A Comparative Machine Learning Survival Models Analysis for Predicting Bank Failure in the US (2001-2023)

Abstract:

Based on Federal Deposit Insurance Corporation statistics, this analysis examines US bank failures between 2001 and April 2023. The dataset contains 564 bank failures and various factors that may influence them. We compare machine learning survival models for bank failure prediction. Our results illuminate bank failure risk variables and suggest ways to improve banking risk management.

1. Introduction

The forecast of company failure is important in both economics and society. Bankruptcies cause a breach in the business environment's stability, making estimating the sustainability of partners, clients, and financial institutions a particularly difficult and crucial problem for business players.

There is now a large number of bankruptcy prediction models (see Aziz et al., 2006; Alaka et al., 2017), however virtually all of them are classification based, which means they may estimate the posterior probability that a certain business would fail based on its financial features. The estimated time to failure is not expressly considered. For example, if a classification model is based on data collected one year prior to failure, the model's output is the posterior probability that a certain business would fail within one year. Decisions based on this probability may not be made in time to avert a failure that occurs in much less than a year.

A survival analysis, on the other hand, is concerned with the time of occurrence of the event of interest. Despite its prevalence in the medical and technological disciplines, survival analysis is seldom used to forecast financial failure. In their assessment of bankruptcy prediction models, Aziz and Dar (2006) included 12 kinds of classification models (ranging from discriminant analysis and logit to case-based reasoning, neural networks, and rough sets), but did not discuss survival analysis. According to this publication, the most often used approaches are multiple discriminant analysis and logistic regression; these two models account for more than half of the papers assessed. A 2018 study from Alaka at al. identified eight common technologies, including two statistical approaches (multiple discriminant analysis and logistic regression) and six machine learning models.

As a result, we may infer that survival analysis is not a primary focus of financial failure prediction experts. Our research aims to assess the usefulness of survival analysis (SA) to bankruptcy prediction. SA models and classification approaches are classified into two types: statistical and machine learning based. Statistical SA models originally debuted in the early 1970s, whereas machine learning SA models are the outcome of contemporary research. A large body of research confirms that machine learning models outperform statistical models in classification and regression tasks, particularly in classification-based bankruptcy prediction (see Barboza, et al., 2017). Several articles offer similar findings on the superiority of machine learning technologies in different areas of survival analysis.

Despite these findings, most writers of bankruptcy prediction approaches, especially when using SA, use the most basic statistical models (see Beretta, et al., 2019; Cox, et al., 2017).

In this paper, we analyze the results of our model comparison and the economic interpretation of these results. Our analysis focuses on the performance of different models in predicting bank failures using a set of relevant variables. Specifically, we compare the predictive power of several machine learning survival models, including the Kernel SVM, DeepSurv, Survival Random Forest and MTLR models. To compare the different machine learning algorithms, we use the concordance index (C-index)

Our goal is to identify which model provides the most accurate and informative predictions of bank failures and to interpret the economic significance of the model's results. To do so, we consider the significance and magnitude of the estimated coefficients for each variable in the model and compare these results to economic theory and intuition.

2. Empirical Analysis

In this section, we present the empirical analysis of the risk of bank failure in the United States. We analyze all 564 bank failures that occurred between 2001 and April 2023, as reported in the "Bank Failures in Brief - Summary 2001 through 2023" by the Federal Deposit Insurance Corporation (FDIC). The study of bank failures is of great importance in finance and economics, as it has significant implications for financial stability and the broader economy. In this section, we describe the models used in our analysis, the data source, and the evaluation metrics.

2.2. Data

In this analysis, we examine data on all 564 bank failures that occurred between 2001 and April 2023, as reported by the Federal Deposit Insurance Corporation (FDIC) in the "Bank Failures in Brief - Summary 2001 through 2023". The dataset contains information on several variables that may be related to the probability of bank failure. These variables include, asset amount, deposit amount, ADR, deposit level, asset level, inflation rate, short-term interest rates, bank reserves, and GDP growth rate. The database does not contain censored data.

Asset (Millions): The amount of assets a bank owns can be a good indicator of its financial strength and ability to withstand a crisis. A bank with a large amount of assets is less likely to fail. Deposit (Millions): The amount of deposits of a bank is another indicator of its financial strength, since it represents the confidence of depositors in the bank. A bank with a large number of deposits is less likely to fail.

ADR: The level of ADR (loan to deposit ratio) can be a good indicator of a bank's exposure to credit risk. A bank with a high ADR level could be at higher risk of bankruptcy in a recession or financial crisis. Deposit Level: The level of deposits in relation to the size of the bank can be an indicator of the financial strength of the bank. A bank with a high deposit-to-size ratio is less likely to fail.

Asset Level: The level of assets in relation to the size of the bank can be an indicator of the financial strength of the bank. A bank with a high asset-to-size ratio is less likely to fail. Inflation: The rate of inflation can affect the financial strength of a bank. High inflation can increase the risk of loan defaults, which would increase the probability of bank failure.

