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# Exploring Credit Relationship Dynamics in an Interbank Market Benefiting from Blockchain-based Distributed Trust: Insights from an Agent-based Model

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**Abstract.** Trust is crucial in economic complex adaptive systems, where agents frequently change the other side of their interactions, which often leads to changes in the system's structure. In such a system, agents who seek as much as possible to build lasting trust relationships for long-term confident interactions with their counterparts decide whom to interact with based on their level of trust in existing partners. A trust crisis refers to the time when the level of trust between agents drops so much that there is no incentive to interact, a situation that ultimately leads to the collapse of the system. This paper presents an agent-based model of the interbank market and evaluates the effects of using a voting-based consensus mechanism embedded in a blockchain-based loan system on maintaining trust between agents and system stability. In this paper, we rely on the fact that blockchain as a distributed system only manages the existing trust and does not create it on its own. Furthermore, this study uses actual blockchain technology in its simulation rather than simply presenting an abstraction.

**Keywords:** Agent-based simulation, Asymmetric information, Confidence, Distributed ledger, Interbank call loan market, Uncertainty.

## 1 Introduction

Trust seems to be a focus in promoting the ability of agents to collaborate across a complex adaptive system [1,2]. Models developed in this area seek to avoid the failure of agents' collaborative efforts by entering them into a relationship in order to collaborate [3]. However, trust may be damaged due to unforeseen changes in the environment. In addition to the agents' selfishness due to different ownerships, which sometimes makes them unreliable, one primary source of mistrust in such systems is their lack of global perspective and complete knowledge of the whole environment and their peers with hidden intentions [4].

An interbank market, as a highly stochastic economic environment [5], is a complex adaptive system [6,7] where banks lend large amounts of money to each other at interbank rates when they need liquidity in a short period [8], thus adapting to this stochastic

environment. Establishing more lending relationships in this market helps borrowers with more diverse sources of liquidity [9] and enables them to borrow at lower interest rates from lenders with whom they have a relationship [10]. However, these relationships dynamically change due to the short-term nature of unsecured funding [11]. In order to preserve credit relationships, maintaining a level of trust is essential for all market participants, as its evaporation can lead to instability and liquidity crises [8].

These days, the notion of distributed trust [12] has been reintroduced through the use of blockchain [13]. As a cryptographically secured, distributed ledger, this technology is widely believed to spread trust in digital environments [14]. In this study, using the aggregate balance sheet of French banks, we model an interbank market as a multi-agent system and examine whether blockchain is able to compensate for the loss of trust among peers during economic declines. Concretely, the contributions of this paper are twofold: (i) adding to the literature on trust in multi-agent systems and (ii) using blockchain as part of the simulation platform. The rest of the paper is organized as follows: Sect. 2 gives background information on related work previously performed in this area. Sect. 3 describes the components of the model and the behavior of various agents in different circumstances. The results of simulating this model based on a number of scenarios are presented in Sect. 4. Finally, Sect. 5 concludes the paper and gives avenues for future research.

## 2 Related Work

### 2.1 Distributed Trust

The notion of distributed trust is not new and dates back to the late 1990s [12]. Among the methods proposed for building trust in multi-agent systems, one can find those that benefit from this notion. Jordi and Sierra [15] use a reputation mechanism in which each agent records its direct trust in other agents resulting from interacting with them in a local database and shares these data with other agents so that they use them in their indirect trust estimation. Jurca and Faltings [16] propose a set of broker agents responsible for gathering reports from other agents on their interactions with each other. The broker agents also provide reputation information to agents who need it. Tweedale and Cutler [17] attribute trust to the collective decision of a hierarchical team of which the agent is a member. Huynh et al. [18] integrate all of these methods into a framework called FIRE. However, in the past, there were many obstacles to the objectification and implementation of distributed trust in practice because it is unreasonable to expect such information to be shared by all members of the system [18].

