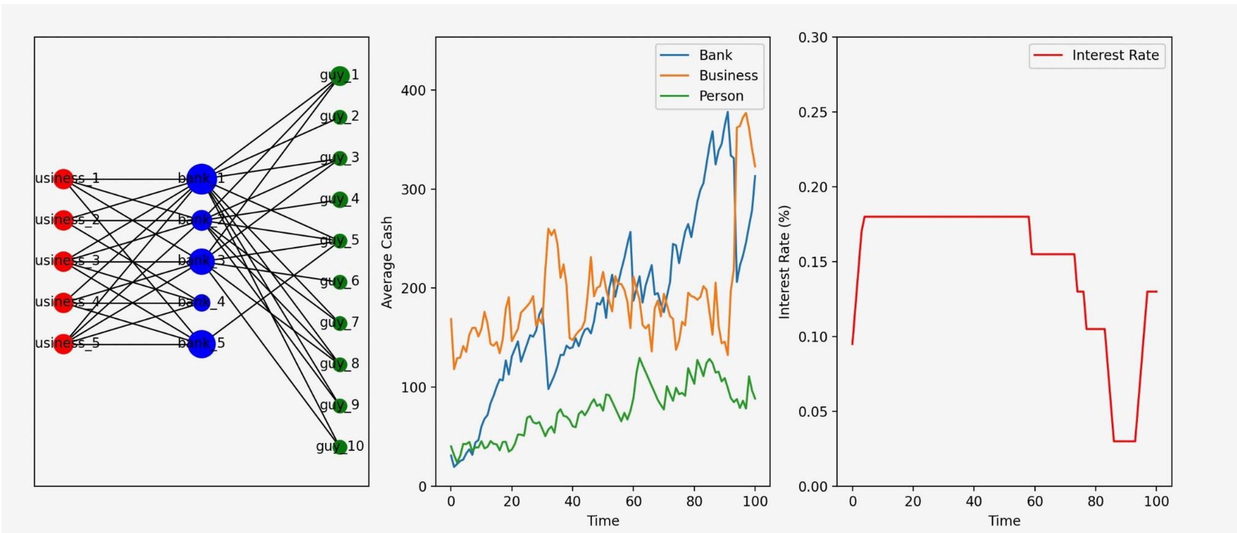
Modeling Banks: Easier Said than Done

The motivation for this project originated from the crash of the Silicon Valley Bank. In macroeconomic terms, it is simple to describe the events that lead to SVB's failure. Vo and Le (2023) attributed this to its small group of large account holders and investments made in 2021 when interest rates were low. These investments made less money once interest rates rose which contributed to account holders losing confidence in the bank and taking their millions elsewhere. Inevitably, SVB was forced to declare bankruptcy. Luckily in this situation, account holders were secured by the federal treasury. A model by Huang et al. (2013) shows the potential cascading effects of banking risk propagation. Our model attempts to simulate the crash of assets similar to this model.

Our model, which was scaled down to an economy of 5 banks, 5 businesses and 10 account holders attempted to model similar behavior. The relationship between the gross capital of banks, account holders/consumers, businesses and interest rates is complex and interconnected. To break it down by situation:

- If interest rates are low, banks are able to borrow at lower rates and have more capital to lend to businesses and consumers. Borrowing will be cheaper as you lock in at lower rates meaning consumers and businesses are more willing to make larger purchases and loan money from the bank. In an economy of high spending and economic growth, interest rates will rise.
- If interest rates are higher, borrowing money is more expensive meaning consumer spending and overall economic activity will slow. This may limit a bank's lending capacity and impact their profitability. In a weak economy with slow credit, there will be a lower demand for credit, leading to lower interest rates.

It is important to note that on a macroeconomic level these effects are seen as margins of millions of dollars per month in a multi trillion dollar economy. To make our economy more variable and expressive, we kept our initial values in the hundreds.



