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Original Research Article

Investigating the Bank Run Phenomenon and the Effect of Deposit Insurance in the Interbank Network Based on an Intelligent Multi-Agent Model

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In a situation where the country's banking system is vulnerable, the behavior of depositors based on their assessment of the banks' risk level can lead to an increase in the probability of systemic crises and instability of the banking network. Recently, network theory and agent-based simulation have been used to investigate complex banking systems. Agent-based modeling (ABM) is a new computational method that studies economic phenomena by representing the behavior of individuals and agents. Using this approach, the present study evaluates the phenomenon of bank runs and the effect of deposit insurance on the country's banking network. The agents in this ABM include banks, central bank, firms and depositors. Banks and depositors are intelligent agents that operate on an adaptive learning model. This research was conducted with the aim of investigating the effect of depositors' behavior on the banking network and evaluating the safety policy of deposit insurance based on the balance sheets of 25 banks that are members of the Iranian interbank market during the years 2006 to 2019. We find that when depositors act strategically, bank operations occur and banks choose adaptive strategies with lower capital adequacy ratios (CARs). Also, our findings are that when depositors are intelligent, the safety of the banking network through deposit insurance has not been significantly successful in reducing the risk of contagion in the system.

Keywords: Intelligent Multi-Agent Model, Adaptive Learning, Interbank Network.
JEL Classification: C63, D83, G21.

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1 Introduction

In Iran's economy, banks, as the main financial intermediaries, provide a uniform flow of financial resources from savers to borrowers and investors, and in this way, they play a significant role in providing liquidity and necessary capital for economic units. These financial intermediaries are in contact with households and production enterprises through the mechanism of deposit attraction and transfer of facilities, and they also interact with other banks and the central bank through debt to banks and the central bank. Therefore, banks are connected with all the main agents of the economy, and any kind of change in the bank's resources affects the amount of funds allocated by the bank, finally, according to the connection of the bank with other economic factors, the amount of investment and economic growth is affected. The statistics of the central bank show that about 90% of the financing of companies in the country is through the banking system, therefore, poor performance and the emergence of a crisis in the banking system will spread to the real sector of the economy and will cause a lack of liquidity and fluctuations in macroeconomic variables (reports Central Bank statistics, 2022).

Iranian banks have faced a lot of accumulated losses in recent years. Also, the growth of deposits has been declining and the portfolio of banks' deposits has changed from long-term to volatile deposits. Banks are facing many challenges, including the risk of bankruptcy, in order to generate profits and cash flows for satisfying debts and provide capital from internal sources, and this fragility of banks may lead to bank runs. Banks in this situation, on the one hand, will face the rush of depositors to withdraw their deposits, and on the other hand, they will face a high volume of non-performing loans and assets with low liquidity, which may make banks face the risk of bankruptcy. The graph below shows the growth rate of term investment and current deposits.

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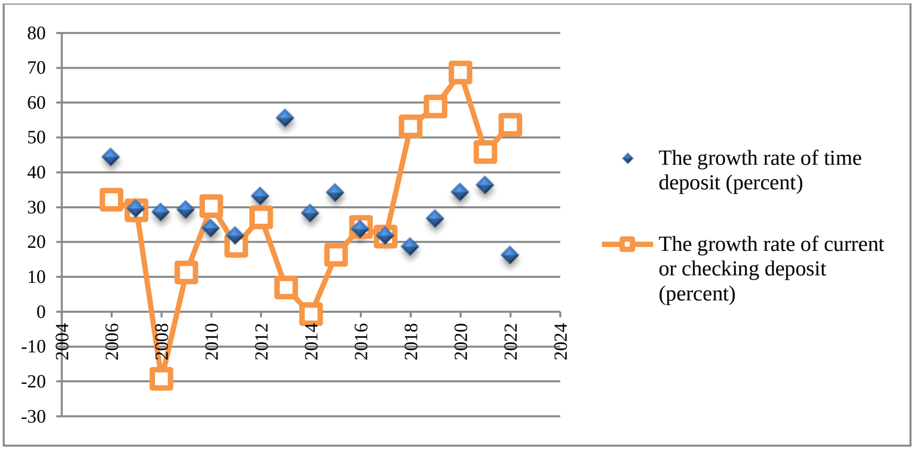

Figure 1. The growth rate of time investment and current deposits (percent)
Source: Central Bank of the Islamic Republic of Iran

