AGENT-BASED MODELING OF A MORTGAGE CRISIS

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Abstract

The paper describes a simplified model of the mortgage crisis, highlighting how simple individual decisions made by entities, in this case, banks and households, within a given environment lead to emergent behavior across the entire market. The paper employs the agent-based modeling method (also known as ABM), as this simulation approach is highly suitable for modeling such situations. Using graph theory, the model considers random networks of banks that issue mortgages to households. It tracks the repayment and non-repayment of mortgage loans, the spread of shocks where insolvent banks pass on losses to neighboring banks, and the updating of property prices. The model's key determinants include the interest rate level, loan-to-value ratio, graph density (the probability that a connection exists between a pair of banks), and the so-called default threshold, which represents the critical level of financial loss at which an agent (in this case, a household) becomes unable to meet its mortgage obligations and thus enters a state of insolvency (default). The study observes how partial changes in individual input determinants affect indicators such as unpaid debt, banks in bankruptcy, and households in bankruptcy. The simulation results illustrate the formation of a mortgage crisis in an imaginary economy.

Key words: mortgage crisis, agent-based modeling, network of banks, households

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Introduction

The mortgage crisis represents a situation where a large number of entities in the economy take out mortgage loans without being able to repay the borrowed amount. When borrowers cannot repay their debts, the bank may seize their property or sell it through a forced sale. Due to the excessive sale of properties, real estate prices decrease, meaning that either the borrowers receive less money than they owe the bank, leaving them still in debt, or the bank acquires a property whose current market value is less than the amount owed by the borrower, causing the bank to incur losses during the mortgage crisis (Begany, 2022). Banks are interconnected through interbank markets and financial instruments (e.g., Credit Default Swaps), so financial problems caused by the non-payment of loans by one bank can negatively affect other banks (Hayes, 2024).

The mortgage crisis often leads to tightening credit standards, such as raising the requirements for applicants' credit scores, lowering the maximum loan-to-value (LTV) ratio, and imposing stricter income verification rules. At the same time, rules for lenders (banks) may be tightened, for instance, by increasing interest rates and mandatory minimum reserves, which should contribute to the solvency of banks (Hamerling, Morgan, & Sporn, 2020).

The most well-known mortgage crisis case is often referred to as the subprime mortgage crisis, which occurred in the U.S. in 2007. The crisis was precipitated by activities starting in 2000. At that time, foreign investors invested their money in the U.S. real estate market. They purchased mortgage-backed securities, bundles of mortgage loans with highly positive ratings (AAA), and pressured banks to issue more mortgages. As a result, banks began issuing mortgages even to people with low incomes and credit scores. These loans are now known as subprime mortgages. Banks employed so-called predatory lending practices—initially, low adjustable interest rates were applied to mortgages, making them accessible to borrowers. However, the interest rates increased over time, and people could no longer keep up with their payments. Consequently, investments in mortgage-backed securities were no longer safe, but investors continued to invest in them as the data on their returns remained positive (Kagan, 2024).

The initial low interest rates led to an increase in the demand for real estate, which in turn raised home prices. Borrowers were no longer able to repay their debts, leading to the mortgage crisis. In 2007, New Century Financial Corp., a major subprime mortgage lender, declared bankruptcy, which caused other companies to stop issuing subprime mortgages. At the same time, the ratings of mortgage-backed securities began to decline—signaling to investors that these were no longer safe investment vehicles (Duca, 2013).

In this paper, we focused on modeling the mortgage crisis and observing the factors that led to it.

1 Agent-based modeling

We chose the agent-based modeling (ABM) approach for our mortgage crisis modeling. This methodology has roots dating back to the 1960s and 1970s. It gained its current form in the 1980s, thanks to new models developed primarily in sociology.

ABM is a simulation approach aimed at understanding the behavior of society (all individuals) as a whole in a complex system based on the simple behavior of individuals and interactions between individuals and their environment. This is sometimes referred to as emergence (Bonabeau, 2002).

One of its advantages is that it can be visualized, making it easier to present the situation to the public. Generally, the goal of an agent-based model is not to perfectly replicate reality but to depict the parameters under observation.

