CSBS 2023 Annual Data Analytics Competition

A Study of the Impact of Interest Rate Risk on Community Bank of the United States of America

Team
Cleon Demiao Sun
Manikandan Palaniappan
Niharika Patil
Yilin Lyu
Zeinab Yasmine Soumahoro

Faculty Advisor
Gabriela Gongora-Svartzman, Ph.D.

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Abstract

This research investigates how interest rates affect community banks in the United States and aim to determine important indicators of bank health that regulatory institutions should track in order to minimize the likelihood of bank failure. The study draws on data from the FDIC Bank Failure API and financial information for 13,937 community banks and their branches.

To predict bank failure over the next six quarters, the study employs a two-stage model approach that involves elastic net regression and penalized logistic regression for feature selection, as well as a generalized linear model to predict bank health metrics. The results of the study demonstrate that interest rates have a significant impact on the financial stability of community banks, and the study identifies nine essential indicators that provide useful insights into this impact. In addition, the study reveals that three metrics out of the nine can be anticipated based on other financial data, partially confirming the hypothesis about the influence of interest rates on bank performance.

This research offers important information for policymakers and investors who are concerned about the effects of interest rates on bank performance and provides advice on the key indicators to track to reduce the risk of bank failure.

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I. Introduction

1) Interest Rate and Inflation

The Federal Reserve, also known as the Fed, is the central bank of the United States. One of its main responsibilities is to conduct monetary policy to promote price stability, maximum employment, and moderate long-term interest rates. The Federal Open Market Committee (FOMC) is a policy-making body within the Fed that is responsible for setting monetary policy. The FOMC meets several times a year to review economic conditions and decide whether to adjust the federal funds rate, which is the interest rate at which banks lend to each other overnight. When the FOMC wants to stimulate the economy, it may lower the federal funds rate to encourage borrowing and spending. Conversely, when the FOMC intends to slow down the economy to prevent inflation, it may raise the federal funds rate to make borrowing more expensive.

The COVID-19 pandemic has led to significant economic disruptions in recent years, prompting the Fed to act. In 2020, the Fed slashed interest rates to near zero to encourage spending by households and businesses during the crisis. However, as the economy began to recover in 2021, inflation soared to 7.1%, reaching its highest point in nearly four decades. In response, the Fed decided to raise interest rates nine times between March 17, 2022, and March 2, 2023, with the goal of slowing down economic growth and alleviating inflationary pressures.[1]

Understanding the history of the federal funds rate and its impact on the economy and financial markets is crucial for investors, banks, and policymakers alike. Banks play a significant role in transmitting the Fed's monetary policy, as changes in the federal funds rate directly influence the interest rates that banks charge their customers for loans and offer on savings accounts. This, in turn, affects consumer spending, business investment, and overall economic activity.

2) Interest Rate Impact on Banks

Interest rates play a crucial role in the financial landscape, influencing how much banks can earn from lending money to their customers and the cost they must bear for borrowing money from other sources.

[1] Tepper, "Federal Funds Rate History"

These rates also impact the demand for loans and consumers' and businesses' spending and saving habits. In the United States, the Federal Reserve, or the Fed, serves as the central bank and sets the federal funds rate, the interest rate at which banks lend to each other for overnight loans[2]. By adjusting the federal funds rate, the Fed aims to manage overall economic interest rates and achieve stable prices and maximum employment. When the Fed raises the federal funds rate, borrowing becomes costlier and saving becomes more attractive, which can lead to slower economic growth and lower inflation. Conversely, lowering the federal funds rate makes borrowing cheaper and saving less attractive, stimulating economic growth and inflation.

Banks are directly affected by fluctuations in interest rates. High-interest rates allow banks to charge more for loans, such as mortgages, credit cards, and business loans, increasing their income from lending activities. However, high-interest rates also raise their expenses for paying interest on deposits and borrowings, reducing revenue from deposit-taking activities. High-interest rates may also cause consumers and businesses to postpone borrowing or seek cheaper alternatives, decreasing loan volume and income for banks. On the other hand, low-interest rates lead to lower revenue from lending activities as banks charge less for loans. Yet, they also reduce banks' expenses for paying interest on deposits and borrowings, increasing income from deposit-taking activities. Low-interest rates may also encourage consumers and businesses to take out loans, boosting bank loan volume and income.