On the other hand, if banks face a banking crisis, they may choose strategies to solve their lack of liquidity, which leads to greater exposure to interbank connections and greater vulnerability of the system to contagion. The likelihood of contagion implies that any crisis in the banking network should be systematically evaluated, and this issue should not be ignored in designing the desired policy. To determine optimal regulatory policies, the complex mechanism of the banking network must first be investigated; then, regulatory policies must be evaluated to prevent the occurrence of risks, including contagion risk and systemic risk. Financial contagion in the banking network is a situation in which liquidity or Insolvency risk is propagated from one bank or financial institution to another (Macchiati et al., 2021). One of the factors that increase the probability of systemic crises and banking instability and lead to the phenomenon of bank runs is the depositors'fear. In such a situation, if people's bank deposits are not insured, some depositors will lose their savings. To prevent from the influx of deposit withdrawals and also to support small depositors and thus create safety in the banking system, the deposit insurance policy can be effective. The Deposit Guarantee Fund was established to guarantee the repayment of the funds belonging to the depositors of banks and other credit institutions in case of bankruptcy in the country, following the formulation of Article 95 of the Fifth Development Plan Law of the Islamic Republic of Iran approved in 2011. However, at the end of 2015, the regulations of the fund were reviewed, amended, and promulgated due to some deficiencies. Therefore, the establishment and formation of the fund have practically started from this date. According to the law, all banks and credit institutions are required to be members of this fund, currently, 36 banks and credit institutions in the country are members of the fund.

The preferred approach for the crisis in the banking network is agent-based modeling (Bookstaber et al., 2018). Bottom-up agent-based modeling builds a space for such a network of heterogeneous agents that the local actions and reactions of these agents with bounded rationality give rise to systemic models (Poledna et al.,., 2020). In other words, only agent-based modeling can explicitly combine the complexity of individual behaviors and interactions existing in the real world (Liu et al., 2020; Streit and Borenstein, 2009). Therefore, the present study employs a multi-agent model for bank run modeling. In this model, the behaviors of banks (25 member banks of the interbank market), central bank, depositors, and firms are considered. Banks and depositors are intelligent. The behavior of these agents is based on the adaptive learning model.

Also, for bank run modeling, it is necessary to use learning models given the essential assumptions of the banking crisis, including its turbulence and unpredictability, and the different behavior of financial network players in critical situations compared to normal times. The behavior modeling of each agent, including depositors, based on learning models, is a distinctive feature of the agent-based approach. This study seeks to investigate the Iranian banking network as an endogenous network using a multi-agent model based on the adaptive learning algorithm and it aims to examine bank runs and the consequent interbank contagion and deposit insurance policy. In this regard, the present study seeks to answer the following questions:

- What effect does the intelligent behavior of the depositors (based on the assessment of banks' risk level) have on the bank runs in Iran?
- What is the effect of deposit insurance on interbank contagion and banking system stability when depositors are intelligent?
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Other sections of the paper are as follows: After the introduction, the second section is the literature review. The next section is dedicated to introducing and discussing the research methodology. The fourth section presents the research findings, and the final section presents the conclusion and suggestions.

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2 Literature Review

Financial contagion affects the stability of the banking network (Liu et al., 2020); therefore, the contagion in the banking network and its mechanism is significant. When the demand for the withdrawal of deposits in the banking system increases, the phenomenon of a bank run occurs. If a bank run propagates from one bank to another, there may be a systemic banking crisis.

In the last two decades, bank runs have occurred repeatedly with traditional and new styles. British Bank Northern Rock ; 2007, Busan Savings Bank; 2011, Greek banks; 2015, and Capital Home Group; 2017 were among the banks that suffered from bank runs. Thus, classical economic and financial theories of the bank run phenomenon were re-examined.

Theoretically, there are two contradictory views of the classical bank run models: one is bank runs caused by banks' basic problems (Allen and Gale, 1998; Calomiris and Mason, 2003) and the other is the failure of the coordination among the depositors (Diamond and Dybvig, 1983; Jackson and Pernoud, 2021). For the first time, Diamond and Dybvig (1983) presented an effective analysis of a bank run. A bank run occurs because depositors decide to withdraw their deposits simultaneously, and the bank does not have enough liquidity to respond. So a bank run results from a failure of pure coordination. Withdrawals can harm the bank and worsen the situation, forcing the bank to sell its long-term capital. Also, this process could be expanded due to predictions so that even banks with healthy assets may be exposed to a bank run because depositors believe they are or may be bankrupt. Allen and Gale (1998) provided the antithetic view: a bank run is endogenous in a world with complete uncertainty about the return on assets (ROA). But bank runs are caused by various agents in the real world, so it is difficult to determine whether a bank run is due to poor coordination or a deterioration in the quality of a bank's assets. Also, the classic models ignore the likelihood of a bank run however the likelihood of a bank run is crucial for a policy or investment analysis. Therefore, it is better to have a model that considers the likelihood of a bank run, the interaction of heterogeneous agents (Lux and Westerhoff, 2009; Qiao, 2019), and the agents themselves and their environments (Chen, 2017). To this end, dos Santos and Nakane (2021) simulated a bank run using an agent-based model (ABM) to evaluate depositor behavior with different scenarios within the Diamond–Dybvig model. Their results showed that with the growth of banks and increasing long-run market concentration, the bank run rate would reach zero. Also, Liu et al., (2020) examined interbank financial contagion with an agent-based

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model (ABM). They showed how the losses and failures of banks arise from network intercommunications and the liquidity of the lending market.