The individuals in ABM are called agents, acting autonomously, meaning independently, based on their characteristics. A significant advantage of ABM is that each agent can have different characteristics. In more complex models, agents can learn from past behavior and make future decisions based on their experiences (Wilensky & Rand, 2015, p. 32).

ABM is used in economic modeling, epidemiology, decision-making processes, and education. It remains widely used in sociology and political science nowadays.

Among the original and significant agent-based models are the Game of Life (John Conway), which illustrates how organisms can survive or die based on simple individual rules, either due to isolation or overcrowding (Roberts, 2020), and the Model of Segregation (Thomas Schelling), which depicts how households would relocate based on simple rules depending on which of the two groups they and their neighbors represent. Schelling himself referenced urban migration based on race (white and black), but later, it was also linked to the political situation in the USA—households are categorized based on whether they support Republicans or Democrats (Ubarevičienė, van Ham, & Tammaru, 2024).

1.1 Agents – banks

The banks are randomly connected to a network. We used the Erdős–Rényi model (Erdős & Rényi, 1959) to establish connections between banks, and by adjusting the parameter *p*, the network density can be controlled (a higher value of *p* increases the likelihood that a connection exists between a pair of banks).

Banks lend money to households (another type of agent). The model is simplified, assuming households without an existing mortgage can take out a loan from any bank, and all banks offer mortgages at the same interest rate.

Banks interact with each other such that if there is a connection between them, a failing bank transfers its debt to the banks it is connected with.

1.2 Agents – households

Households take out mortgages from banks in a state where they have a mortgage or do not have one. If they have a mortgage, two situations can occur: either the household can afford to repay the mortgage, in which case they do so, or they cannot, affecting the banks. The ability to repay is influenced by the household's income (an agent property) and the default threshold (not an agent property).

Household incomes were randomly simulated. Households do not interact with each other.

2 Model parameters

Various parameters influence the modeling results. The study examines the impact of different parameter combinations on the development of the mortgage market and the potential emergence of a mortgage crisis, which is why the parameters differ across simulations.

The loan-to-value (LTV) ratio expresses the ratio between the loan amount and the value of the mortgaged property. The model uses this variable to calculate the loan amount.

$$Loan - to - value\ ratio = \frac{Loan\ amount}{Property\ value}. \quad (1)$$

The initial property price affects the loan amount and, consequently, whether households, based on their randomly simulated incomes, can repay the debt. During the simulation, property prices evolve randomly. It is assumed that at the start of the simulation, all properties have the same value.

The interest rate determines how much additional percentage of the loan amount households must pay to the banks over a specific period. Simply put, it represents the banks' profit. For simplicity, the model assumes that the interest is paid in full without considering the repayment period so that the total repayment amount can be expressed as:

$$Total\ repayment\ amount = Loan\ amount \times (1 + Interest\ rate), \quad (2)$$

where the Loan amount can be expressed as:

$$Loan\ amount = Loan - to - value\ ratio \times House\ price, \quad (3)$$

where the House price is adjusted randomly with each tick (step of the simulation) based on the following rules:

Each simulation consisted of 1000 steps (ticks). The first 400 ticks represent the period before the crisis when house prices were mostly rising. The next 400 ticks represent a period of crisis when house prices were mostly falling. The last 200 ticks represent the period after the crisis, when the market "recovers" from the crisis and prices did not have a clear development trend.

The default threshold represents the debt-to-income ratio at which a household is unable to repay the mortgage and thus becomes insolvent. The model uses this parameter to determine whether a household can repay the mortgage based on its income.

If a bank goes bankrupt, part of its debt is transferred to the banks it is connected with. The previously defined Erdős–Rényi model with the parameter p establishes bank connections.

3 Model description

The model simulates a mortgage crisis scenario with two main types of agents: banks and households. It tracks their financial interactions and the spread of financial distress through the system.

The model simulates the interaction between households and banks over time. Households try to acquire mortgages and repay them. Banks grant loans and face potential losses due to bad investments and defaults. If a bank makes a bad investment, it loses 50 units. The spread of shocks through the bank network can trigger a cascade of bankruptcies and a mortgage crisis.