Here is an example of a single run to 100 timesteps just looking at the cash of each entity. Before this paper goes into too much detail, note the relationship between businesses and banks as interest rates begin to drop. Around timestep 70, the banks begin to make a lot of money due to the investments at 18% they are collecting on. Shortly after, we can see the amount of cash our people have decreases as their spending increases. As a result, the businesses make money. The dramatic spike for businesses and dip for the banks at timestep ~90 is multiple businesses taking out loans. After this the interest rate rises again dramatically as spending increases to simulate a slowing of the economy.

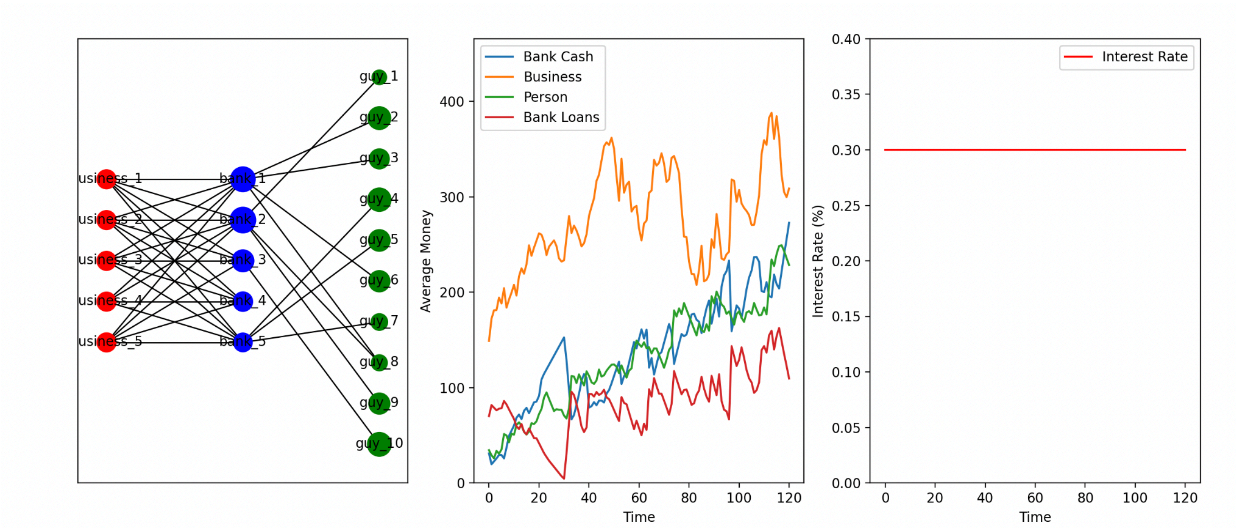
Specifically in our model we have one core update function called each timestep. This function loops through each node, seeing its transactions through to completion before continuing to the next node. This means that we are never double counting transactions and never skipping an individual. Each iteration is intended to model a month of economic activity of that node. We also model the network, average cash of each node type and updated interest rate.

Every month a person gets a salary which goes directly into one of their bank accounts. They then buy items with their money. Due to the fact that a majority of Americans live paycheck to paycheck, a person can spend anywhere from 50-100% of their monthly income. This is scaled inversely by the interest rate such that if interest rates are higher, they will be willing to spend up to 80% they would typically and 120% if interest rates are 3%. If they need more cash they will withdraw it from their bank accounts to always hold about 10% of their net worth as cash. They will deposit more money into the bank if they have over 30% cash. If they can, they will open a new bank account. 3% of the time, people will take out loans from the bank if they need to hypothetically purchase something large.

The businesses simply buy supplies each month. This decreases the amount of money that they have enough to balance out the model. Otherwise, the businesses are essentially a sinkhole of bank investments. With a 5% chance, the business will take out a loan from the bank with the best cash to loan ratio. With a 20% chance they will "buy supplies" for their business. These supplies can cost from anywhere from 0% to 100% of their on hand cash.

