

A Sensitivity Analysis on ABBA: An Agent-Based Model of the Banking System.

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Introduction:

The 2007-2008 financial crisis, or the Global Economic Crisis (GEC), was the most severe worldwide economic crisis since the Great Depression. Predatory lending in the form of subprime mortgages targeting low-income homebuyers, excessive risk-taking by global financial institutions, a continuous buildup of toxic assets within banks, and the bursting of the United States housing bubble culminated in a "perfect storm", which led to the Great Recession¹. The banking system, which lies at the financial system's core, suffered during the financial crisis in 2007-9. In the United States alone, in the four years following the inception of the crisis in 2008, the number of failed banks in the United States reached 414².

The lessons learned from the crisis have spurred a large body of research toward understanding and identifying vulnerabilities in financial systems. Since financial systems are fundamentally systems of individual players and institutions making decisions, agent-based models are a powerful tool to model and analyze our financial systems and networks. One such model is ABBA: An Agent-Based Model of the Banking System developed by Jorge A. Chan-Lau. As one of the major components of the financial system, understanding vulnerability in the banking system can play an important role in preventing future crises. In this paper, I will run a sensitivity analysis on saver's probability of withdrawing their deposits from banks with respect to the frequency of bank credit and liquidity failure. The withdrawal rate is a tangible statistic of the general population that can be measured and predicted. Thus, understanding the interplay between withdrawal rates and bank failures may serve as a useful indicator in anticipating and mitigating future bank failures.

Related Literature:

In the years after the 2007-2008 financial crisis, there has been a rapid increase in the number of studies analyzing banking and financial systems using agent-based models. An analysis of the effectiveness and limitations of ABMs is "Agent-Based Models of Financial Markets: A Comparison with Experimental Markets" by Nicholas T. Chan, Blake LeBaron, Andrew W. Lo, and Tomaso Poggio, examines the efficacy of agent-based models in replicating and understanding financial market dynamics. The researchers constructed a computer-simulated double-auction market where artificially intelligent agents, endowed with varied learning abilities, engage in trading. The study explores several market aspects through six experimental designs, including price efficiency, market convergence to rational expectations equilibrium, wealth distribution among agents, and the impact of agent heterogeneity on market dynamics. Notably, the simulation effectively mirrored several outcomes observed in human-based experimental

¹ (2007–2008 financial crisis 2024)

² Chan-Lau, "ABBA."

markets, while also revealing distinct differences in agent-based scenarios, which may highlight unique aspects of human decision-making and learning in financial markets. The findings underscore the utility and limitations of using agent-based models to probe complex market behaviors and the potential of such models to supplement theoretical and experimental approaches in economic research.

Methods:

Model Description:

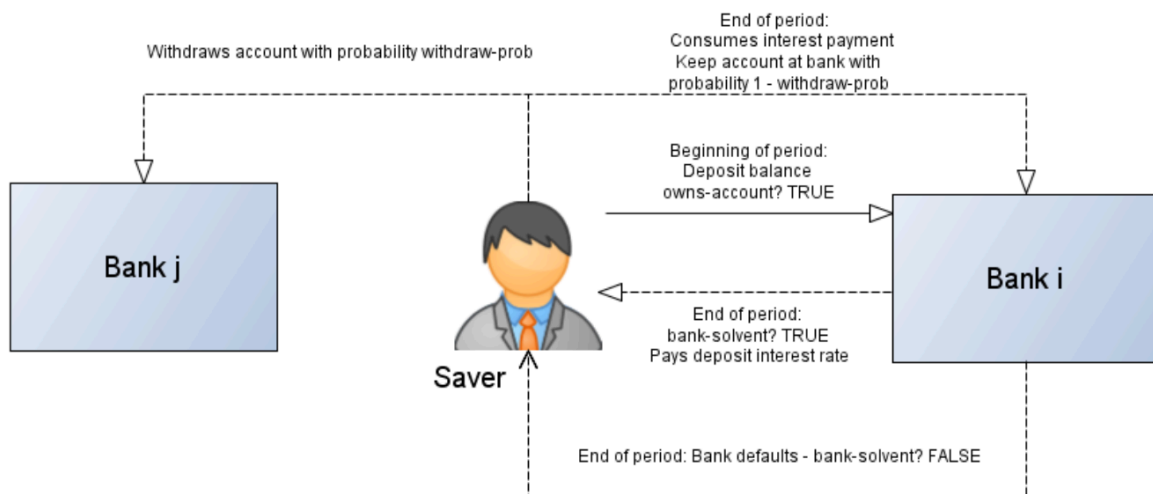
The ABBA model is comprised of 3 agents, savers, loans, and banks. The model outlined in Jorge-Chan is organized as follows:

Savers: heterogeneous, simple adaptive behavior, does not modify behavior/exhibit autonomy.