In this paper, we used the model to perform sensitivity analysis by varying the input parameters (e.g., interest rate, default threshold, LTV ratio, network density) and observing how these changes affect the output variables (e.g., unpaid debt, banks with bankrupt, households with bankrupt).

Households are created with a random income between 50 and 100 units, an initial house price, no mortgage debt, and are initially not bankrupt.

Banks are created with assets equal to a portion of the total market value. The market value is calculated as the total house prices of all households multiplied by a loan-to-value ratio.

A network of banks is generated randomly, where each bank has a chance (*p* rate) to establish a link with other banks, representing financial connections.

4 Key findings

For individual input variables, we determined their default values, namely:

- *p*-rate = 0.5

- loan-to-value = 0.8
- interest rate = 0.05
- default threshold = 0.3

We performed a sensitivity analysis by gradually changing the values of only one of these variables while leaving the values of the other variables unchanged (ceteris paribus). We performed simulations on 10 banks and 100 households.

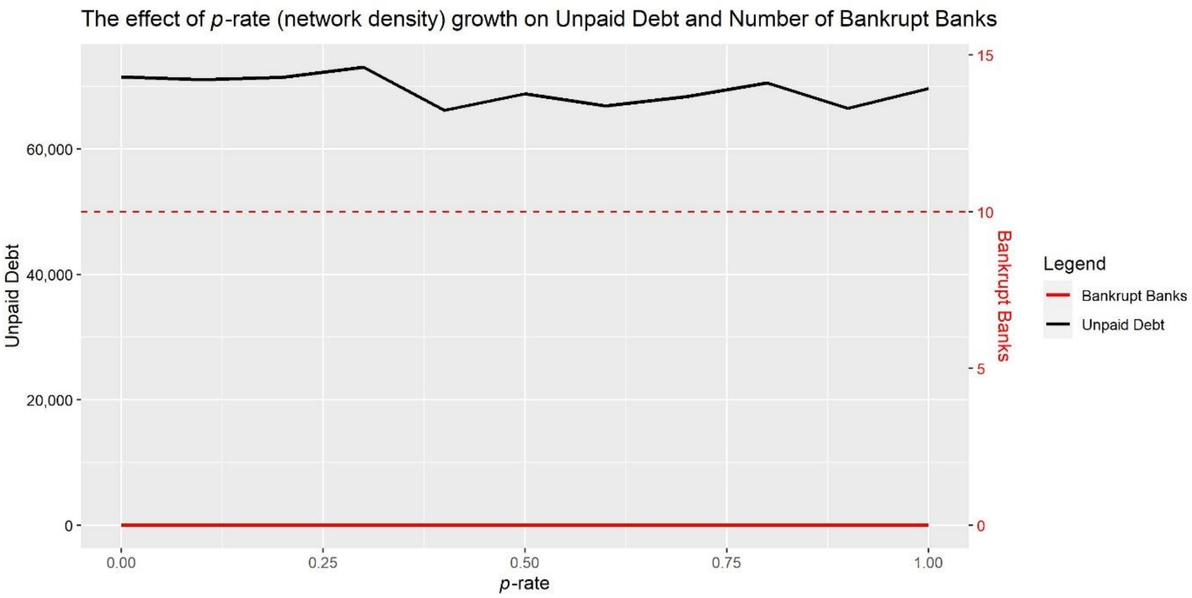
Simulations were performed using NetLogo software, and analysis was performed using the statistical programming language **R**.

Using our simulations, we found some interesting conclusions.

4.1 Effect of *p*-rate growth

The first of the conclusions is that the degree of interconnection between banks (*p*-rate) does not have a significant effect on the number of bankrupt banks and bankrupt households. This suggests that other factors, such as individual bank risk management, economic conditions, or other parameters, may play a more crucial role in determining financial stability and the likelihood of bankruptcies. This can be seen in the Fig. 1.