The net effect of interest rate changes on bank profitability depends on various factors, including the net interest margin (NIM), which is the gap between the interest rates charged on loans and those paid on deposits and borrowings. A higher NIM indicates higher profitability and vice versa. Additionally, the composition of a bank's assets and liabilities, whether fixed-rate or variable-rate, can affect its sensitivity to interest rate changes. Duration, or the time it takes for an asset or liability to repay its initial value in cash flows, also plays a role, with longer-duration assets and liabilities being more sensitive to interest rate changes. Finally, the quality of a bank's assets and liabilities, or their likelihood to default or become impaired. Lower-quality assets and liabilities pose more significant risks due to a higher chance of non-repayment[3]. In such a scenario, an examination of the loan loss reserves maintained by the bank is important to determine bank stability.

[2] Glaze, 'How Rising Interest Rates Hurt or Help Banks.
[3]Hall. "What Affect Do Interest Rates Have on Banking Profitability?

3) Community Banks

Compared to larger banks, community banks are a vital component of the local economy that provides loans to the neighborhoods where their depositors live and work. According to the Federal Reserve's Small Business Credit Survey, community banks are the small business lender of choice, providing roughly 60% of all small business loans, making more than 80% of agricultural loans, having nearly 50,000 locations nationwide, and employing nearly 700,000 people[4].

However, with all the advantages, due to their small size, community banks are more sensitive to interest rate changes as it has a high reliance on interest income and more interest rate-sensitive asset and funding structures[5].

Therefore, understanding how interest rate change impacts community bank performance and being able to take proactive steps are critical for community banks to keep supporting the local community and help build a healthy economy overall.

4) Hypothesis

To understand how interest rate change impacts community banks, we will be looking into the impact of interest rates on community banks' performance indicators. Moreover, we will take a step further and look into how interest rates correlate with community bank's failure. Thus, we hypothesize: there are some key factors that are both influenced by the interest rate and can act as a predictor for bank failure.

5) Literature Review

We conducted a literature review to understand what kind of study has been done on bank performance and failure prediction. Among all the studies, we picked three studies, conducted by various authors, to help design our approach.

[4] ICBA, 'Community Banking.'
[5]Carl. "Rising Interest Rates Bring Opportunities and Risks for Banks."

The first study, by Timothy B. Bell in 1997, examines the performance of two methodologies in predicting bank failures across a range of model cutoff values. The study finds that both methods offer similar predictive accuracy, with neural networks performing marginally better in the "gray area" where some failing banks appear to be less financially distressed. This suggests that both traditional and advanced models can effectively predict bank failures, and combining different models may improve accuracy[6].

The second study, conducted by Rebel A. Cole and Lawrence J. White in 2012, focuses on identifying the determinants of bank failures, using a combination of traditional and portfolio variables. The study finds that while traditional proxies for the CAMELS ratings are important determinants of bank failures, portfolio variables such as real estate construction and development loans, commercial mortgages, and multifamily mortgages are consistently associated with a higher likelihood of bank failure. This highlights the importance of considering both traditional and portfolio variables in predicting bank failures[7].

Finally, the third study, conducted by Justin Yiqiang Jin, Kiridaran Kanagaretnam, and Gerald J. Lobo in 2011, identifies several predictors of bank failure, including auditor type, auditor industry specialization, Tier 1 capital ratio, the proportion of securitized loans, growth in loans, and loan mix. The study suggests that these factors can be reliable indicators of banks that are more likely to fail. This reinforces the importance of considering various variables when predicting bank failures, including financial and non-financial factors[8].

After reviewing all the previous studies and consulting with field experts and professionals, we decided to use FDIC Data about community banks that includes a variety of financial factors and non-financial factors and take a two-model approach to study and predict interest rate impact on bank performance and failure.

[6] Bell, " A Comparison of Each Model's Ability to Predict Commercial Bank Failures."
[7] Cole, et al "The Causes of U.S. Commercial Bank Failures This Time Around."
[8] Jin,et al. "Predict Bank Failure during the Financial Crisis."

II. Datasets

1. Bank Failure API

We extracted all the available data for community banks from the FDIC Bank Failure API between April 20, 1990, to December 2022 as 'failure_data.csv'. This dataset consists of 833 records with certificate numbers and dates of failure, providing valuable insights into patterns and trends of bank failures over a 30-year period. This data serves as the target variable for the study.