- Homogeneously distributed in different regions of the world, each dominated by 1 bank.
- Withdraws from account with probability W .
- When banks default, savers are paid on a first come, first serve basis.

Figure of saver behavior from Chan-Lau:

Figure 1. Savers' behavioral decisions



Saver recovers deposits if value of liquidated portfolio and reserves exceeds bank deposits.

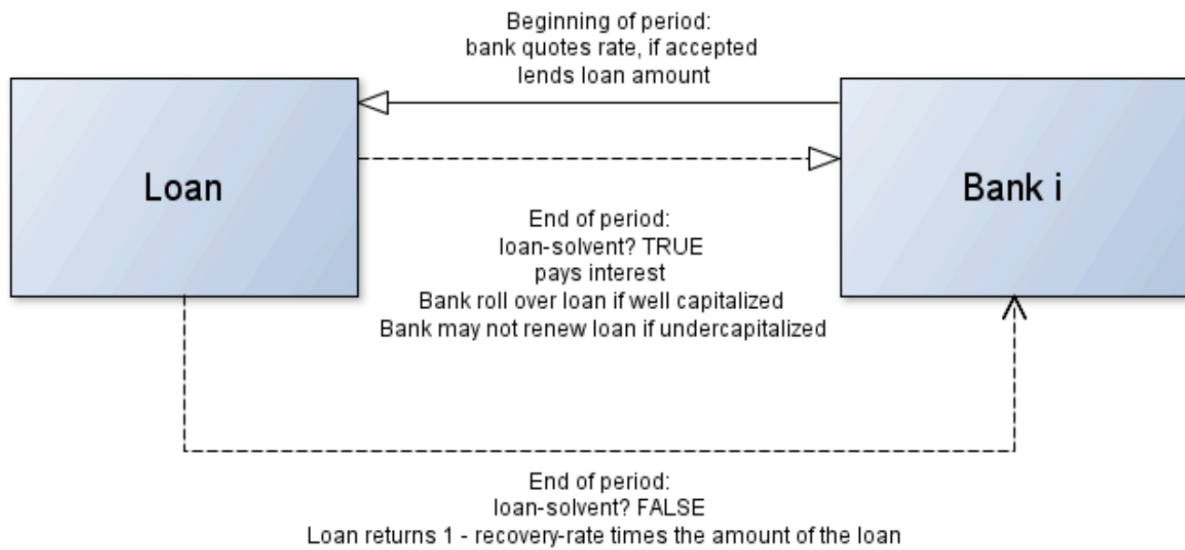
Otherwise, first-come, first-serve applies

Loans:

- Homogeneously distributed in different regions.
- Properties: amount, probability of default, risk weight, rating, recovery rate in case of default, loss rate associated w/ fire sales.
- Based on credit risk characteristics, Banks quote loan rates to borrowers at the beginning of a period according to a simple pricing rule.
- If a firm goes to a bank for a loan, the bank quotes if they meet capital and reserve requirements after adding to their portfolio.

Figure of loan behavior from Chan-Lau:

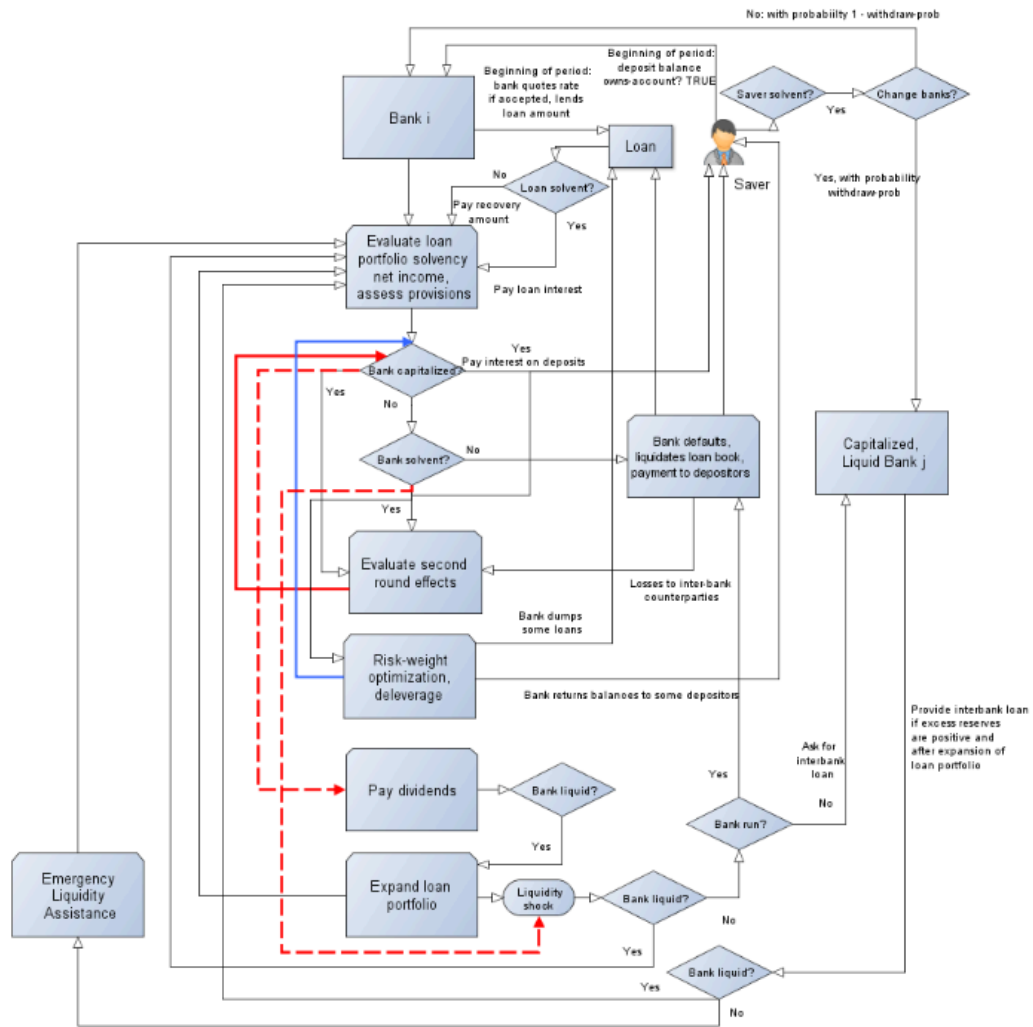
Figure 2. Loans payoffs



Banks:

Banks can raise and deploy deposits to fund risky loans while provisioning against expected losses. Determine the amount of equity and reserves needed to satisfy minimum regulatory capital and reserve requirements. Solvent banks not meeting requirements can deleverage or conduct risk-weight optimization to increase reserves and boost capital to risk-weighted assets. Figure of Bank behavior from Chan-Lau.

Figure 3. Bank's actions and interactions with other agents
The solid red line represents the loop induced by second-round effects; the solid blue line the loop induced by risk-weight optimization actions by the bank; and the dashed red lines the flows and decisions following the completion of the second-round effect and risk-weight optimization loops (see section III for details).



3) Model scheduling

In one period of the model:

1. Evaluate solvency of banks after loans experience default
2. Evaluate second-round effects owing to cross-bank linkages
3. Undercapitalized banks undertake risk-weight optimization
4. Banks that are well-capitalized pay dividends
5. Reset insolvent loans, i.e. rebirth lending opportunity
6. Build up loan book with loans available in the bank neighborhood
7. Build up loan book with loans available in other neighborhoods
8. Evaluate liquidity needs related to reserves requirements

Each simulation is run for 300 periods.

Model Analysis

In the base model provided by Chan-Lau, savers take on a random withdrawal probability sampled uniformly from $[0, 21]$. To better simulate the behavior of a general population, where people's choices tend to follow a normal distribution, I sample the withdrawal probability from a normal distribution. Originally, I planned to sample the potential means and standard deviations using Latin hypercube sampling. However, due to the organization of the Chan-Lau model in NetLogo, a grid search was a much more convenient approach. Due to runtime constraints, I had to limit the number of parameters I searched through. Thus, the grid search was performed with mean values of $[10, 20, 25, 30, 40, 60]$, standard deviation values of $[5, 15, 20]$, and minimum reserve ratios of $[0.03, 0.06]$. Each parameter set is run 5 times and the average of the number of liquidity failures is recorded.

Results:

Figure 1.