By using blockchain, which refers to a cryptographically secured distributed ledger with a decentralized consensus mechanism, it is easier to implement such ideas. Calvaresi et al. [19] provide a JADE-based architecture and implement a system that computes agents' reputations using smart contracts and enables tracking of how their reputation changes. Khalid et al. [20] propose maintaining trust in an agent-based distributed energy trading system by publishing information on inter-agent agreements in the blockchain. Alaeddini et al. [21] consider blockchain in designing a multi-agent interbank trading system, where trust is regarded as a significant concern. It is worth

noting that none of these studies addresses an individual agent's threshold for the trust it needs to have in another agent to interact, and in fact, they all have given the same recommendation to all agents, regardless of their specific characteristics. Also, none of the models uses a real blockchain as part of their simulation system.

## 2.2 The Selected Trust Mechanism

Unlike the mentioned methods of trust in multi-agent systems, we propose a new method to develop a trust model based on the consensus reached by agents and using some variables found by Bülbül [22]. The following features are the main distinctions of this method from others:

- Both the expected level of trust of the agent responding to the interaction and the level of trust met by the agent requesting the interaction are considered;
- It uses a blockchain-based consensus algorithm to establish distributed trust; and
- Unlike some other methods (e.g., Khalid et al. [20]), it does not publish any confidential information of agents on the blockchain.

The model uses a reputation system as an additional trust layer based on counterparts' relationships [23] and applies six values from  $-1$  (distrust) to  $4$  (complete trust) for both direct and indirect trust. The value of direct trust is the result of assessing the lender's trust in a borrower for a loan transaction, while an indirect value is based on reputation information. An agent uses values of its direct trust in other agents in order to arrive at a consensus on their reputation and recommend them to other agents.

To calculate the level of trust desired by the lender agents, the model uses three determinants, including current interaction with the central bank ( $X_{1i,t}$ ), equity ( $X_{2i,t}$ ), and size ( $X_{3i,t}$ ) of the lending bank as follows at every time step  $t = 1, 2, \dots, T$ :

$$X_{1i,t} = \begin{cases} 1, & \text{bank } i \text{ has a debt to the central bank in time } t \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

$$X_{2i,t} = \begin{cases} 2, & \text{bank } i \text{'s capital at time } t > \text{average capital of banks of similar size} \\ 1, & \text{bank } i \text{'s capital at time } t = \text{average capital of banks of similar size} \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

$$X_{3i,t} = \begin{cases} 1, & \text{bank } i \text{ is small in size} \\ 0, & \text{bank } i \text{ is medium in size} \\ -1, & \text{otherwise} \end{cases} \quad (3)$$

$$\tau_{i,t} = \max[-1, (X_{1i,t} + X_{2i,t} + X_{3i,t})] \quad (4)$$

where  $\tau_{i,t}$  denotes bank  $i$ 's observed ordinal variable as the trust threshold at time  $t$ .

Let  $\theta_{i,j,t}$  denote the trust level between banks  $i$  and  $j$  at time  $t$ . A lending relationship between lender  $i$  and borrower  $j$  is allowed at time  $t$  if  $\theta_{i,j,t} + \tau_{i,t} > 4$ . The level of direct trust between banks  $i$  and  $j$  at time  $t$  is obtained from the Eq. 5, where  $H_{i,j,t}^{good}$  indicates the history of good records of bank  $j$  in repaying the loans it has received from bank  $i$  until time  $t$ , and  $H_{i,j,t}^{bad}$  denotes the history of bad records in the same

period.  $H_{i,j,t}$  indicates the number of lending relationships between banks  $i$  and  $j$  from the beginning to time  $t$ .

$$\theta_{i,j,t} \approx \max \left[ -1, \left( \frac{H_{i,j,t}^{good} - H_{i,j,t}^{bad}}{H_{i,j,t}} \times 4 \right) \right] \quad (5)$$

To calculate the level of indirect trust between two peers who did not have a lending relationship with each other before time  $t$ , each agent asks endorsers to examine the level of trust of the new counterpart. Endorsers, which are nodes located in the credit paths leading to the endorsee node, calculate its trust level by tracking the points assigned to that node and their credit paths that lead to it. The final score, subject to consensus, would be obtained based on the recommendations of other related nodes before the time of the loan transaction. The model defines the indirect trust of bank  $i$  to bank  $j$  as the direct/indirect trust of the counterparts  $k$  of bank  $i$  to bank  $j$ , weighted by the trust of bank  $i$  towards these neighbor agents  $k$ . Let  $w_{i,j,t}$ , defined as follows, denotes the elements of the stochastic matrix for normalizing the values of  $\theta_{i,j,t}$  ( $= 0$  if there is no link between agents  $i$  and  $j$ ).