2. Financial Data API & Interest Rate

We downloaded financial data for 13937 community banks and their branches every quarter from 1990 to. For each bank at each quarter, there are 93 indicators to describe various themes, such as assets and loans, liabilities, and deposits/expenses, products/income, and loss. On top of that, we merged Fed Funds Rate Historical Interest Rate[9] and interest rate for each time period into this data to better understand the correlation (See Appendix 1 for more Data Collection and Preparation details).

[9] Macrotrends. "Federal Funds Rate - 62 Year Historical Chart."

III. Exploratory Data Analysis

1. Community Banks Distribution Across the United States

There are 4,750 community banks in the country with more than 29,000 branches. These banks are present in different concentrations across the country with the highest in Texas and the lowest in Hawaii. There is a clear indication of a higher number of community banks across the central states (TX, OK, MO, NE, KS, IA, MN, IL) as compared to the rest of the country. Additionally, states along the East coast tend to have a higher number of community banks in contrast to the West coast.

Figure 1. Number of Community Banks in each state of the US

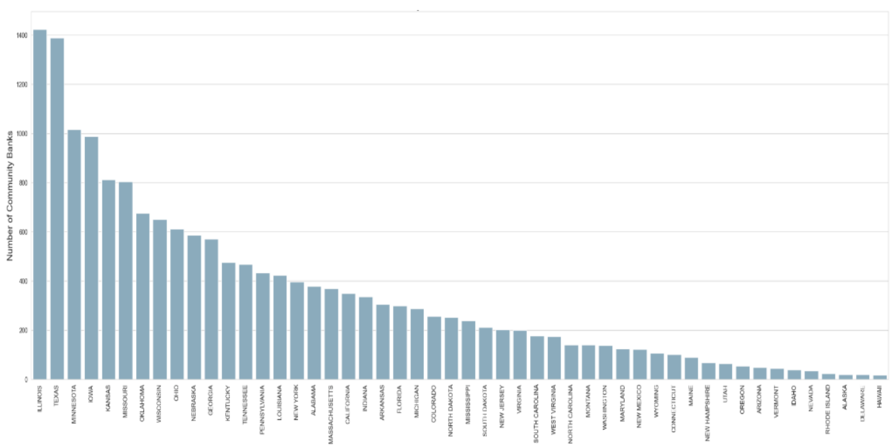
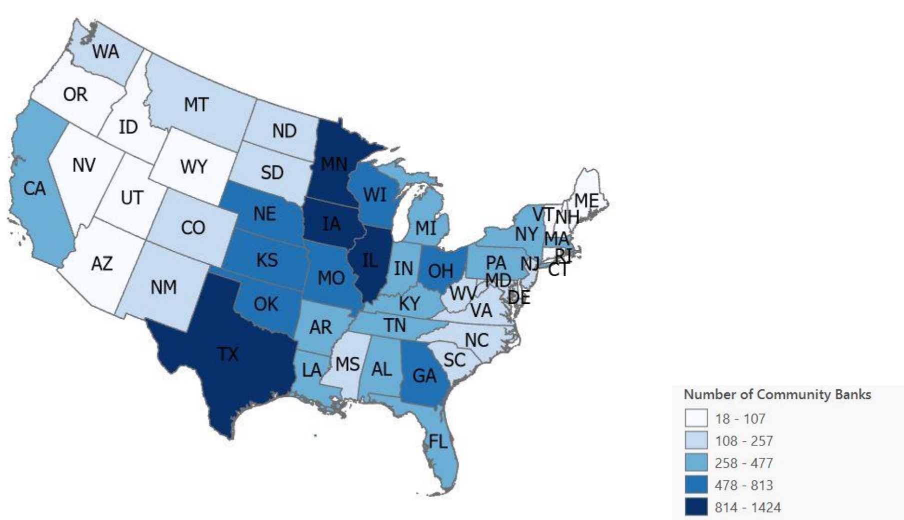