Due to the problems in classical models for considering the limited rationality of human beings, we employ a bottom-up behavioral model to model a bank run. This article introduces human behavior into the banking network model in a bank run. The intelligent agent-based approach shows that depositor behavior can cause liquidity shocks and that liquidity shocks can be transmitted to the entire system and affect network stability. In this model, based on the Diamond and Dybvig framework (1983), depositors' withdrawal decisions lead to liquidity shocks in banks. When banks lose more than their capital, they go bankrupt, and the central bank is responsible for selling their assets and repaying their debts. The central bank prioritizes central bank loans in repaying the debts of bankrupt banks. Then, the interbank loans are repaid, and finally, the remaining resources are allocated to the depositors. Therefore, in this model, transmission occurs through direct interbank exposure. Depending on the relationship between banks, interbank default can propagate losses in the system. The number of bankrupt banks resulting from interbank transactions has been used to measure the contagion rate.

In response to the global financial crisis, some countries have significantly increased their financial safety nets to gain confidence, thus preventing possible contagious bank runs. According to economic theories, deposit insurance has benefits and costs that vary with economic conditions. For the first time, Merton's (1977) studies showed that deposit insurance can improve social welfare by helping to prevent a bank run. In times of economic recession, when a contagious bank run is more likely to occur, the positive stabilizing effect of deposit insurance is even more critical. According to this view, accepting deposit insurance has led to lower banking risk (Gropp and Vesala, 2004; Ashraf et al, 2020), better financial intermediation (Chernykh and Cole; 2011), and stabilizing effects for US credit unions (Karels and McClatchey, 1999).

Despite the stabilizing effects of deposit insurance, there is considerable consensus in the literature that deposit insurance exacerbates the problems of moral hazards in the banking sector by encouraging banks to accept excessive risk. Depositors have no incentive to supervise when deposits are insured (Demirgüç -Kunt and Huizinga, 2004; Ioannidou and Penas, 2010). excessive risk-taking peaks due to a lack of market discipline in banking crises (Demirgüç-Kunt and Detragiache, 2002; Demirgüç-Kunt and Kane, 2004, Barth et al, 2021)

The stabilizing and positive effects of deposit insurance can outweigh the negative moral hazard effects during a recession when banks are likely to face limited financial resources and limited investment opportunities. Deposit insurance can increase depositors' confidence (Fahlenbrach and Stulz, 2011; Beltratti and Stulz, 2012) and prevent a systemic bank run, hence reducing risk and increasing system stability. But during stress-free and boom periods: despite the many investment opportunities, there will not be a great need to prevent a bank run.

Furthermore, the effect of deposit insurance can be destabilizing (or stabilizing) throughout the sample period. Anginer et al., (2014) found supportive evidence that the effect of deposit insurance on banking risk varies during normal periods in the face of global systemic recessions. In particular, they showed that insurance coverage was associated with less systemic stability and higher banking risk in the pre-crisis period (2004-2006) but was reversed during the crisis (2007-2009). However, the overall effect of deposit insurance on the complete sample studied remained negative since the destabilizing effect.

Good oversight affects the various benefits and government costs of deposit insurance. Good oversight and strong regulation can increase the effects of stability during periods of crisis and reduce the negative effects of moral hazard during normal times (Fahlenbrach and Stulz, 2011; Beltratti and Stulz, 2012).

Barroso et al. (2016) employed an ABM to study the effect of some regulatory policies, including deposit insurance, on the banking system. This model is based on the adaptive learning model of agents. The results showed that the approval of deposit insurance could effectively prevent bank runs.

In the present study, the banking network stability is via a multi-agent approach and the dynamics of the network are based on an adaptive learning algorithm. The effect of depositor behavior on the banking network and bank runs, also the deposit insurance safety policy on interbank contagion is evaluated.

It should be noted that the effect of a bank run on contagion between banks has not been investigated in Iran so far. In this article, the stability of the banking network is based on a multi-agent approach and considers the dynamics of the network based on the adaptive learning algorithm. Also, the effect of deposit insurance on interbank contagion has been evaluated for the first time.

Ahmadian and Kianvand (2014) presented a model that allows policymakers to check the probability of a bank attack. In this sense, the logit panel method has been used. The results of this research show the importance of bank health and deposit substitute variables such as exchange rate on the possibility of sudden deposit withdrawal.