Fig. 1: The effect of *p*-rate (network density) growth on Unpaid Debt and Number of Bankrupt Banks

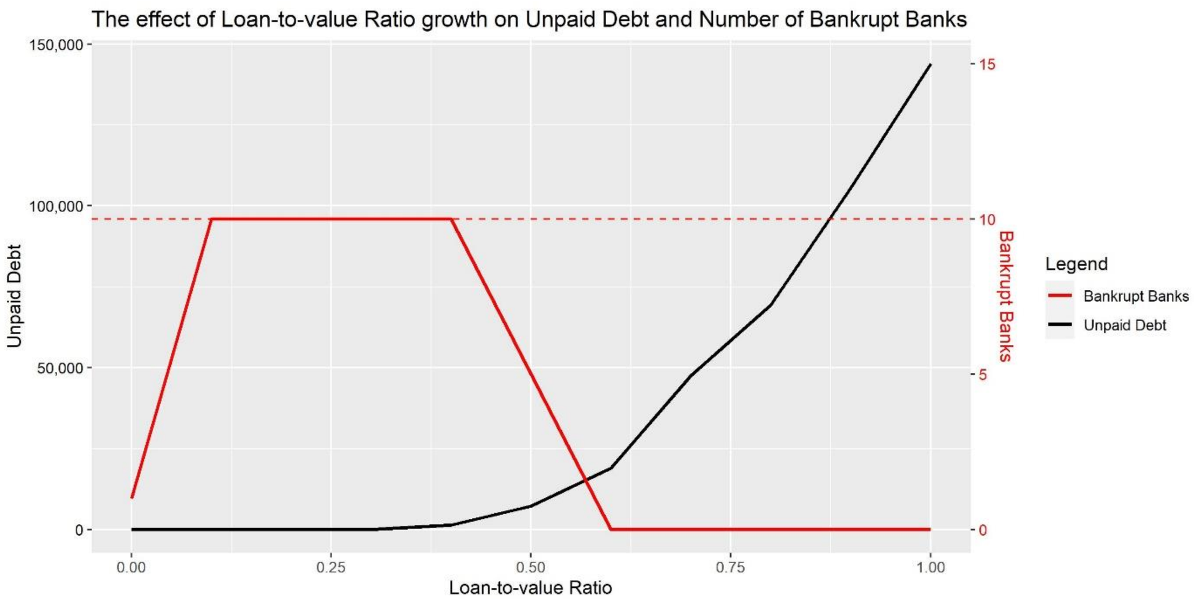


Source: own processing using R and NetLogo

4.2 Effect of loan-to-value ratio growth

Another conclusion is that as the loan-to-value ratio increases, the value of the unpaid debt indicator increases due to the increase in bankrupt households and the number of bankrupt banks decreases. This is because when the LTV ratio increases, households are borrowing a larger proportion of the property value. For example, a higher LTV ratio (e.g., 90% versus 80%) indicates that households are taking out larger loans relative to the property's value. With a higher LTV ratio, households are taking on more debt. This makes the mortgage payments larger relative to their income, increasing the likelihood that households will struggle to make payments and, therefore, default. This can be seen in the Fig. 2.

Fig. 2: The effect of Loan-to-value Ratio growth on Unpaid Debt and Number of Bankrupt Banks

