A Markov Model of Bank Runs under Interest Rate Shocks

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Project Summary and Goals

We built a Markov model to represent how bank withdrawals and asset liquidations evolve over time under changing interest rates and sentiment. Failure occurs when available resources can no longer meet the immediate withdrawal demands.

We assume that the banks assets are divided into only three asset classes: cash-like, short-term, and long-term. We further assume that there is no interest paid on deposits, much like most consumer banks today. We also assume that there is no hedging, or ability to take loans to meet cash withdrawls.

When a bank reaches the failure state, we will estimate the magnitude of losses and probability of failure under a certain intial conditions. The model will be implemented through Monte Carlo simulation and a discrete state transition framework. Our goal is to build intuition for how Markov models can describe financial systems under stress and quantify how risk propagates to depositors.

In particular, we decided to set the stage as if we are the risk management team at Silicon Valley Bank, right before the collapse. Given the bank's balance sheet structure, we use a Markov process with simulation to stress-test interest-rate shocks. The goal is to estimate how often the bank fails under different market scenarios. We entered with the following questions; What conditions cause higher/lower probability of failure? How do interest rates stocks affect depositor behavior? How do the various parameters interact? What is the distribution of losses?.

The Model

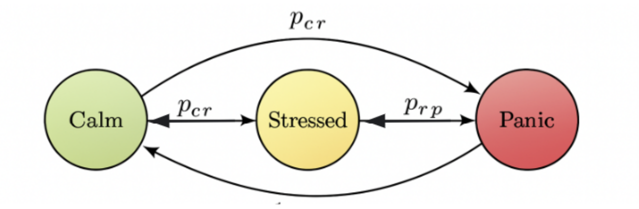
First, we model interest rates using Vasicek stochastic differential equation and we added with jumps. The Vasicek part captures normal day-to-day drift in interest rates, and the jump term represents sudden shocks, which is what really drives stress events.

$$\mathrm{d}r_t = \kappa(\theta - r_t)\,\mathrm{d}t + \sigma\,\mathrm{d}B_t + J_t\,\mathrm{d}N_t,$$

Second, we treat deposits and withdrawals as Poisson processes. The intensities change over time when rates rise, people are more likely to withdraw and less likely to deposit, and that effect becomes stronger when confidence is low.

$$\lambda^{\text{in}}(t) = \lambda_0^{\text{in}}\,\exp\big(-\beta\,\Delta r_t - 1_{C_t=Stressed}\alpha_1 - 1_{C_t=Panic}a_2\big),$$
$$\lambda^{\text{out}}(t) = \lambda_0^{\text{out}}\,\exp\big(\beta\,\Delta r_t + 1_{C_t=Stressed}\alpha_1 + 1_{C_t=Panic}a_2\big),$$

And third, we capture confidence using a simple three-state Markov chain: calm, stressed, or panic. The system can move between these states based on what's happening for example, a fire sale, and btw fire sales is just selling your assets as quick as possible at a steep discount, increases the transition probability toward panic. Together, these components let us simulate how the bank reacts to interest-rate shocks and how small confidence changes can escalate into a run.



To set the parameters, we used the balance sheet parameters that we got from Silicon Valley Bank, and for the SDE parameters, we used the established calibration of the non-jump Vasicek for US short-term rates. However, for the other transition probabilities and the sensitivities in the poisson process are less concrete. We used data and reasonable estimates to establish parameters that made sense and are based on some underlying ideas, however, for example, in real life the sentiment state is not easily observable. There is existing research on the sensitivity of deposits to changing interest rates.

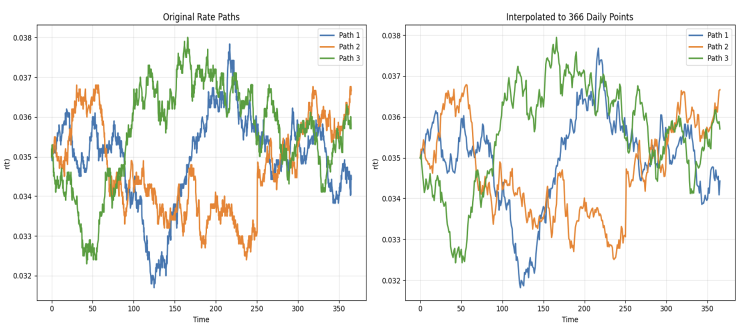
Simulation

The SDE: The stochastic differential equation was simulated using the modified birth death process introduced in chapter 8.8. N = 10000 was chosen for a fine approximation while maintaining low computational complexity for Monte Carlo simulation. The paths were then interpolated to a 366 day grid for daily calculations using the rate.

The state dependent rates for the approximating birth death process are:

$$a_{\frac{1}{N}} = Nb^{+}(\frac{1}{N}) + \frac{N^2\sigma^2(\frac{1}{N})}{2}, \quad s_{\frac{1}{N}} = Nb^{-}(\frac{1}{N}) + \frac{N^2\sigma^2(\frac{1}{N})}{2}$$

Where, $b(x), \sigma(x)$ are the drift, and diffusion terms and $b^{+}(x) = \max(b(x), 0), \quad b^{-}(x) = b^{+}(x) - b(x)$



Withdrawals/Deposits: For our withdrawals and deposits, we modeled them as Poisson processes, where the inflow and outflow rates depend on customer-confidence Markov states; Calm, Stress, and Panic; as well as the current interest rate. For example, if interest rates suddenly increase, more people may withdraw their deposits to earn a higher return elsewhere. Moreover, if the bank has to unwind its assets due to a liquidity crunch, this can shift customer sentiment from Calm to Stress or Panic, further accelerating withdrawals. Lastly, we used the NumPy library in Python to simulate the withdrawal and deposit Poisson processes

Sentiment Chain: We assume the sentiment chain starts in calm. The rates for the chain change depending on the conditions; if there was a large withdrawal in the previous round, there is a higher chance of moving up to a higher-risk state, same with if there was a fire sale in the previous round. It was simulating, simply just using a Uniform(0,1) random variable and comparing with the probabilities.

