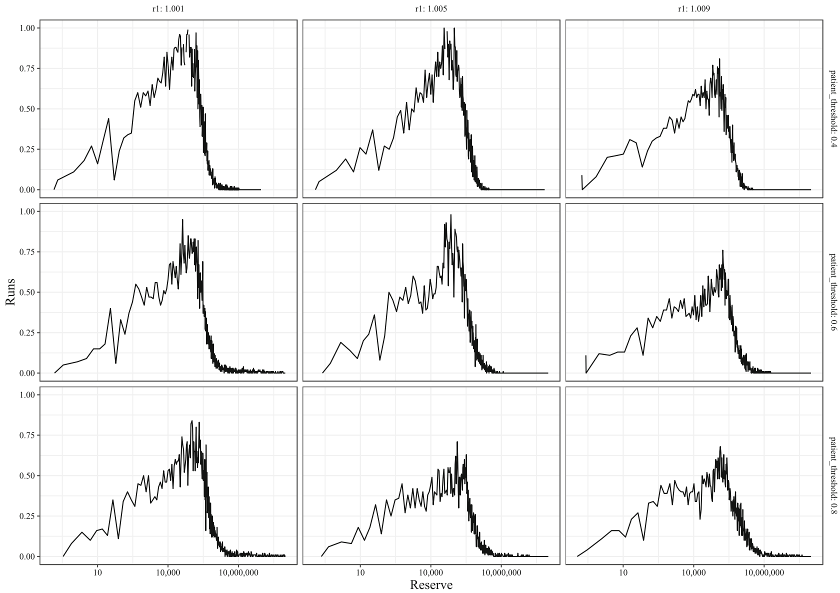

Fig. 19 Banks' reserves versus Number of runs. Each row represents a different proportion threshold to patient agents that run by imitating their neighbors. This proportion is 0.4 in the first row, 0.6 in the second, and 0.8 in the third. Each column represents a different r_1. They are, from left to right: 1.001, 1.003, 1.005, 1.007 and 1.009

less prone to runs. Few banks dominate the market with even higher concentration than in the benchmark case.

5 Conclusion

This paper adapts the contagion model of Grasselli and Ismail (2013) to a context of bank runs. We add the sequential service constraints, a feature considered in the bank run literature. Sequential service constraints do not stop bank runs, but they discipline the market, because agents are no longer customers of a bank that did not honor the contract and look for another bank instead. In this process, they punish smaller banks and there is increasing bank concentration as a result.

We also add the impact of social networks to trigger bank runs, a relevant feature in the empirical literature. The social network is represented by the depositor's immediate neighbors. Their influence is captured by our imitation rule by which a patient depositor decides to withdraw early if he or she sees some of his or her neighbors doing the same.

Allowing agents to save resources between cycles leads to a society with high wealth concentration. We also let the agents deposit their total wealth instead of one unit endowment as in our benchmark formulation. The impact of this extension is to reduce volatility in the indicators, to make banks accumulate more reserves and, as a result, to reduce bank runs. The number of banks is the same, but the market concentration is higher with wealth accumulation.

In the context of adaptive complex systems, we could extend the model to allow for random mutations in the rules followed by the agents. We can also allow switching rules between them. Such an approach would assess the effect of the emergence of new rules in the evolution of the financial system. Another possible improvement would be to allow the emergence of a lender of last resort for banks and to measure the number of bank runs in such environments. In our paper, we do not implement the case of informed patient agent who has knowledge about their bank's situation. We also do not consider deposit insurance in this paper, which we can be implemented in a future work.

Acknowledgements We would like to thank valuable comments received from two anonymous referees, Andre Minella, Carlos Viana de Carvalho, Carolina Ripoli, Francisco Marcos Rodrigues Figueiredo, Fernando Antonio Slaibe Postali, Jose Raymundo Novaes Chiappin, Lais Camargo Bartalotti, Paulo Evandro Dawid, Rafael Felipe Schiozer and Sergio Mikio Koyama. The remaining errors are our own responsibility.

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