$$w_{i,j,t} = \frac{1}{4} \times \frac{\theta_{i,j,t}}{n(N_{i,t})} \quad (6)$$

where  $N_{i,t}$  is the set of neighbors of agent  $i$  at time  $t$ , and  $n(N_{i,t})$  denotes the number of elements in this set. The indirect trust score of bank  $i$  to bank  $j$  is calculated as follows:

$$\theta_{i,j,t} \approx \sum_{k \in N_{i,t}} w_{i,k,t} \theta_{k,j,t} \quad (7)$$

This means that in order to calculate the level of trust of a counterpart if there is a direct relationship, agents use Eq. 5; otherwise, they need the consensus of other agents based on Eq. 7 (maybe in a recursive mode).

### 3 The Model

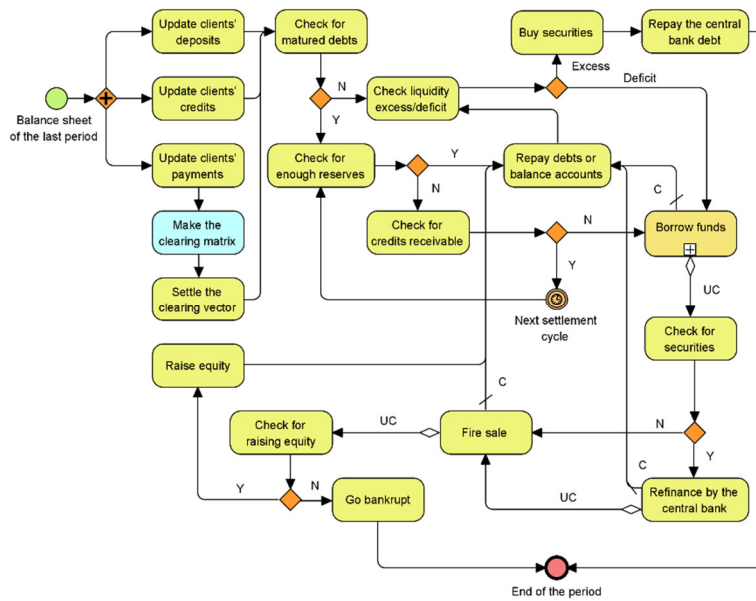
#### 3.1 The Agent-Based Simulation System

Our model developed in Repast Symphony builds on a number of recent studies [5,24-26] and is populated by two types of agents: (i)  $N$  banks that interact with and lend to each other, and (ii) one central bank that regulates the market and helps banks avoid failure when necessary. Furthermore, a lending contract has been developed to support interactions among the agents.

Banks are heterogeneous, imperfect, autonomous, and, to some degree, adaptive agents. They follow base-level rules to make interbank placements and must meet all regulatory requirements in their transactions and changes in their balance sheets. The initiation stage in our model creates random counterparts for banks, assigns their initial assets and liabilities according to banks' sizes, and determines each bank's balance sheet. The natural and financial sides of the market are linked by multiple, non-linear feedbacks and evolve in a finite time horizon. In each time step (one day), the items on

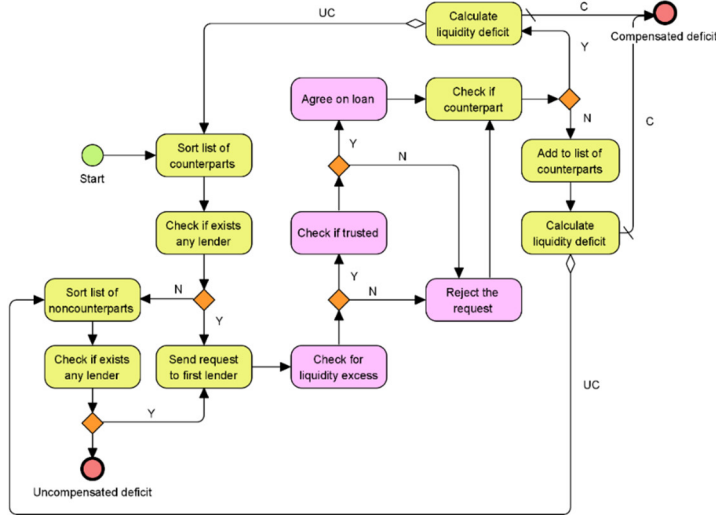
the banks' balance sheets change stochastically by following Gaussian random walks with related moving drifts  $\mu_{o_{i,t-1}}$  and noises  $\sigma_{o_i}$  (see Sect 3.2 for details).