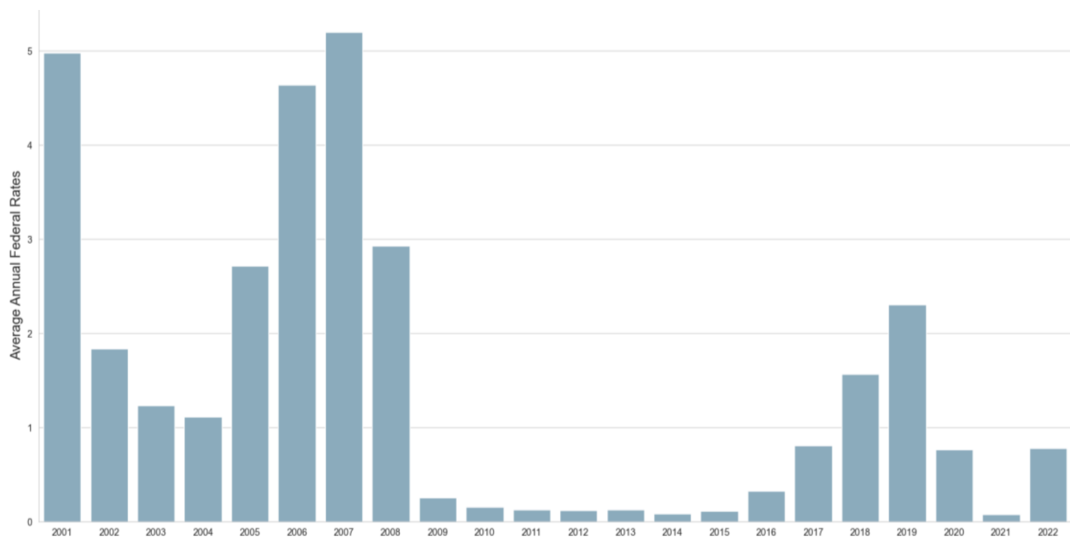
Figure 2. Distribution of Community Banks across the US



2. Average Interest Rates Over the Years (2000 - 2022)

There has been a fluctuation in the average interest rates over the years, especially in the years leading up to 2008 (The Financial Crisis) as observed from Figure 3. From 2009 to 2015, there appears to be a stable trend in the interest rates that could be attributed to the recovery from the crisis. In 2016, Interest rates seemed to climb up and resume previous trends of inflation. Additionally, there is an anomaly in 2020 and 2021 that could be attributed to the inflation following Covid-19 Pandemic.

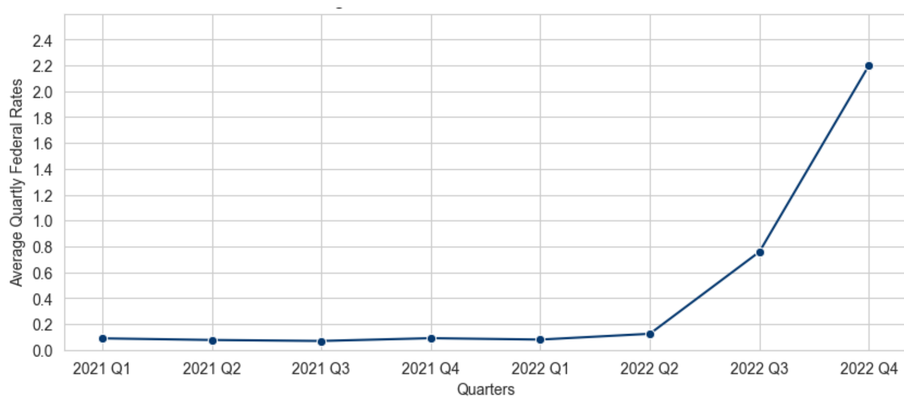
Figure 3. Average annual federal interest rates



3. Average Interest Rates over the past 8 Quarters (2021 - 2022)

The first five quarters from 2021-2022 seem to have had a pretty stable trend in terms of the average interest rate. This rate however exponentially increased in Q2 of 2022 and reached an all-time high in the last quarter of 2022.