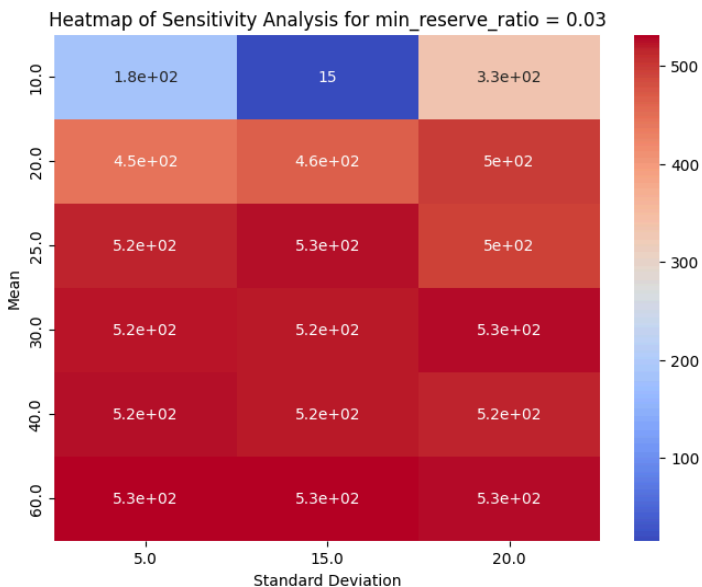
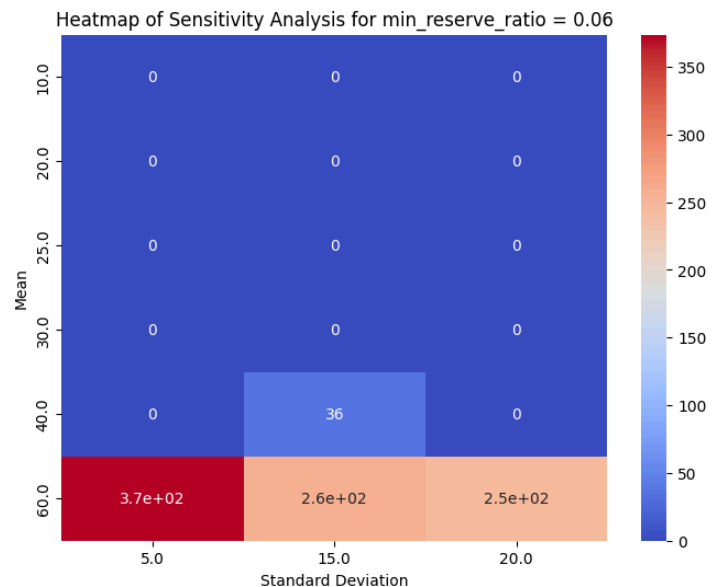


Figure 2.

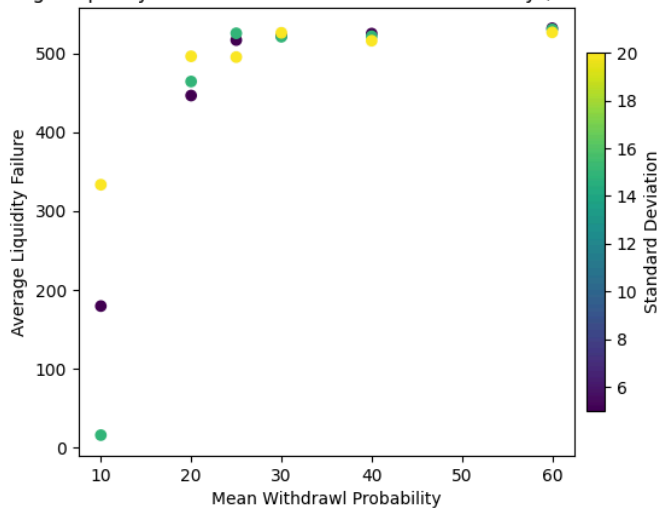


The rate of liquidity failures is highly dependent on the minimum reserve ratio requirement, a regulatory requirement that banks must adhere to. This is expected, as higher reserve requirements force banks to hold more reserves, which lessens the impact of liquidity shocks and their associated failures. When the minimum reserve ratio is set to 0.03, the rate of bank failures is very high for mean withdrawal probabilities greater than 10. The rate of failures is lowest for a mean of 10 and a standard deviation of 15. When the minimum reserve ratio is 0.06, the rate of bank failures is very low for mean values below 60. The rate of failures is highest for a mean of 60 and a standard deviation of 5. Below are some visualizations of the relationship between mean withdrawal probability and liquidity failures.