The general logic of the simulation is that banks manage their liquidity (cash) by exchanging funds in the market. It is assumed that, at first, there are no loans to be repaid by banks (none of the banks owes to other banks). After the change in the banks' balance sheets in the first time step, the interaction of banks to borrow funds overnight in order to compensate for their lack of liquidity forms the interbank lending network in our model. The payments settlement is managed by a central clearing counterparty (i.e., the central bank), and all interbank loans are simulated to be paid in the blockchain (see Sect. 3.2). Fig. 1 shows the sequence of actions performed at each time step.



**Fig. 1.** The simulation process in BPMN (Y: yes; N: no; C: compensated; UC: uncompensated).

As shown in Fig. 1, at the beginning of each period, the amounts of clients' deposits, loans, and interbank payments resulting from the total transactions of clients with clients of other banks are updated stochastically. The central bank makes a clearing matrix for the payments, and banks use their reserve balance to settle their clearing vector. Then banks repay their matured interbank debts by their cash (reserve) balance and are evaluated by the lender. Banks that do not have enough reserves to repay their debts, if they have credit receivable on the same day due to the repayment of other banks' debts, wait until the successive settlement cycles on the present period; otherwise, they repay their debts by borrowing first from their counterparts and then from other banks (see Fig. 2). Banks then calculate their liquidity excess or deficit and provision their reserve. Banks that have excess liquidity pay part of the surplus to buy securities (investment) and then lend to other banks, according to Fig. 2. Finally, if banks owe money to the central bank, they repay it.



**Fig. 2.** The loan process in BPMN (Y: yes; N: no; C: compensated; UC: uncompensated).

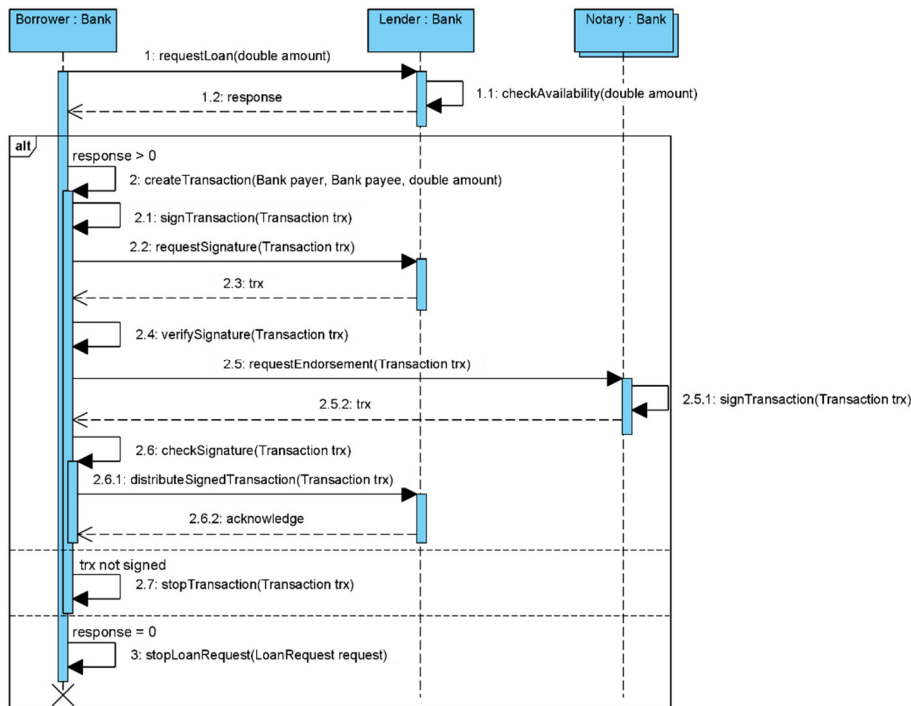
As shown in Fig. 2, in order to manage their liquidity, banks borrow or lend in the market. For this purpose, based on their history, borrowing banks send their loan requests first to their lending counterparts. Lending partners respond to requests based on their excess and borrowing banks' history. If banks cannot borrow from their existing counterparts, they will apply for a loan from other banks with a lending position in the network. If lending banks meet all or part of the liquidity needs of the applicant banks, they adopt two different strategies against the two off-chain (traditional) and on-chain (blockchain-based) modes (see Sect. 4.1). In either case, both borrowing and lending banks add each other to their counterparty list if the loan is agreed upon.