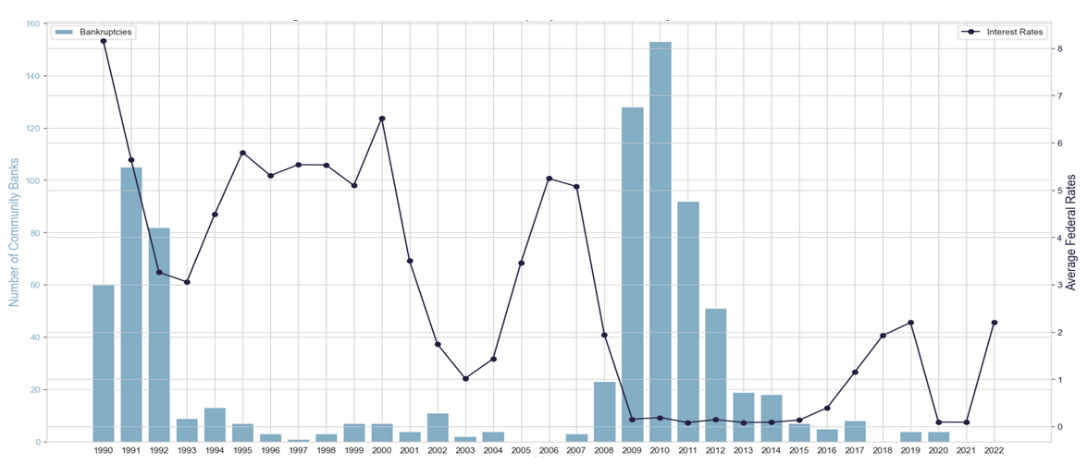
Figure 4. Quarterly Average Interest Rates, 2021-2022



4. Interest Rates and Community Bank Failures (Bankruptcies)

While there is not enough information available to assert causation, there appears to be a correlation trend between an anomalous rise in interest rates and a rise in bankruptcies almost exactly a year later. This assertion of correlation is based solely on the data available and the analysis should be considered to have been conducted in an almost isolated environment.

Figure 5. Average Annual Federal Funds Rates and Community Bank bankruptcies



IV. Analysis and Modelling

In order to identify the key bank health metrics that regulatory institutions should monitor to mitigate the risk of bank failure, we employed a two-step model approach. The first step is to identify key features that would help predict bank failure and the second step is to predict the value of some of the features into the next quarter to enable further analysis and recommendation of remedial steps by regulatory authorities. We identified features that correspond to different themes of liquidity, leverage, profitability, and asset quality in order to have a holistic picture of bank performance.

Model 1: Feature Selection and Failure Prediction

We selected the most important features related to bank performance that can predict bank failure through classification models. Based on historical bank failure data, the model identifies the best features based on their importance in predicting whether a bank will fail within the next six quarters. In addition to identifying the features that would be used as targets for subsequent prediction models, Model 1 can predict whether a bank will fail within 6 quarters with only 5 variables at minimum as input at the accuracy of 94.46%. More details are provided in the appendix.

For all the banks that have failed, we used data from the last six quarters before the failure of the bank. For the banks that have never failed in history, we randomly pick data from any of 6 continuous quarters. After the initial data collection, we split the dataset into training data and testing data and then rebalanced the training dataset to correct for imbalance in the target variable which is a yes/no variable indicating bank failure.

Elaborating on the model design, we built an elastic net regression and penalized logistic regression with standardized features and the target variable as input. We took an average of the features' estimated coefficients yielded by two regressions and got a list with features sorted by their estimated coefficients. We selected K features by the absolute values of the estimated coefficient of each feature. We then trained an ensemble learning model (Voting classifier) which included a bagging tree model, the Gaussian Naïve Bayes model, and a KNN model with K-selected features as input, with K ranging from 5 to 10 inclusively. The model's accuracy on the testing dataset is approximately 97% when K=9, which proves the success of our feature selection and the nice features identified will be used for Model 2. To avoid multicollinearity and redundancy between variables we conducted a correlation analysis between each outcome variable (See Appendix 2. Feature Selection Table and 3. Correlation Graph for more details).

Model 1 selected nine final features, including ‘mortgage-backed securities, ratio’(SCMTGBKR) , ‘Allowance for Loans Loss Adjusted’ (LNATRES), ‘Allowance for Loans and Leases in Tier 2 Ratio’(RB2LNRESR), ‘Leverage Ratio-Primary Component Analysis’ (RBC1AAJ), ‘Domestic Office Loans, Domestic, Quarterly Ratio’ (ILNDOMQR), ‘Loans and Leases-Net Ratio’ (LNLSNETR), ‘Long-Term Assets (5+ years) - QBP Ratio’(ASSTLTR), ‘ Return on Asset’ (ROA), and ‘Total Loans / Equity’ (total_loans_equity). All those nine features can significantly predict the failure of a bank and they will be passed down to Model 2. .