Ahmadian (2016) used the New Keynesian stochastic dynamic general equilibrium method and using the annual statistics of Iran's economy from 1981 to 2013, to Investigate the reaction of macroeconomic variables such as production and inflation and banking variables to shocks of sudden deposit withdrawal and debt increase paid to the central bank. Calibration and Bayesian methods were used to extract DSGE model parameters. The results of the model have shown that the sudden withdrawal of deposits reduces the lending power of banks and as a result decreases investment and production. According to the results of this research, the increase in debt to the central bank will increase the interest rate of deposits and loans, and the supply of credits will increase, as a result, the financing of production will increase.

Amiri and Tawfighi (2018) investigated the relationship between bank deposit insurance and bank resistance in 41 private banks in Iran using panel data during the period of 2018-2019. Explanatory variables in this research are include : the ratio of non-performing loans to total facilities, capital adequacy, bank size, asset return, economic growth rate, money growth rate, and inflation rate. The results of this research show that there is a negative and significant relationship between deposit insurance and bank resistance. In other words, with the increase in the deposit insurance rate, bank resistance decreases.

Afshari et al. (2009) based on the evidence of 23 developing countries including Iran, between 1980 and 2002, by using the multivariable logit model, investigated the effect of explicit deposit insurance system on the occurrence of banking crises. Their results show that the explicit deposit insurance system increases the probability of a banking crisis, and the wider the level of insurance coverage of depositors, the more this system is funded and the membership in it is optional, and the more If it is managed by the public sector instead of the private sector, this possibility increases.

Lotfali pour et al. (2018) used the New Keynesian Dynamic Stochastic General Equilibrium (DSGE) model to investigate the impact of the resource shock affected by the bank run on consumption and investment. The results of the simulation and estimation of the model in the period of 1982-2018, along with the appropriateness of the presented model for Iran's economy, indicate that the occurrence of a shock in banking resources will increase consumption and decrease investment.

3 Methodology

The emerging approach of agent-based macroeconomic modeling, starting from the early 2000s, differs from past approaches in many ways. In this approach, agents are heterogeneous and interact with each other with behavioral rules and explicitly represented market protocols. These independent agents are not controlled by any mechanism from above and there is interaction between them at the micro level. In this bottom-up modeling, macro phenomena are explained based on a large number of primary micro economic variables that interact with each other based on rules and protocols. In this way, agent-based macroeconomic models obtain inherently micro-representations, based on individual behaviors and interactions, and validate models by comparing characteristics at the aggregate level with empirical data. Therefore, the computational scenarios in these models generate fluctuations and economic cycles endogenously without external shocks (Cincotti et al. 2010).

Before the 2008-2009 crisis, the use of agent-based macroeconomic models had begun to emphasize the important role of contagion mechanisms and interaction between the real and financial sectors as agents of instability and sudden economic slowdown. These emerging features, along with the ability of agent-based macroeconomic models to incorporate many behavioral assumptions and represent institutional characteristics relevant to the analysis of real policy proposals, have increased policymakers' interest in agent-based macroeconomics (Cincotti et al. 2022).

Despite the advantages of agent-based models, these models have limitations compared to other macro modeling frameworks (Richiardi; 2017, Dawid et al., 2019). An important limitation of agent-based modeling is related to data. In these models, real data are usually used to calibrate parameters and initial conditions. Then, in the validation phase, this real data is used to measure the performance of the model in reproducing "stylized realities". Translating the results of agent-based models into data is a difficult task, and criticisms of these models focus on the inaccuracy of their validation and calibration methods (Platt, 2020). In other words, agent-based models are not suitable for data-based simulations. This is due to the endogenous nature of agent interactions in these models, which makes it difficult to synchronize the agent-based model's artificial economy with real data. Therefore, it can be concluded that the main weakness of factor-based models is reaching the data that is caused by endogenous interactions between factors, and these interactions are the main strength of these models. So, providing quantitative predictions and overcoming the limitations of these models is an important challenge.

In the present paper, the Iranian banking network is considered an endogenous network modeled based on an intelligent multi-agent model. For the model parameters, data from the Central Bank of Iran (CBI)[1] and the Securities and Exchange Organization of Iran (SEO) [2] for the years 2006-2019 have been used. The structure of the model is based on the framework proposed by Barroso et al. (2016). Agents in this model have limited rationality and can learn based on adaptive strategies following the EWA learning model.

3.1 EWA Learning Model

In a financial system with an endogenous network, the logic of agents' decision-making is a key aspect in determining how they interact with each other. The models are created in the system, and, ultimately, policy outcomes appear. An experience-weighted attraction (EWA) learning model was adopted for how agents choose strategies. This learning model, proposed by Camerer and Ho (1999), includes aspects of two different approaches to modeling agents' behavior, namely reinforcement learning and belief-based learning (Fudenberg and Levine, 1998).