Banks that have not been able to make up for their need in the market will be refinanced by the central bank if they have enough securities; otherwise, they will have to fire sell—selling assets at heavily discounted prices. Then, banks try to repay their overdue loans, if relevant. At the end of each period, a bank goes bankrupt if it fails to make up for its liquidity deficit or its equity is zero or less and does not compensate for these problems by raising its equity. The failed bank is removed from the model. The bank's failure also leads to losses resulting from its zero debt to the banks from whom it has borrowed. This is the unique source of systemic risk and instability in our model. It is worth noting that the flow diagrams in Fig. 1 and Fig. 2 represent real bank behaviors [24,25].

### 3.2 The Blockchain-based Loan System

Adapted from Cucari et al. [27], we develop a simple loan system on the consortium blockchain Corda that records loan transactions of agents. To develop this system, we use the logic of a simple CorDapp already implemented by the Corda team and make changes based on our specific needs. One of the items that the loan system records and

maintains is loan state, which is an immutable object representing facts (loan data) known only by counterparts. The system also benefits from smart contracts between banks by turning the contract terms into code that executes automatically when they are met. The contract code is replicated on the nodes in the network. All these nodes have to reach a consensus that the terms of the agreement have been met before they execute the contract. Fig. 3 shows the sequence of consensus in the system.



**Fig. 3.** The UML sequence diagram of consensus in the blockchain-based loan system.

Loan transactions must achieve both validity and uniqueness consensus to be committed to the ledger. The first determines if a transaction is accepted by the smart contracts it references, while the latter prevents double-spends, i.e., the risk that the money is paid twice or more. A transaction must have all the necessary signatures to reach the validity consensus, meaning that the qualification of a borrower who has no previous relationship with a particular lender must be endorsed by a notary consisting of the banks that have already lent to that borrower. Uniqueness consensus is when the notary checks that the lender has not used the same input for multiple transactions.

Communication between banks is point-to-point using a flow, which automates the process of agreeing on ledger updates between the banks. Our agent-based simulator communicates with the loan system through an API that we developed. The initiation stage in our model deploys one node in the blockchain for each agent. The deployed blockchain nodes containing the API that records loan transactions on the blockchain are then run at this stage. Therefore, the environment we implement to simulate agents'



behavior is as similar as possible to the real environment that banks may use in a real market by employing a real blockchain to record their loan transactions.

## 4 Experimental Evaluation

### 4.1 Scenarios

We study the interbank market dynamics with and without using blockchain. We first test three economic cycle scenarios in the absence of blockchain (off-chain mode) using the parameters from a uniform distribution shown in Table 1. In the next step, we intervene with consensus in the blockchain on the level of trust between banks and test the three scenarios again (on-chain mode). To investigate the number of simulations required to smooth out irregularities, we apply the convergence of subsequent mean values at the aggregation level by forming a moving mean value. As soon as the deviation of the calculated mean value from the convergence mean value is less than 0.05, we consider it to be robust. Although 40 simulations on average are enough to reach a robust mean, we only run each simulation ten times because of time constraints. Finally, we compare the average of results of these six experiments.