Model 2:

For Model 2, we used the rest of the bank performance indicators and interest rate to study the interest rate impact on the variables identified from the previous classification model and predict possible failures. To reach this goal, we follow a two-step method to explain the relationship: an evaluation model, Model 2.1, which focuses on estimating the interest rate impact on those nine key variables, and a prediction model, Model 2.2, which is concerned with prediction of those key variables into the next quarter, so that further remedial actions can be made, if the situation is dire. Both of those models are Generalized Linear Models (GLM) which use time fixed effects at a year level.

For both models, we cleaned the data by dropping columns with too many missing values and reduced the multicollinearity within the dataset by dropping the columns that are highly correlated to each other, to avoid unstable parameter effect.

Model 2.1: Interest Rate Impact Evaluation Model

The evaluation model aims to evaluate the impact of interest rates on each one of the nine target variables. We used a GLM model with each of the features as the target variable in different model iterations. In Model 2.1, we consider all other bank performance variables in addition to interest rate indicators, as independent variables. To account for correlations within a particular year, we cluster the data by year. This allows us to measure the effect of interest rate changes across quarters within a given year while ensuring that correlations do not exist across different years. Control year is being used to measure changes or differences in standard deviation over the duration of a year. For this model, we employed time-clustered standard errors to give conservative estimates and allow for the correlations to exist within a year but not across years, thereby enabling interest rate changes across quarters. We set the significance level of the performed at 90%.

The goal is to observe the effect of two interest rate variables: the average interest rate from the last quarter and interest rate change. The focus is whether those two interest rate variables are statistically significant predictors of each key target variable.

The model demonstrates that interest rate has a significant effect on more than half of those nine variables which shows us that interest rate affects leverage, asset performance and liquidity of the bank. The five variables are as follows (See more detailed information in Appendix 4) :

- Leverage Ratio-Primary Component Analysis
- Domestic Office Loans, Domestic, Quarterly Ratio
- Loans and Leases-Net Ratio
- Long-Term Assets (5+ years) - QBP Ratio'(ASSTLTR)
- Return on Asset' (ROA)

Model 2.2: Prediction Model

The prediction model is built to find out how well other bank performance metrics can predict those nine key variables. This model is used to serve as a prediction alert to help both the banks and FDIC to take precautionary steps to avoid bank failure. For this model, we employed state clustered standard errors to give conservative estimates and allow for the correlations to exist within a state but not across state. In addition, we model both years and state as a fixed effect (acted as a dummy variable in the formula) which helps remove the time and state independent effects and helps further understand the impact of interest rate on community banks within a state and a quarter.

The final equation for the model looks as the following:

Sample model formula:
Y(SCMTGBKR)=C(YEAR)+ASSTLTR+AVG_IR+BKPREMR+BRO+BROR+CERT+DELTA_IR+DEPR+EAMINTQR+EINTEXPR+ELNATRR+EQTOTR+IDT1RWAJR+IGLSEC+ILNDOMQR+ILSR+LIABR+LNATRES+LNLSNETR+LNRECON5+OREOTH+P3ASSETR+P9ASSET+RB2LNRESR+RBC1AAJ+ROA+SCMTGBK+SCSNHAFR+SZ100+SZ100MP+SZ100T5+SZ25+VOLIABR+YEAR+total_loans_equity

The model performance evaluation was assessed using mean squared error (MSE) and R-squared metrics. Our model shows that there are three variables that can be precisely predicted by our current dataset they are as follows (See more detailed information in Appendix 5) :

- Allowance for Loans Loss Adjusted - *R-squared of 0.7677*
- Allowance for Loans and Leases in Tier 2 Ratio- *R-squared of* 0.4625
- Loans and Leases-Net Ratio - *R-squared: 0.5206*

Model Conclusion:

Observing Model 1 and Model 2, we run the classification model for bank failure one more time with three prioritized target variables from Model 2.2, which are centered around the theme of bad loans and allowance for such loans, to assess their predictive power. All three features can be predicted one quarter ahead by putting the interest rate information and other bank features in the prediction model. Further, we can put back the predicted values of the three features mentioned above into the Failure Prediction model to predict whether they will fail in 6 quarters, at an accuracy rate of approximately 80%. Further drill down of the data on a state would help us identify stressed banks without sufficient loan loss allowances, earmarked for remedial actions.