The Results

Below is an example of a single run, where we found that the deposit and withdrawal behavior are plausible and highly interesting. One can see the current state of the bank's balance sheet, the underlying rates, and the state.

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Simulation Result: FAILED
Failure Time: 0.3233 years (118 days)

Final Values:
  Total Deposits: $59.60B
  Total Assets: $84.61B
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Day	Rate (%)	Cash ($B)	Short ($B)	Long ($B)	Deposits ($B	Cum Dep ($B)	Cum With ($B	State
0	3.901	,900,000,000	,150,000,000	,950,000,000	,000,000,000	$ 0	$ 0	CALM
3	3.906	,916,000,000	,165,998,574	,947,479,615	,016,000,000	$412,000,000	$396,000,000	CALM
6	3.912	,916,000,000	,181,248,867	,940,572,874	,016,000,000	$792,000,000	$776,000,000	CALM
9	3.915	,968,000,000	,199,920,368	,952,362,858	,068,000,000	,212,000,000	,144,000,000	CALM
12	3.918	,864,000,000	,218,633,486	,964,212,451	,964,000,000	,548,000,000	,584,000,000	CALM
15	3.921	,904,000,000	,237,437,861	,976,398,359	,004,000,000	,936,000,000	,932,000,000	CALM
18	3.923	,920,000,000	,257,966,194	,998,054,923	,020,000,000	,340,000,000	,320,000,000	CALM
21	3.925	,852,000,000	,278,522,475	,019,750,595	,952,000,000	,740,000,000	,788,000,000	CALM
24	3.927	,868,000,000	,299,106,722	,041,485,395	,968,000,000	,080,000,000	,112,000,000	CALM
27	3.929	,932,000,000	,319,718,956	,063,259,343	,032,000,000	,500,000,000	,468,000,000	CALM
30	3.931	,980,000,000	,340,359,196	,085,072,459	,080,000,000	,896,000,000	,816,000,000	CALM
33	3.946	,948,000,000	,343,425,024	,007,020,333	,048,000,000	,296,000,000	,248,000,000	CALM
36	3.951	,924,000,000	,360,096,740	,005,706,223	,024,000,000	,632,000,000	,608,000,000	CALM
39	3.946	,028,000,000	,389,957,534	,079,416,527	,128,000,000	,128,000,000	,000,000,000	CALM
42	3.943	,028,000,000	,416,959,439	,136,961,902	,128,000,000	,548,000,000	,420,000,000	CALM
45	3.944	,012,000,000	,439,227,611	,167,408,655	,112,000,000	,960,000,000	,848,000,000	STRESSED
48	3.946	,200,000,000	,460,211,956	,190,384,814	,300,000,000	,016,000,000	,716,000,000	PANIC
51	3.959	,284,000,000	,465,781,713	,124,138,498	,384,000,000	,052,000,000	,668,000,000	PANIC
54	3.953	,552,000,000	,496,560,238	,203,384,988	,652,000,000	,060,000,000	,408,000,000	PANIC
57	3.958	,008,000,000	,513,577,432	,202,822,551	,108,000,000	,088,000,000	,980,000,000	PANIC

Here we can see the results from the Monte Carlo simulation with (n=100,000). We see that the mean loss for failures was \$0.38B and \$0.37B overall. The true loss of SVB, to which the parameters are based on was around \$1B, so we were a bit off but still well within 1 standard deviation.

We believe the model has strong potential to model risk in banking; however, due to our lack of exact data, which is often not public, we are unable to finely tune the model transition parameters for the inflows and outflows, along with the sentiment, as well as we could if we were an insider. The model is also highly adaptable and can be expanded on with more complex balance sheet dynamics.

Challenges, Limitations and Improvements

Firstly, parameter estimation was a big challenge. Data is not widely public, and data

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Failure Time Statistics:
  Mean:      0.3777 years (138 days)
  Median:    0.3233 years (118 days)
  Std Dev:   0.1843 years
  Min:       0.1397 years (51 days)
  Max:       1.0000 years (365 days)

Loss Statistics (for failed banks):
  Mean Loss:      $0.38B
  Std Dev:        $2.13B
  Min Loss:       $0.00B
  Max Loss:       $41.04B

Average Loss (across all 100000 simulations): $0.37B

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that is public is highly selective. We attempted to work backwards from the information that we had from SVB, and we tried multiple values and watched their dynamics and landed where we did. A key improvement that could be implemented is Rejection Inference to eliminate selection bias and generate more useful data.

Another challenge with the model is computational; if we wanted to use our model for a more stable bank with strong inital parameters we would need a massive number of runs because we expect the real probability to be tiny.

Next, we simplified a lot of the bank dynamics; they cannot react in our model to near-failure situations by implementing different risk management methods; furthermore, they cannot borrow, and they have a very simple balance sheet. We could add more asset types to improve the mode.

Lastly, we could use a hidden Markov model for Calm, Stressed, and Panic via observable economic factors.