FFRate: The short-term interest rate set by the Federal Reserve can affect the financial strength of a bank. A high interest rate increases borrowing costs and reduces the number of loans that can be made, which can increase the likelihood of bank failure.

BanksRes: Bank reserves are funds that banks hold to cover potential losses on their loans and other assets. The higher a bank's reserves, the greater its ability to withstand a financial crisis and the lower its probability of failure.

GDP1pch: Represents the annual percentage change in the real Gross Domestic Product (GDP) of the United States relative to the previous year. The higher the GDP rate, the greater the bank's ability to survive based on the operation and health of its activity.

3. Results

The Kaplan-Meier curve displays the survival probability over time for a group of banks. The x-axis shows the time, and the y-axis displays the survival probability. At the start of the observation period, all banks are assumed to be "alive," represented by the value of 1. Over time, some banks may "die," meaning they fail, and their survival probability decreases.

The analysis shows the evolution of the risk of bank failures over time. At time 1.07, there were 395 banks in the sample, and one bank failed. This translates to a survival probability of 0.99747 (i.e., 395-1/395). The survival probability at time 4.07 is 0.99494, indicating that two more banks have failed since the first observation.

The survival probability decreases as time progresses. At time 42.37, 382 banks remained in the sample, with 13 banks having failed over the observation period. The survival probability at that time was 0.96456. This means that the risk of bank failures increased from 1.07 to 42.37. After that time, the survival probability continued to decrease rapidly, suggesting that there was an increase in the risk of bank failures during that period.

Between 120 and 150 days, there is a significant drop in the survival probability from 0.4000 to 0.1038. This indicates a much higher risk of failure during this time period. This drop in survival probability could be indicative of some event or factor that increases the risk of failure during this time.

It's important to note that the analysis does not provide any insight into the cause of the bank failures, and further investigation would be necessary to determine the reasons behind the increase in the risk of bank failures.

3.1. Model comparison

The paper analyzed the performance of different machine learning survival models in predicting bank failures using a set of relevant variables. The concordance index (C-index) was used to compare the predictive power of different models.

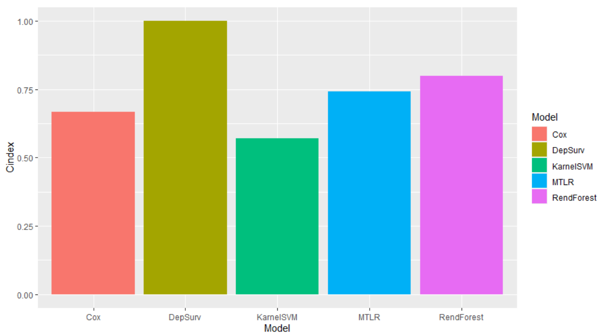

Figure 1: results from different machine learning models, based in FED, Federal Deposit Insurance Corporation, and World Bank data.

According to the results presented in the paper, the model with the highest C-index value of 0.985 was the DepSurv model, indicating that it performed the best in predicting bank failures using the selected variables. The RendForest model had the second-highest C-index value of 0.798, followed by MTLR with a C-index of 0.741. The Cox model had a C-index of 0.666, while the KarnelSVM model had the lowest C-index of 0.571.

These results suggest that the DepSurv model was the most effective in predicting bank failures, followed by the RendForest and MTLR models. This information is valuable for banks and regulatory agencies in predicting the likelihood of bank failures and taking necessary actions to mitigate the risks.

The variables analyzed in the study, including asset amount, deposit amount, ADR, deposit level, asset level, inflation rate, short-term interest rates, bank reserves, and GDP growth rate, can provide insights into the factors that contribute to bank failures. By understanding these variables, banks and regulatory agencies can take measures to reduce the likelihood of bank failures.

These results highlight the potential of machine learning survival models in predicting bank failures and provides insights into the factors that contribute to these failures. This information can be used to improve the stability of the banking system and reduce the risk of financial crises.

3.2. Economic perspective

The relative weights matrix can be useful in understanding how regulators and analysts assess a bank's risk of failure and which factors they consider most important at different times. However, it is also important to note that these weights may change over time as markets and the economy evolve, and that different regulators and analysts may have slightly different approaches to assessing bankruptcy risk.

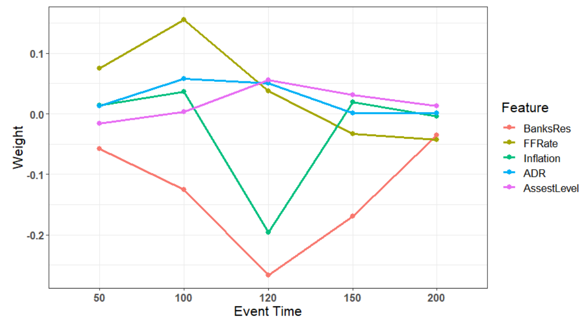

Figure 2: Relative weight of each variable based on MTLR model based in FED, Federal Deposit Insurance Corporation, and World Bank data-.