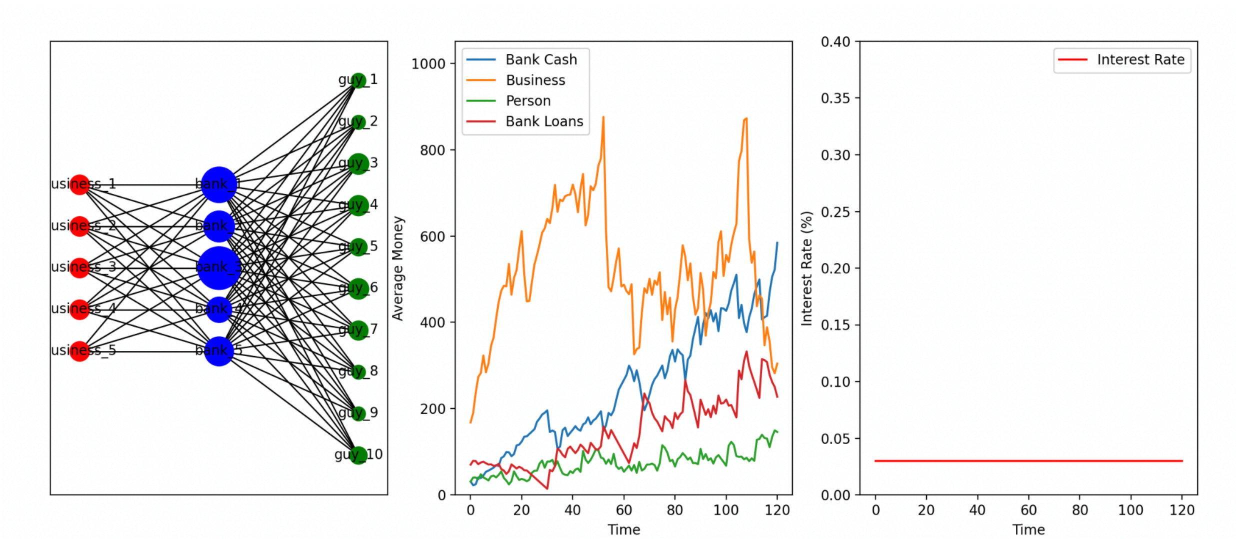
The banks collect on each of their loans. This forces businesses or people to make their monthly payment with the proper interest. If they cannot pay in cash, it will force money out of their bank accounts or send the business into debt. Then, we make sure that the bank's cash/loaned ratio is within realistic limits. This is at least 10% and at most 30% cash on hand. If a bank has too much cash on hand, it will loan it to a business with the smallest cash to evaluation ratio. If it does not have enough cash, we loan from another bank with enough cash to bail us out. If no bank can bail the bank out, it will crash.

This model is reliable through 120 timesteps, or 10 years. We can see that if interest rates are fixed very high at 30%



People do not have much cash on hand and therefore do not make many bank accounts. Person 8 is the only person to make another bank account.

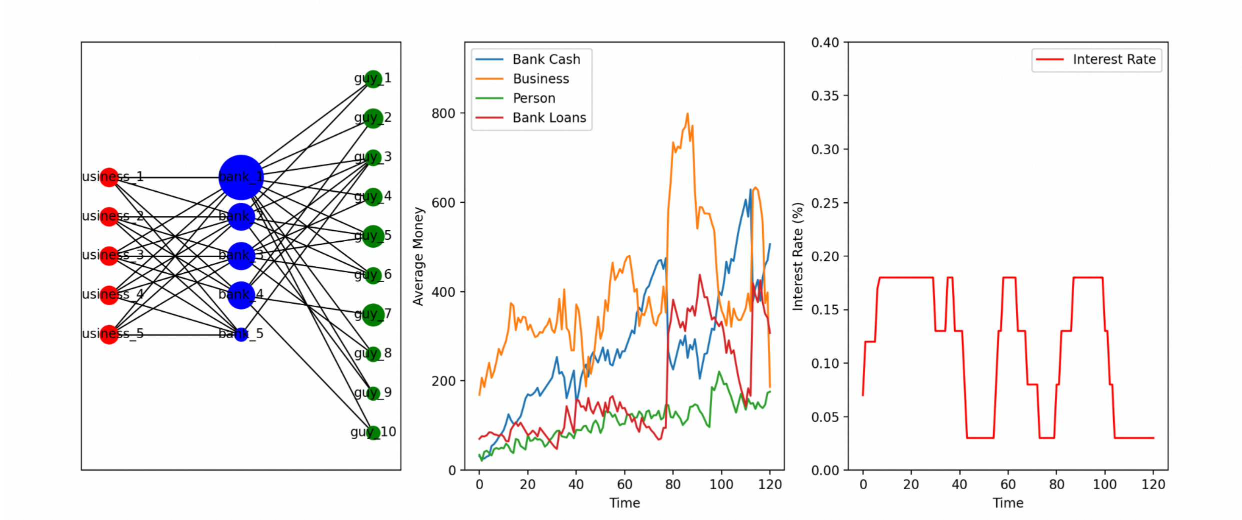
Versus if interest rates are fixed low at 3%