In this model, a game state, including n agents. For player I, we have the S_i strategy space, including M_i's possible choice, i.e. S_i. $S = S_1*\ldots*S_n$ is the game's strategy space. s_i is the strategy chosen by agent I and its return at time t is π_i. This learning model assumes that each strategy has a numerical attraction updated with experience and determines the probability of choosing that strategy. Two main variables in this model are updated after each cycle: the first variable of experience weight is N(t), which is interpreted as the number of observations equivalent to past experience. The initial value of the experience weight is N(0), which is updated as $N(t) = \rho N(t-1) + 1$. The second variable is $A_i^j(t)$, which indicates the attraction of the I player's strategy after the t period (Yu et al., 2019).

The attractions of Strategy J for the agent I in t are updated as follows:

[1] www.cbi.ir
[2] www.codal.ir

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$$A_i^j(t) = \frac{\varphi.N_i(t-1).A_i^j(t-1)+\left[\delta+(1-\delta).I(s_i^j,s_i(t)\right].\pi_i(s_i^j,s_{-i}(t))}{N_i(t)} \quad (1)$$

In the above formula $I(s_i^j, s_i(t))$ is an indicator function that contains the value of one for $s_i^j = s_i(t)$ and zero for the other modes. In the EWA learning model, the basic parameters include φ, δ, and k.

– The weight of foregone payoffs, δ.
– The decay rate to the previous attraction, φ
– The attraction growth rate, k (Yu, et al., 2019).

In the EWA learning model, the logit model is employed to allow player I to choose strategy J:

$$P_i^j(t+1) = \frac{e^{\lambda.A_i^j(t)}}{\sum_{k=1}^{m_i} e^{\lambda.A_i^k(t)}} \quad (2)$$

That λ is the players' sensitivity to attractions and includes aspects of perception and motivation.

The Learning parameters are shown in Table 1 as follows:

Table 1
Learning parameters

Value	parameter	symbol
0	Experience depreciation	ρ
1	Past attractions depreciation	φ
1	Initial experience	N(0)
1	Foregone payoffs' weight	δ
0	Initial attractions	$A_i^j(0)$
1	sensitivity to attractions	λ

Source: Research findings

3.2 Agents

Agents in this model include banks, central banks, depositors, and firms. Banks' balance sheets in this endogenous network are connected through interbank loans and as the following: liabilities include capital, deposits, interbank loans, and central bank loans and assets include liquid assets, interbank loans, and real sector loans. In the simulations, the banks play an iterated game simultaneously and try to maximize their return on equity (ROE). At the beginning of each cycle, the total balance sheet is determined by selecting the S_b^j strategy with the exogenous parameter T_b. At the end of each cycle, Bank b calculates its profit (loss) as follows:

$$\Pi = K_b^2 - K_b^0 \tag{3}$$

The above symbols indicate times when capital is measured. Also, for bank B, we have the return of equity (ROE) and capital adequacy ratio (CAR) as follows:

$$ROE_b = \frac{\Pi}{K_b^0} \tag{4}$$

$$CAR_b = \frac{K_b}{IL_b + \sum_{f \epsilon F_b} R_{b,f}\omega_f} \tag{5}$$

The above equation shows that firms can carry different risk weights. It should be noted that $R_{b,f}$ is the loan amount to firm f and ω_f is its risk weight. Also, K_b and IL_b are capital and interbank loans, respectively, and F_b is a set of firms that borrow from bank b.

In the present model, the central bank aims to maintain the stability of the financial system and plays two roles. It acts as the last lender and determines the minimum capital adequacy ratio (CAR_{min}). If the bank's capital adequacy ratio is less than this amount, the central bank forces it to reach the minimum. Firms do not act strategically. However, they are heterogeneous because corporate loans have different ratings, loss-given defaults (LGDs), risk weights, and interest rates. The firm f contains the following parameters:

- $R_{b,f}$: the loan amount of firm f taken from bank b. If, the interest rate paid by the firm is i_f.
- PD_f : the probability of default.
- LGD_f : loss given default.

Due to the depositors' significance in this study, they are described in a separate section:

3.3 Depositors

There are two types of depositors. The first type of depositors are patient and wait for the maturity of their deposits up to t = 2 and withdraw the deposited amount along with its return. The second type of depositors are hasty and withdraw money from their bank accounts at t = 1, which does not include returns.

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In this model, according to the scenario, depositors behave in two ways: either they make their decisions strategically based on the learning pattern, or they randomly decide with a certain probability whether they will withdraw their resources earlier. In the present study's simulations, depositors are not learners in the default scenario but act strategically in scenarios 1 and 2. When depositors do not learn, it is assumed that they are probably bored. When depositors act strategically, they determine if their deposits are at risk. Therefore, because depositors want to maximize their profits, liquidity shocks will occur due to the level of risk of banks. For depositor d, the risk tolerance parameter γ_d is the parameter used to define his strategy, s_d. This parameter indicates the CAR_{min} that the depositor is willing to bear and based on which he decides to withdraw his deposits.