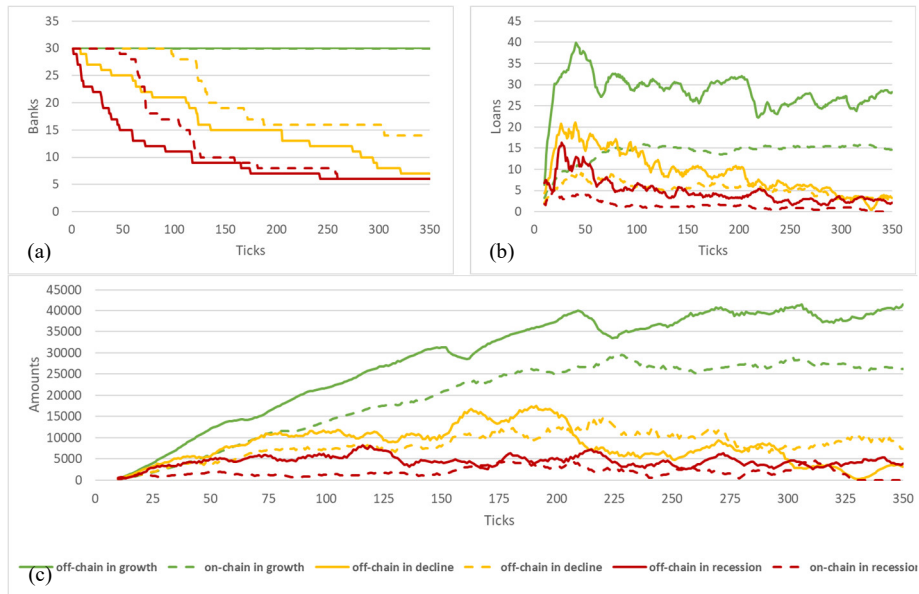
**Table 1.** Parameters for different economic cycles.

Parameter	Growth	Decline	Recession
noise of credits and lending	$\mathcal{U}(0,0.005)$	$\mathcal{U}(0.05,0.1)$	$\mathcal{U}(0.1,0.25)$
noise of deposits and payments	$\mathcal{U}(0,0.003)$	$\mathcal{U}(0.03,0.06)$	$\mathcal{U}(0.06,0.15)$

Each of these setups assumes that banks face an abundance or lack of liquidity with specific dynamics. The values of the other parameters used in our study are the same for all scenarios and are according to the coefficients and minimums set in Basel III and enforced by the ECB.

### 4.2 Experiments

Due to the limited hardware resources for simultaneous allocation to the blockchain network nodes, we perform this simulation with 30 random banking agents of different sizes whose balance sheets are adjusted based on the characteristics of banks operating in the French interbank market. Each experiment is based on an independent draw of the initial network for interbank loans as well as the balance sheet amounts of different banks. All initial networks are formed based on an initial value of 3 as the number of each bank’s counterparts. However, as the simulation progresses, it is possible for banks to make new relationships over time. In off-chain mode scenarios, the acceptance of the request by a new lender is  $1 - \sigma_{l_i}$  likely but at a higher premium than what the other partners of that agent pay. In on-chain mode scenarios, condition  $\theta_{i,j,t} + \tau_{i,t} > 4$  must be met for the request to be accepted by a new lender (see Sect. 2.2), and the interest rate will be subject to the same procedure as the agent’s other counterparts.



**Fig. 4.** Evolution of banks (a), the number of interbank loans (b), and total amount of interbank loans (c) in times of different economic situations: off-chain vs. on-chain modes.

Comparing the number of banks in both off-chain and on-chain modes during 350 days of activity in times of economic growth in Fig. 4(a) shows the stability of banks throughout the period. This means that when uncertainty is low, banks meet each other's liquidity needs well, and no default or failure is observed. From Fig. 4(b), as the economy grows, the total number of loans in 40% of days in the off-chain mode is in a position above the 'number of banks' line ( $n = 30$ ). It seems that in this mode, the general tendency of the borrowing banks is to borrow from more partners, and most of the lending banks tend to diversify their loan portfolio and lend to more banks. Another possible reason for this could be the dual activity of some banks, which act as both the lender and borrower in one day. By the intervention of blockchain, this trend goes surprisingly below the line (100%), meaning that a higher level of trust is interpreted as having narrower yet a deeper relationships with peers.