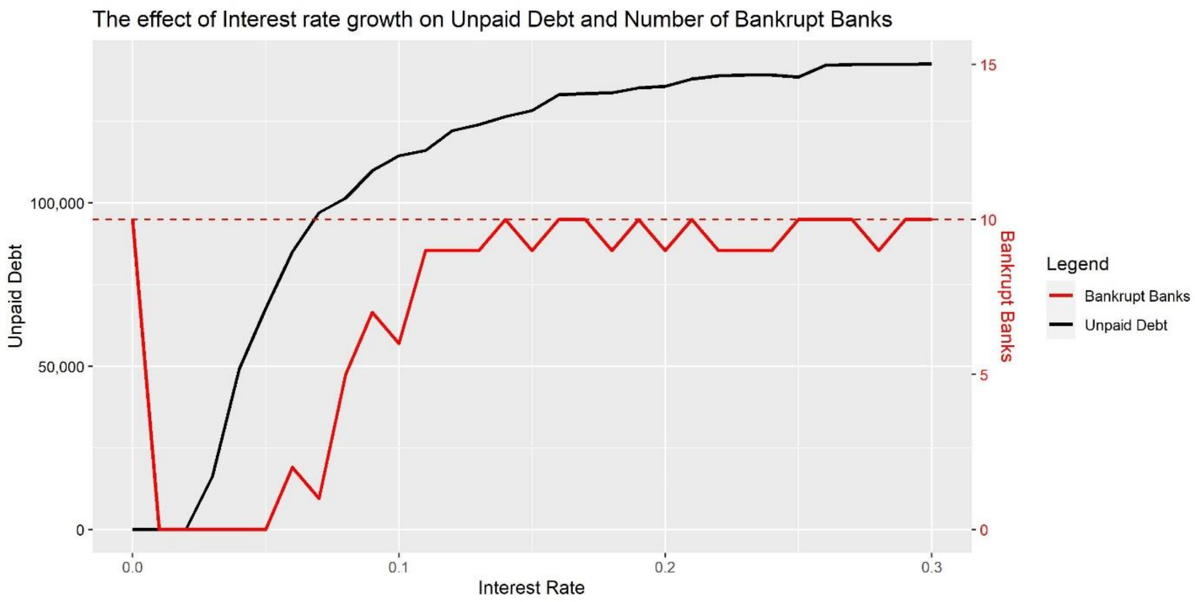


Source: own processing using R and NetLogo

4.3 Effect of interest rate growth

The development of interest rate changes is interesting. If the interest rate were at the level of 0, it would logically mean zero profit for the banks, and therefore, they would all go bankrupt. With the gradual increase in the interest rate, we see an ideal situation: no bankrupt bank or household. However, if the interest rate rises above the limit of 3-4%, many of our households begin to go bankrupt. As the interest rate continues to rise, more and more households begin to go bankrupt, and gradually, due to the increase in the value of unpaid debt, some banks also begin to go bankrupt while at an interest rate level of around 13 percent or more, all banks already go bankrupt. It is interesting that the change in the interest rate does not affect all households but only the "poorer" ones. Those "richer" households that have a sufficiently high income do not go bankrupt even with the increasing value of the interest rate. This can be seen in the Fig. 3.

Fig. 3: The effect of Interest Rate growth on Unpaid Debt and Number of Bankrupt Banks