3.4 Contagion and Insolvency

In this model, when banks lose more than their capital, they go bankrupt, and the central bank is responsible for selling their assets and repaying their debts. The central bank prioritizes central bank loans in repaying the debts of bankrupt banks. Then, the interbank loans are repaid, and finally, the remaining resources are allocated to the depositors. Therefore, in this model, transmission occurs through direct interbank exposure. Depending on the relationship between banks, interbank default can propagate losses in the system. The number of bankrupt banks resulting from interbank transactions has been used to measure the contagion rate.

3.5 Calibration of Model Parameters

The model parameters after calibration are shown in Table 2 as follows:

Table 2
Model parameters

	Name	Value	Description
1	Number of simulation repetitions	100	
2	Number of banks	25	Number of banks in Iran's interbank market, except for Qarzol-Hasaneh banks; based on data available in 2018;
3	Interest rates on deposits	12.17 (percent)	The weighted average interest rate paid on total deposits in 2018 (the end of the period) based on research calculations
4	Rial interbank market interest rate	19.72 (percent)	Weighted average rate (percent) in 2018(Year-end of interval);

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5	Interest rates on Liquid assets	0	
6	The discount rate of the non-Liquid assets	0.97	Discount rate of the banking sector, (Based on domestic studies);
7	Banks size distribution	Uniform	
8	Number of depositors	100	Assumption
9	Number of corporate customers	50	Assumption
10	Central Bank lending interest rate	34 (percent)	
11	CAR_{min}	8 (percent)	According to the instructions for calculating the regulatory capital and capital adequacy of credit institutions of the Central Bank, the revised version of 2020;
12	Amount Withdrawn	1	The total size of the deposit
14	Probability of Withdrawal (Probability of bank Run)	37 (percent)	based on research calculations: (Variation range in volatile deposits in Iran in the study period);
15	Standard Corporate Client Default Rate	0.4	The average probability of default (Sajjad Kordmanjiri et al. (2021))
16	Standard Corporate Client Loss Given Default	50	(percent)
17	Standard Corporate Client Loan Interest Rate	18	(percent)
18	Wholesale Corporate Client Default Rate	0.4	
19	Wholesale Corporate Client Loss Given Default	50	The Basel Committee considers the LGD to be 50% of the debt for a more valid guarantee and the LGD to be 75% of the debt for a lower guarantee. (Basel Committee, 2001) (percent)
20	Wholesale Corporate Client Loan Interest Rate	18	(percent)
21	Retail Corporate Client Default Rate	14	Mahmoud Khatai et al. (2015) (percent)
22	Retail Corporate Client Loss Given	75	(percent)

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	Default		
23	Retail Corporate Client Loan Interest Rate	18	(percent)
25	Cash Risk Weight	0	
26	Corporate Loan Risk Weight	100	(percent)
27	Interbank Loan Risk Weight	0.5	The total balance of the principal and interest for the facilities granted in the form of non-participatory contracts to natural persons, small and medium firms, and legal entities (with a maximum of 100 employees), which is the principal of the facilities granted up to a maximum of 20 billion rials.
28	Retail Corporate Loan Risk Weight	75 (percent)	Retail Corporate Loan: The total balance of the principal and interest for the facilities granted in the form of non-participatory contracts to natural persons, small and medium firms, and legal entities (with a maximum of 100 employees), which is the principal of the facilities granted up to a maximum of 20 billion rials.
29	Wholesale Corporate Loan Risk Weight	100 (percent)	Wholesale Corporate Loan: Balance of principal and interest for facilities granted in the form of non-participatory contracts to natural persons as well as small and medium firms and legal entities (with a maximum of 100 workers) whose principal of facilities granted is more than 20 billion Rials and also the balance of principal and interest for facilities granted to other legal entities (with more than 100 employees)with poor credit rating;

Source: Research findings

4 Discussion

For the likelihood of a bank run, it should be noted that if the Iranian banking sector has not been facing a bank run, it was due to government support for banks. Therefore, according to the extensive studies conducted in forecasting banking crises in Iran, the hypothesis of no crisis in Iran is not confirmed. In this study, government interventions in preventing bank failures are eliminated. Python Software implemented the research modeling as100 repetitions of Monte Carlo simulations for each scenario and 2000 cycles. Therefore, the distribution of the results for each cycle was obtained. The mean and 95% confidence interval are plotted for those distributions in the diagrams. The results are smoothed by the LOWESS method to draw each diagram.