A look at the starting points and progression trends of the failures in Fig. 4(a) provides a similar comparison for the economic decline situation. The simulation results of the employed consensus algorithm to build trust among market members show that although the use of blockchain to realize this algorithm cannot ultimately prevent cascades of banks' failure, they can delay the collapse at least for a considerable time (89 days). During a recession, this opportunity is reduced to 45 business days. This means that the impact of using blockchain in restoring trust in the market during an economic decline is almost twice as great as during a recession. According to the almost uniform distance between the two on-chain diagrams in these two states in Fig. 4(a), it seems that this is more affected by the severity of uncertainty caused by the economic situation

than due to the blockchain features.

Similar to economic growth scenarios, there are significant gaps between off-chain and on-chain modes in both the number and the total amount of loans in times of economic decline and recession (see Fig. 4(b) and Fig. 4(c)). It means that if the blockchain is used in an unstable economic situation, both parties would prefer to reduce the number of agreements and increase the amount instead (i.e., trustworthy relationships). The gap between the number of loans in these two modes remains almost constant.

## 5 Conclusion and Future Work

This paper presents a multi-agent simulation platform for the interbank market and integrates the notion of trust using a blockchain-based consensus algorithm to explore dynamics of lending relationships and the effects of uncertainty caused by different economic conditions. In order to compensate for the lack of liquidity of their peers, banks lend each other overnight. Unlike Khalid et al. [20], we do not publish information on inter-agent agreements in the blockchain. Instead, we ask endorsing nodes in the network to determine how reliable is the borrower based on their previous track records, and finally to validate the transaction through a voting mechanism.

Based on the simulation results, the banking network remains stable during periods of economic growth without any additional need for a mechanism to strengthen trust. The issue of which of these two strategies in times of economic growth leads to lower cost and more operational advantage for the system and members can be the subject of new research. However, by increasing the uncertainty caused by changes in economic conditions, the establishment of a blockchain-based consensus mechanism in the market can help maintain trust between banks and, consequently, system stability (i.e., continuation of the presence of agents in the system). Although such a mechanism is not able to fully protect the market from contagious failures in the long run, it undermines the destructive effects of uncertainty for a significant period. An important point for the regulator and market participants is that since blockchain is an important factor in ensuring market resilience, the resiliency of the blockchain infrastructure should also be taken into account in times of stress so that it can meet expectations.

Good and bad history kept by the agents in our model can be interpreted as belief and disbelief [28]. Also, because uncertainty is considered as a parameter affecting the agents' behavior, we are interested in combining our method with the method of Cheng et al. [28], which basically uses these items in calculating trust. As a limitation of our model, banks' decisions about lending, like other events outside their control, have a stochastic basis. Another future agenda is adding learning capabilities to the model so that agents make decisions based on their current and future goals, use what they learn from the past, and consider other agents' behavior. Maintaining trust between agents can be one of the goals to which they apply what they learn in using blockchain to conduct more trustful transactions in the future. Furthermore, the results do not model the case of a black swan event that could be the cause of a systemic collapse. A scenario in which economic growth is abruptly followed by recession can be of interest to scholars and practitioners to analyze the market in off-chain and on-chain modes.