People have significantly more cash when interest rates are low and put it into banks to maintain less than 30% cash on hand. Hence why all people have accounts in every bank. Also, businesses have significantly more cash as they peak at an average of $900 around timestep 50.

Their decrease is likely due to an unlucky random roll in which businesses spend a majority of their money.

If we let interest rates fluctuate:



You can see interest rates drop at timestep 40 in response to the businesses losing their cash. At timestep 90 interest rates max out to control the businesses high amount of cash.

The limitations of this are when it comes to an actual bank crash. While this was the purpose of our model it proved to be very difficult to model this behavior. Killing a bank node, or closing all of its accounts and defaulting on all loans would lead to a crash of the global economy. Before the crash, the bank would lend from other banks to try and maintain 10% cash. So when a bank crashes and they have loans with other banks, the ratio of loans to cash in the alive banks is too high. This is further increased by individuals depositing their money in live banks as they may have up to 100% of their cash on hand as their account disappears. The banks compensate by lending their money. Although, if there is no business in the network to lend to, their cash to loans ratio skyrockets. If their loaned money goes negative, the bank will then crash. This happens very quickly. Without a ‘FED’ node to prop up account holders and business loans, it is inevitable. Therefore, we never got accurate bank crashes as the macroeconomic factors that play into a bank crash are situational and too difficult to code.

We also wanted to expand this model to include a parameter that is associated with people's confidence in a bank. Although this proved to be too difficult as people's relationship with a bank is dependent on many factors other than how much money a person has in a bank. Also, to communicate confidence with other people this model would need another network of interconnected people nodes, further complicating this model.

In the end we sacrificed economic consistency to make the bank nodes behave as accurately as possible. People nodes generate money from thin air, represented as monthly income. Business and people nodes spend money, which goes out of the network. On the other hand, banks only get money from their loans and account holders. They are only able to spend money on loans to maintain a proper cash to loan ratio.

This model can make few assumptions about the internal operations of banks and we suggest that this model is not used by bankers to predict market behaviors and how they will impact bank revenue. While the interest rates set by the federal government are proactive to balance economic activity, interest rates in our model are reactive to bank activity. While the cash to loan ratio of the banks in this model follows real solvency laws, the loaning behaviors and cash management techniques used by these nodes are likely illegal and should not be replicated.

References

Vo, Lai Van and Le, Huong T. T., From Hero to Zero - The Case of Silicon Valley Bank (March 19, 2023). Available at SSRN: https://ssrn.com/abstract=4394553 or http://dx.doi.org/10.2139/ssrn.4394553

Huang, Xuqing & Vodenska, Irena & Havlin, Shlomo & Stanley, H.. (2013). Cascading Failures in Bi-partite Graphs: Model for Systemic Risk Propagation. Scientific reports. 3. 1219. 10.1038/srep01219. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4394553https://www.researchgate.net/figure/Bank-asset-bipartite-network-model-with-banks-as-one-node-type-and-assets-as-the-other_fig4_235406706