V. Conclusion

By analyzing data from the FDIC Bank Failure API and financial data for 13,937 community banks and their branches, we were able to identify key bank health metrics that regulatory institutions should monitor to mitigate the risk of bank failure. Our two-step model approach, which included an elastic net regression and penalized logistic regression for feature selection and a generalized linear model for performance outcome, demonstrated an innovative way of predicting bank failure within the next six quarters. The nine most important features identified by the model, including 'Structured Notes-Fair Value Ratio' and 'Return on Asset,' provide valuable insights into the impact of interest rates on community banks' financial health. On top of that, we find out the interest rate has a significant impact on five variables, and three variables can be predicted by other financial information. It partially proved our hypothesis about how the interest rate impacts bank performance.

By using the two-step model approach, FDIC and banks can better evaluate bank performance under interest rate changes and assess their risk of failing. It should be noted that the data used in this study has its limitations due to data access and time constraints, which could affect the accuracy of the results. Future studies could focus on incorporating additional financial metrics and data from press releases into more sophisticated models like Long Short Term Memory models (LSTM) to improve prediction accuracy. Nonetheless, the models developed in this study provide a new approach for banks and the FDIC to evaluate and predict community bank performance under interest rate changes and assess their risk of failure.

VI. Appendix

1. Data Collection and Preparation

i. Financials Data (Web-scraping):

The FDIC provides API services for users to gather various information about banks. For this analysis, we have used the ‘Financials’ APIs to collect bank financial information about community banks across the United States, filed every quarter. The data was collected for a period starting 1990 to 2022. The following steps were followed:

1. Python HTTP library was used to make get requests. The endpoint was obtained from the FDIC Bankfind website.[10]
2. Since the API has a limit of 10000 rows per transaction, each transaction was separated by states and the three decades in the chosen time period. We iterate through all the states and time periods and made the HTTP get requests.
3. The responses in the form of JSONs from each transaction were stored in a list.
4. The final responses list was parsed using the Python JSON library. It was then converted into a .csv file.

ii. Failure data:

Failure data or the bankruptcy data was collected directly from the FDIC Bankfind website.[11] We are mainly interested in the dates the community banks filed for bankruptcy historically. Data were collected between 1990 and 2022.

iii. Federal Funds Rate:

The historical data for federal funds rate on a daily basis starting in 1954 was obtained and downloaded from the MacroTrends website.[12]

iv. Merging the Federal Funds Rates with Financial Data:

For our modeling and analysis, we require federal funds rate for the period community banks have filed their financials for. To obtain this, the following steps for following:

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[10] “BankFind Suite: API for Data Miners & Developers,” n.d., https://banks.data.fdic.gov/docs/#/Financials.

[11] “BankFind Suite: API for Data Miners & Developers,” n.d., https://banks.data.fdic.gov/docs/#/Failures/getFailures.

[12] “Federal Funds Rate - 62 Year Historical Chart,” MacroTrends, n.d., https://www.macrotrends.net/2015/fed-funds-rate-historical-chart.

1. Identify quarters for each entry in the Federal Funds Rate dataset. Calculate the average for each quarter.
2. Create a combination of month and year (coYYYYMM) to act as the key for merging the two datasets.
3. Merge the data sets.