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## References

1. Ramchurn SD, Huynh D, Jennings NR (2004) Trust in multi-agent systems. *Knowl Eng Rev* 19(1):1-25
2. Kim W-S (2009) Effects of a trust mechanism on complex adaptive supply networks: An agent-based social simulation study. *Journal of artificial societies and social simulation* 12(3):4
3. Wooldridge M, Jennings NR (1999) The cooperative problem-solving process. *J Log Comput* 9(4):563-592
4. Pinyol I, Sabater-Mir J (2013) Computational trust and reputation models for open multi-agent systems: a review. *Artificial Intelligence Review* 40(1):1-25
5. Steinbacher M, Jagrič T (2020) Interbank rules during economic declines: Can banks safeguard capital base? *Journal of Economic Interaction and Coordination* 15(2):471-499
6. Chiriță N, Nica I, Popescu M (2022) The Impact of Bitcoin in the Financial Market. A Cybernetics Approach. In: *Education, Research and Business Technologies*. Springer, pp 197-209
7. Glass RJ, Ames AL, Brown TJ, Maffitt SL, Beyeler WE, Finley PD, Linebarger JM (2011) *Complex Adaptive Systems of Systems (CASoS) Engineering: Mapping Aspirations to Problem Solutions*. Sandia National Laboratories, Albuquerque, New Mexico USA
8. Alaeddini M, Madiès P, Reaidy P, Dugdale J (2022) Interbank money market concerns and actors' strategies – A systematic review of 21st century literature. *J Econ Surveys* 00:1-82
9. Craig BR, Fecht F, Tumer-Alkan G (2015) The Role of Interbank Relationships and Liquidity Needs. *J Bank Financ* 53:99-111
10. Cocco JF, Gomes FJ, Martins NC (2009) Lending relationships in the interbank market. *J Finan Intermediation* 18(1):24-48
11. Anand K, Gai P, Marsili M (2012) Rollover risk, network structure and systemic financial crises. *Journal of Economic Dynamics & Control* 36(8):1088
12. Abdul-Rahman A, Hailes S A distributed trust model. In: *Proceedings of the 1997 workshop on New security paradigms, 1998*. pp 48-60
13. Calvaresi D, Dubovitskaya A, Calbimonte JP, Taveter K, Schumacher M Multi-agent systems and blockchain: Results from a systematic literature review. In: *International conference on practical applications of agents and multi-agent systems, 2018*. Springer, pp 110-126
14. Shin DD (2019) Blockchain: The emerging technology of digital trust. *Telematics and informatics* 45:101278
15. Jordi S, Sierra C Regret: A reputation model for gregarious societies. In: *Proceedings of the fourth Workshop on Deception Fraud and Trust in Agent Societies, Montreal, Canada, 2001*. pp 61-70

16. Jurca R, Faltings B Towards Incentive-Compatible Reputation Management. In: Trust, Reputation, and Security: Theories and Practice: AAMAS 2002 International Workshop, Bologna, Italy, July 15, 2002. Selected and Invited Papers, 2003. Springer, p 138
17. Tweedale J, Cutler P Trust in multi-agent systems. In: International Conference on Knowledge-Based and Intelligent Information and Engineering Systems, 2006. Springer, pp 479-485
18. Huynh TD, Jennings NR, Shadbolt NR (2006) An integrated trust and reputation model for open multi-agent systems. *Auton Agent Multi-ag* 13(2):119-154
19. Calvaresi D, Mattioli V, Dubovitskaya A, Dragoni AF, Schumacher M Reputation management in multi-agent systems using permissioned blockchain technology. In: 2018 IEEE/WIC/ACM international conference on web intelligence (WI), 2018. IEEE, pp 719-725
20. Khalid R, Samuel O, Javaid N, Aldegheishem A, Shafiq M, Alrajeh N (2021) A secure trust method for multi-agent system in smart grids using blockchain. *IEEE Access* 9:59848-59859
21. Alaeddini M, Dugdale J, Reaidy P, Madiès P, Gürcan Ö (2021) An Agent-Oriented, Blockchain-Based Design of the Interbank Money Market Trading System. In: *Agents and Multi-Agent Systems: Technologies and Applications 2021*. Springer, pp 3-16
22. Bülbül D (2013) Determinants of trust in banking networks. *Journal of Economic Behavior & Organization* 85:236-248
23. Pazaitis A, De Filippi P, Kostakis V (2017) Blockchain and value systems in the sharing economy: The illustrative case of Backfeed. *Technol Forecast Soc Change* 125:105-115
24. Popoyan L, Napoletano M, Roventini A (2020) Winter is possibly not coming: Mitigating financial instability in an agent-based model with interbank market. *J Econ Dyn Control* 117
25. Sato AH, Tasca P, Isogai T (2019) Dynamic Interaction Between Asset Prices and Bank Behavior: A Systemic Risk Perspective. *Comput Econ* 54(4):1505-1537
26. Teplý P, Klinger T (2019) Agent-based modeling of systemic risk in the European banking sector. *Journal of Economic Interaction and Coordination* 14(4):811-833
27. Cucari N, Lagasio V, Lia G, Torriero C (2021) The impact of blockchain in banking processes: the Interbank Spunta case study. *Technology Analysis & Strategic Management*:1-13
28. Cheng M, Yin C, Zhang J, Nazarian S, Deshmukh J, Bogdan P A general trust framework for multi-agent systems. In: *Proceedings of the 20th International Conference on Autonomous Agents and MultiAgent Systems, 2021*. pp 332-340