In this paper, three scenarios were performed, each involving one hundred repetitions of the simulation. The default scenario is based on the parameters of Table1. In the default scenario, depositors do not act

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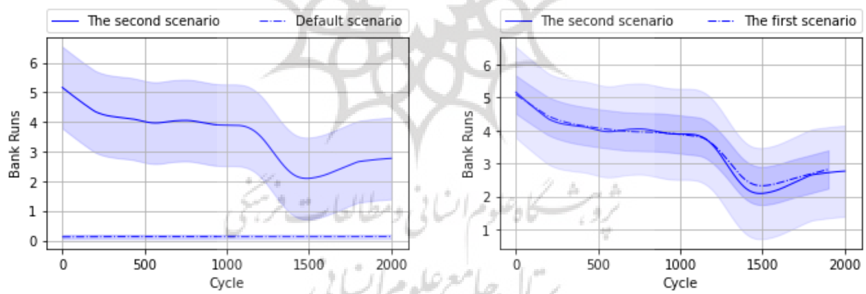
strategically. In scenario one, one of the parameters of the default scenario changes, and that is the change of non-intelligent depositors to intelligent ones. Scenario 2 also includes all the parameters of Scenario 1 with only one difference in deposit insurance that did not exist in Scenario 1. The results of these scenarios are illustrated in the diagrams. The simulations of scenario 1 are compared with those of the default scenario. The results of scenario 1 were compared with scenario 2, showing the effect of learning on the depositor behavior on the interbank network and distinguishing the effect of insurance from it.

The (b-1) diagram compares the default scenario and scenario 2 for a bank run. In the default scenario, depositors do not act strategically, and, as observed in the diagram at the bottom left, the process of the bank run is very low. Nevertheless, in scenario 1, where depositors are learners, the bank runs increase. However, compared to scenario 2, when the same intelligent depositors use deposit insurance, the fluctuation of the bank runs is less ((a-1) diagram). Therefore, if depositors act strategically, the bank runs in the interbank network will increase, and deposit insurance will rise the fluctuation in the bank runs.



(b-1) (a-1)

Figure 2. Bank runs (*Source*: Research findings)

The diagrams below show the average CAR of banks. Comparing the default scenario and scenario 2 shows (b-2) that if depositors act strategically and use deposit insurance, the banks' adaptive strategies are lower CAR levels. Besides, the right diagrams (a-2) display that fluctuations in the average CAR of banks will increase if one uses deposit insurance. Therefore, the decrease in the banks' average CAR is due to depositor strategic

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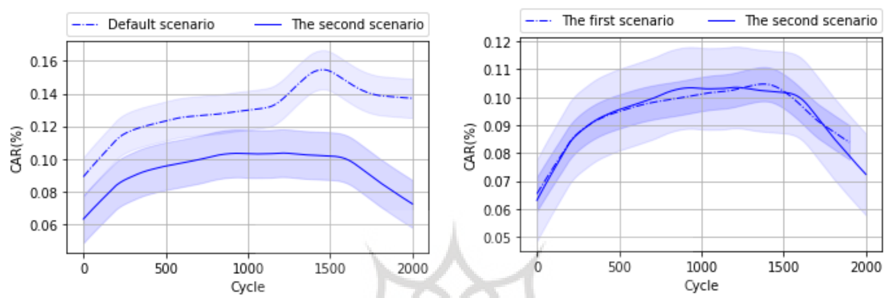
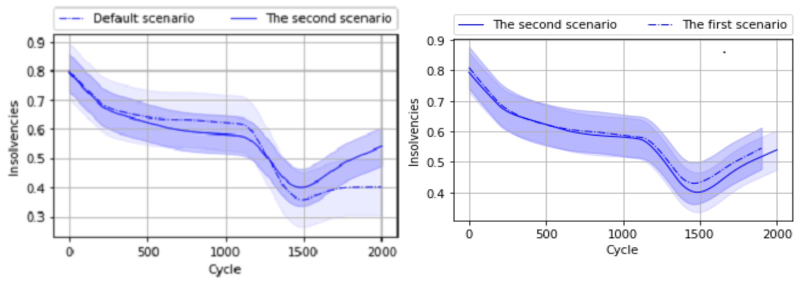
behavior, and the increase in volatility is due to using deposit insurance. In other words, following depositor strategic behavior, banks change their adaptive strategies and choose lower CAR levels. In these circumstances, in the case of using deposit insurance (second scenario), the fluctuation in CAR has increased. Therefore, deposit insurance has only increased the volatility in CAR(a-2).