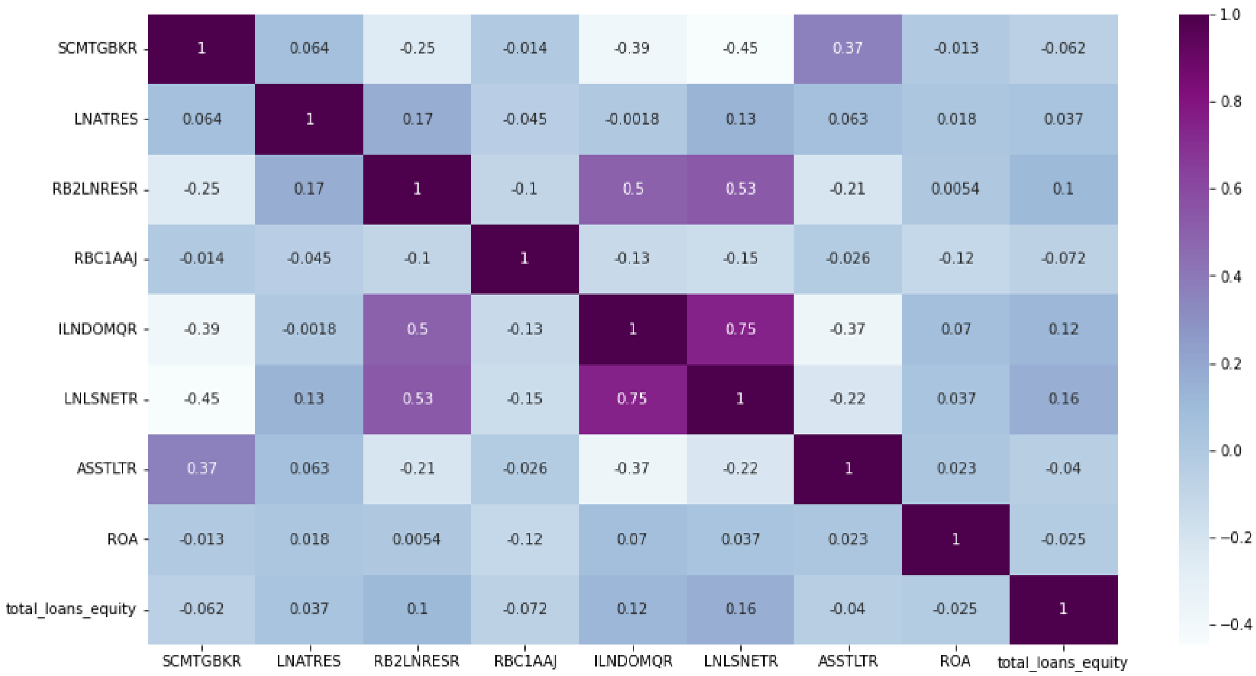
v. Merging the Financial Data with Failure Data:

For merging the two datasets and preserving information of the failed banks' information, an outer join was performed. A binary flag variable was created to identify if a bank was bankrupt at the end of 2022 or not.

2. **Feature Selection**

number of k	features used	accuracy
5	'ILNDOMQR' 'LNLSNETR' 'ASSTLTR' 'ROA' 'total_loans_equity'	94.46%
6	'RBC1AAJ' 'ILNDOMQR' 'LNLSNETR' 'ASSTLTR' 'ROA' 'total_loans_equity'	96.04%
7	LNATRES' 'RB2LNRESR' 'RBC1AAJ' 'ILNDOMQR' 'LNLSNETR' 'ASSTLTR' 'ROA' 'total_loans_equity'	96.46%
8	LNATRES' 'RB2LNRESR' 'RBC1AAJ' 'ILNDOMQR' 'LNLSNETR' 'ASSTLTR' 'ROA' 'total_loans_equity'	97.14%
9	'SCMTGBKR' 'LNATRES' 'RB2LNRESR' 'RBC1AAJ' 'ILNDOMQR' 'LNLSNETR' 'ASSTLTR' 'ROA' 'total_loans_equity'	97.26%
10	'SCSNHAFR' 'SCMTGBKR' 'LNATRES' 'RB2LNRESR' 'RBC1AAJ' 'ILNDOMQR' 'LNLSNETR' 'ASSTLTR' 'ROA' 'total_loans_equity'	97.07%

3. Correlation Graph for the Final Nine Selected Features



4. Measuring the Impact of IR on Bank Features

Dependent Variable	Independent Variable	Coefficient	SE	Z	P>|z|
RBC1AAJ	AVG_IR	0.1257	0.050	2.507	0.012
ILNDOMQR	AVG_IR	0.1507	0.020	7.432	0.000
LNLSNETR	AVG_IR	-1.5926	0.270	-5.906	0.000
ASSTLTR	DELTA_IR	0.5573	0.173	3.215	0.001
ROA	AVG_IR	-0.0578	0.015	-3.941	0.000

5. Prediction Model Results

Dependent Variable	R-square on Training Dataset	MSE on Testing Dataset	R-squared on Testing Dataset
LNATRES	86%	15271431.56	0.833
RB2LNRESR	53.09%	0.04	0.430
LNLSNETR	94.66%	217.86	0.136

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