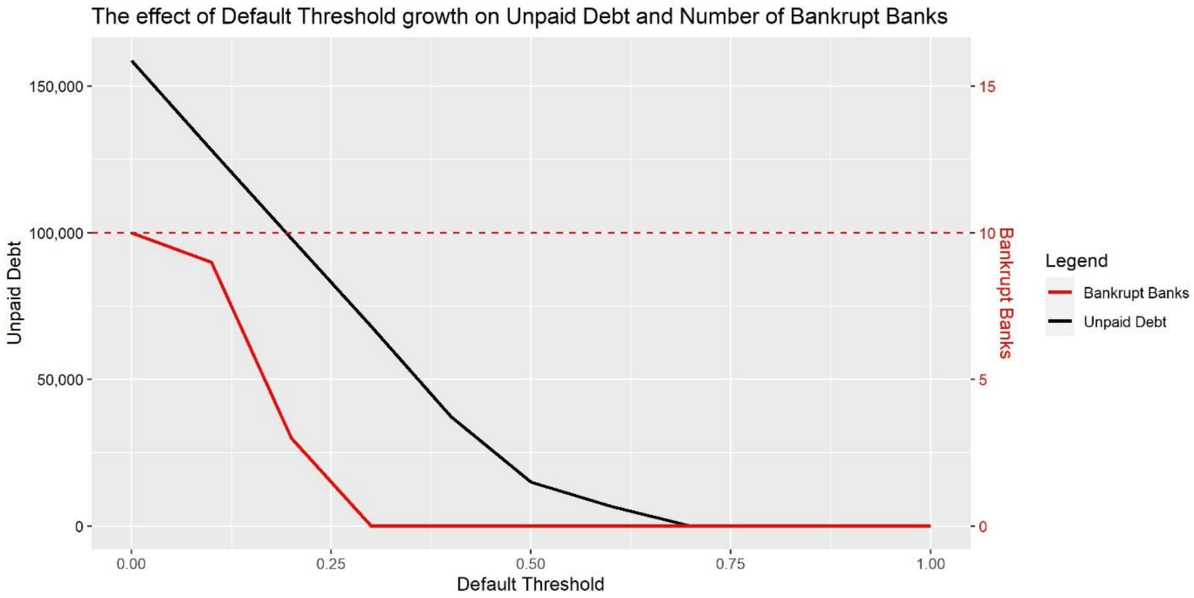


Source: own processing using R and NetLogo

4.4 Effect of default threshold growth

The last conclusion concerns the value of the default threshold indicator. The higher the value of this indicator, the fewer bankrupt banks and households we have. At low values of this indicator, all banks and all "poorer" households go bankrupt. It is because an indicator represents a critical value used to determine whether a household defaults on its mortgage payments. Specifically, it is a multiplier applied to a household's income to establish a threshold for default. When the indicator's value is lower, it means that a smaller portion of a household's income is sufficient to trigger a default. Thus, households are more likely to default when their mortgage payments are relatively high compared to their income. Conversely, a higher default threshold means that households need to be paying a larger proportion of their income before they default. This reduces the likelihood of defaulting because the mortgage payments need to be relatively higher compared to the income for the default condition to be met. This can be seen in the Fig. 4.

Fig. 4: The effect of Default Threshold growth on Unpaid Debt and Number of Bankrupt Banks



Source: own processing using R and NetLogo

Conclusion

The simulation highlights the complex interplay between household debt, bank stability, and financial networks in an economy. It underscores the importance of prudent lending, effective regulation, and the need for a systemic approach to managing financial stability. By understanding these dynamics, policymakers and financial institutions can better anticipate and mitigate the risks of economic crises.

From this simulation, several important conclusions and insights can be drawn regarding the dynamics of household debt, bank stability, and the broader economic system.

The simulation illustrates that household default is directly influenced by their income and the mortgage debt they carry. When mortgage payments exceed a threshold percentage of income, defaults occur, leading to a chain reaction that can destabilize banks, this emphasizes the importance of prudent lending practices, as banks that lend excessively to high-risk households are more likely to experience financial distress.

Banks are vulnerable to household defaults, as they lose assets when a household defaults and its property value decreases. This can set off a feedback loop where bank insolvency leads to additional economic shocks, potentially causing a cascade of defaults in the financial system.

The model demonstrates how financial networks can transmit economic shocks from one bank to another. When a bank goes bankrupt, the shock spreads to its connected banks, which can lead to a broader financial crisis. This underscores the interconnected nature of the banking system and the potential for systemic risk, where the failure of one institution can lead to widespread economic instability.

The results suggest that regulations aimed at ensuring that banks have sufficient capital buffers to withstand shocks are crucial. Policies that limit excessive risk-taking and ensure that banks maintain adequate reserves can help prevent the kind of cascading failures observed in the simulation.

The model shows how house prices can fluctuate over time due to market conditions and economic shocks. These fluctuations can significantly affect both household wealth and bank stability, leading to further economic volatility.

The random adjustments to house prices in the simulation can lead to boom-and-bust cycles in the housing market. During boom periods, prices rise, leading to increased lending and borrowing, which can eventually become unsustainable, resulting in a bust and widespread defaults.

The interest rate directly affects the ability of households to service their debt. Policy decisions that influence interest rates can have far-reaching effects on both household solvency and bank stability. For instance, raising interest rates to combat inflation might increase default rates among households, potentially destabilizing the banking system.

We are aware that the model we presented has many limitations. As it is a simplified representation of a real-world mortgage crisis, it does not include many factors that could influence the dynamics, such as government intervention, complex financial instruments, or behavioral aspects of decision-making. The random network structure might only partially capture the complexities of real-world financial networks.

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