In this analysis, it can be seen that at the beginning of the weighting matrix, a relatively high weight is given to the "FFRate" because interest rate fluctuations can have a large impact on a bank's income and expenses, especially in terms of loans and deposits. Also, interest rate changes can signal changes in the broader economy, which can affect the financial health of banks.

However, as time progresses in the weight matrix, it is observed that the "FFRate" loses weight compared to other variables, such as "Inflation" and "BanksRes". This may be due to a number of factors, including the increasing importance of other risk factors such as inflation and a bank's ability to maintain adequate reserves. It may also reflect a heightened awareness on the part of regulators and analysts that the interest rate alone is not enough to assess a bank's risk of failure and that multiple factors need to be considered.

At the end, the weight matrix suggests that the size of a bank's assets and deposits are important factors in reducing the probability of bankruptcy, while a high level of indebtedness and low level of reserves increase the probability of bankruptcy. In addition, inflation appears to be a protective factor against bank failures.

3.2.1. 2008 Financial Crisis

It is interesting to note that during the period from 100 to 150, which coincided with the 2008 financial crisis, the survival rate of banks ranged from 0.88861 to 0.10380. This suggests that the financial crisis had a significant impact on the ability of banks to consolidate solvent.

Furthermore, it is important to note that the survival rate continued to decline after the crisis period, albeit at a slower rate. This could be indicative of the aftermath of the crisis, such as the economic downturn that followed and its lingering effects on the economy and the banking sector. Overall, these results underline the importance of considering the economic context and external events when analyzing the financial health of banks.

We can combine the information from the survival table and the weights matrix to better understand the variables that emerge from failure after period 150. From the survival table, we can see that the survival of banks decreases significantly after period 150. This It may be indicative that the variables that have a greater weight in the weight matrix after period 150 have a greater impact on bank failures.

In the weight's matrix, we can see that the variables "BanksRes" and "Inflation" have a relatively high weight after the 150 period. This suggests that these variables may be more important in predicting bank failures after the financial crisis of 2008. Post-crisis, regulators may have placed more emphasis on the importance of adequate capital buffers and the ability of banks to stabilize solvents in an environment of rising inflation. Therefore, these factors may have been more important in predicting bank failures in the post-crisis period.

3.2.3 If we include the data from GDP1pch

The variables with the greatest weight in predicting bank failure are Asset (Millions), ADR, Deposit Level and Deposit (Millions), in that order, all of them with negative weights, which means that as these variables increase, the probability of bank failure decreases.

GDP1pch variable has the lowest weight of all, but it is also negative, which suggests that a decrease in economic growth increases the probability of bank failure. The other variables with negative weights are Inflation, FFRate , and BanksRes , indicating that high inflation, high interest rate, and low bank reserve also increase the probability of bank failure.

As for the Asset Level and Deposit Level variables, although they have positive weights, their weights are very low compared to other variables, so their effect in predicting bank failure is probably limited.

4. Conclusion

The risk evolution over time was used to analyze bank failures, and it demonstrated a substantial decline in survival probability between particularly between 120 and 150 months, coinciding with the years 2009, 2010 and 2011. After the global financial crisis, which originated in the US.

According to the relative weights matrix study, interest rate changes, inflation, bank reserves, and the amount of assets and deposits were all critical variables in determining a bank's risk of failure. It is worth noting that during the 2008 financial crisis, the survival rate of banks declined dramatically, implying a severe effect on their capacity to stay viable. The data offered in this research may be utilized to enhance banking system stability and lessen the likelihood of financial crises.

When several machine learning survival models were compared in forecasting bank failures using a collection of relevant characteristics, the DepSurv model was found to be the most successful, followed by the RendForest and MTLR models. The study's variables, which included asset amount, deposit amount, ADR, deposit level, asset level, inflation rate, short-term interest rates, bank reserves, and GDP growth rate, may give insight into the causes that lead to bank failures. Banks and regulatory bodies may lower the chance of bank failures by knowing these characteristics.

References

Adnan Aziz, M., & Dar, H. A. (2006). Predicting corporate bankruptcy: where we stand? Corporate Governance: The international journal of business in society, 6(1), 18-33.

Alaka, H. A., Oyedele, L. O., Owolabi, H. A., Kumar, V., Ajayi, S. O., Akinade, O. O., & Bilal, M. (2018). Systematic review of bankruptcy prediction models: Towards a framework for tool selection. *Expert Systems with Applications*, *94*, 164-184.

Barboza, F., Kimura, H., & Altman, E. (2017). Machine learning models and bankruptcy prediction. *Expert Systems with Applications*, *83*, 405-417.

Beretta, A., & Heuchenne, C. (2019). Variable selection in proportional hazards cure model with time-varying covariates, application to US bank failures. *Journal of Applied Statistics*, *46*(9), 1529-1549.

Cox, R. A., Kimmel, R. K., & Wang, G. W. (2017). Proportional hazards model of bank failure: Evidence from USA. *Journal of Economic & Financial Studies*, *5*(3), 35-45.