(b-2) (a-2)

Figure 3. CAR (*Source*: Research findings)

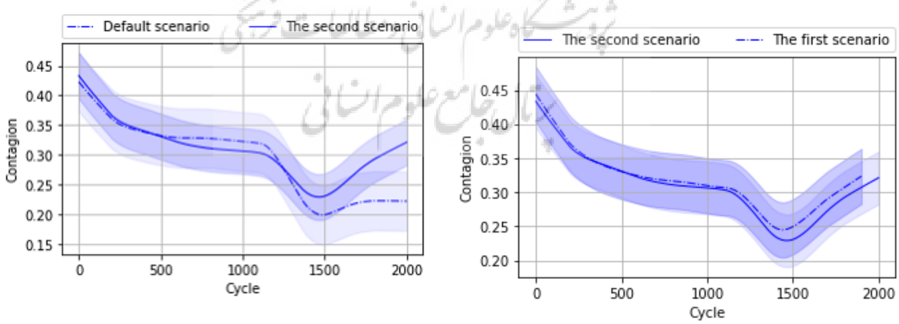
The (b-3) diagram shows the three results of comparing scenario 0 with scenario 2, i.e., adopting deposit insurance and intelligent depositors. They illustrate the number of insolvency banks in each cycle in two scenarios 0 and 2: the increase in the number of insolvency banks after implementing scenario 2 is evident in the diagram. This result shows that if deposit insurance and smart depositors are adopted, the interbank network will be more unstable, and the banking system's stability will decrease. Scenarios 1 and 2 are shown in the (a-3) diagram to distinguish the effect of insurance by learning depositors. Comparing the two diagrams shows that when depositors act strategically, deposit insurance has led to a slight reduction in the number of insolvency banks (a-3).



(b-3) (a-3)

Figure 4. Insolvencies (*Source*: Research findings)

Figure (b-4) shows the results of comparing the zero scenarios with the second scenario, i.e., adopting deposit insurance and smart depositors. These graphs show the number of insolvency banks due to contagion in the interbank market in each cycle in two scenarios, zero and two. Therefore, when depositors act strategically, the effect of deposit insurance is small to reduce interbank contagion. It indicates that banking network safety through deposit insurance has not been significantly successful in reducing the risk of contagion in the system. In fact, in more than 100 repetitions out of 2000 simulation periods, the insolvency of banks due to contagion has decreased very little. Therefore, insurance regulatory policy has not been significantly successful in reducing the risk of contagion and thus the systemic risk in the system (a-4).



(b-4) (a-4)

Figure 5. Contagion (*Source*: Research findings)

The results of this scenario are consistent with recent theories on the subject Anginer et al., (2014); Barth et al., (2004); Bennett et al., (2015). Barth et al., (2004); and Anginer et al., (2014) argued that the results usually involve generous deposit insurance schemes, which is the case in the present study's simulation because deposits are fully covered. They also emphasized that other tools, such as close monitoring, can reduce the ethical risks of deposit insurance. Accordingly, Bennett et al., (2015) argued that policymakers and planners should stimulate the disclosure of bank information to promote market order.

5 Concluding Remarks

In this article, the Iranian interbank network is simulated based on the agent-based approach and as an intelligent multi-agent. This model is in the framework of Dybvig, Allen, and Gale's model and the combination with limited rationality in the experience-weighted attraction learning model and the behaviors of the agents are according to the adaptive learning model. This model allows economic agents to learn through cycles and adapt their strategies to the environment created by policymakers. This ABM showed the effect of learning on depositor behavior on the interbank network. Accordingly, if depositors act strategically, the bank run in the interbank network will occur, and following the depositor's strategic behavior, banks will change their adaptive strategies and choose lower CAR levels. Furthermore, using this simulation, the effect of one of the safety regulations for this market in the form of deposit insurance has been evaluated to investigate the stability of the banking network. Despite deposit insurance has received more attention from academics as part of the International Monetary Fund's best recommendations to developing countries. But researchers and public policymakers need to consider this, while the purpose of deposit insurance is to ensure depositors' confidence and prevent bank run, the unintended consequences have of encouraging banks to take too much risk. Therefore, considering the accumulated losses of the country's banking network and problems such as incorrect risk management and high volume of non-performing loans, any type of supervisory policy should be applied with more detailed investigations which will ultimately lead to solving the main problems of the country's banking system, i.e. liquidity and the ability to repay obligations. . The present study shows that the implementation of the deposit insurance regulatory policy in Iran's interbank market has not been very successful in reducing the risk of interbank contagion despite the presence of intelligent depositors. . It also reveals that

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generous financial safety nets increase volatility in a bank run. Thus, while the research results emphasize the significance of a fundamental regulatory and institutional framework, complex risk management measures need to be implemented and regulated more sensitively by government officials. Timely identification and adequate monitoring are essential since an ever-changing environment has new hazards. Also needed is strengthening the appropriate incentive framework to ensure system stability. For further studies, it is suggested to consider the government as a separate agent.

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