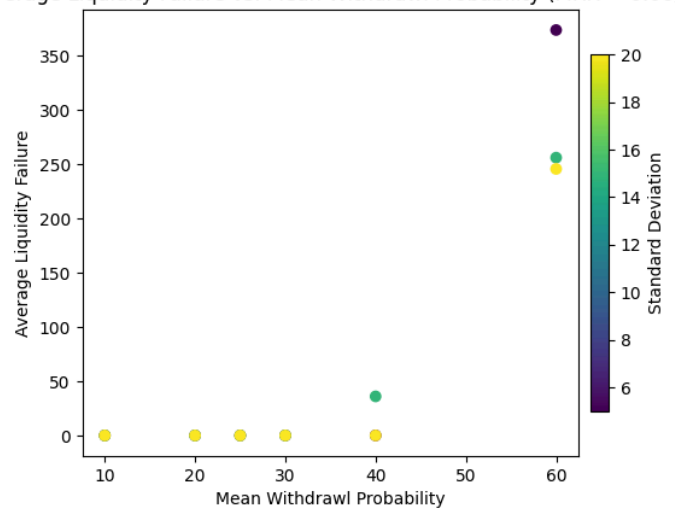
Figure 3.

Figure 4.

Average Liquidity Failure vs. Mean Withdrawal Probability (MRR = 0.03)



Average Liquidity Failure vs. Mean Withdrawal Probability (MRR = 0.06)



Discussion:

The results from the sensitivity analysis indicate a relationship between the rate of withdrawal and liquidity failures. In the low minimum reserve ratio regime where banks are more susceptible to liquidity shocks, liquidity failures are minimized at the lowest mean value of 10 and medium standard deviation value of 15. The fact that liquidity failure isn't minimized at the lowest standard deviation value indicates that there needs to be some sizeable population of savers that have a very low / zero probability of withdrawing from the bank. This makes sense as having a baseline population that will keep their money in the bank helps the bank when they encounter liquidity issues. In the higher minimum reserve ratio regime, banks are more resistant to liquidity shocks. Here, liquidity failures are maximized at the highest mean value of 10 and the lowest standard deviation of 5. This seems to support the idea that savers with lower probabilities of withdrawals help insulate banks to protect against liquidity shocks. This result is unsurprising, as in many crises financial institutions that maintain a higher level of reserves typically exhibit greater resilience. The results align with classical banking theory, which

suggests that a higher reserve ratio provides a buffer against sudden demands for withdrawals, thereby stabilizing the bank's liquidity.

However, it is intriguing that within a higher reserve ratio regime, the highest rate of liquidity failures occurs at a low standard deviation in withdrawal rates, coupled with high mean withdrawal rates. This pattern suggests that even when a bank holds substantial reserves, the homogeneity of withdrawal behaviors (reflected by a lower standard deviation) coupled with a high average withdrawal rate can strain the bank's liquidity. This condition could lead to scenarios where simultaneous high demands exceed even well-prepared reserves, triggering a liquidity shortfall.

The implications of these findings are significant for regulatory frameworks concerning liquidity management. The data advocate for policies that not only mandate higher reserve ratios but also encourage diversity in depositor behavior. Encouraging heterogeneity in withdrawal behaviors can provide an additional layer of security, reducing the systemic risk that occurs when large portions of a depositor base act in unison.

In conclusion, this analysis underscores the complexity of liquidity management within banking institutions. While maintaining higher reserve ratios is crucial, understanding the behavioral patterns of depositors and their impacts on liquidity also plays a pivotal role. Future research should explore the potential for regulatory policies to incentivize or mandate such diversity among depositors, potentially through differentiated reserve requirements based on depositor behavior profiles. This could enhance the robustness of banking sectors against liquidity crises, promoting greater financial stability. In addition, a denser parameter sweep, including a wider range of minimum reserve ratios, would be helpful to better understand the relationship between saver behavior, minimum reserve requirements, and bank liquidity failures.

Citations:

Wikimedia Foundation. (2024, April 26). *2007–2008 financial crisis*. Wikipedia.
https://en.wikipedia.org/wiki/2007%E2%80%932008_financial_crisis

Poggio, Tomaso and Lo, Andrew W. and LeBaron, Blake D. and Chan, Nicholas Tung, Agent-Based Models of Financial Markets: A Comparison with Experimental Markets (October 2001). Available at SSRN: <https://ssrn.com/abstract=290140> or <http://dx.doi.org/10.2139/ssrn.290140>