What Matters in Bank Bankruptcy: An Empirical Study Based on Variable Selection

Xingdan Feng

Shanghai Starriver Bilingual School, Shanghai 201108, China
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Abstract: This paper explores the prediction of bank bankruptcy in the context of global economic instability and recurrent financial crises. The study concludes that Lasso and elastic-net models are recommended for predicting bank bankruptcies, as they efficiently balance variable selection with model sparsity, maintaining high prediction accuracy. These models are particularly valuable for banking managers and regulators in enhancing risk management and ensuring financial market stability. This research provides significant insights and tools for banking risk management, contributing to the stability and sustainable development of the financial sector.

Keywords**:** Bankruptcy Prediction; Variable Selection; Financial Risk Management

1. Introduction

1.1 Research background

Bankruptcy prediction within banks has consistently been a critical area of focus in the financial sector. In this environment, the accurate prediction of a bank's failure is not just critical for the stability of the individual institution, but also for the security of the entire economic landscape. Enhanced predictive capabilities would allow for better risk management and strategic planning, thus safeguarding not only investors but also the broader public from severe financial shocks. This makes the study of variable selection in predicting bank bankruptcies a crucial area of research, aiming to refine the tools and methodologies used to assess and mitigate risks effectively.

Research on bank bankruptcy prediction originated from the Altman Z-score model [1] in the 1960s. It successfully predicted the possibility of bank bankruptcy by selecting several key financial ratios and applying multiple discriminant analysis [2]. As time goes by, researchers keep on improving and developing new approaches, including the Logit model, the Probit model and machine learning methods that are widely employed in recent years [3]. Through processing vast amounts of complex data, machine learning methods can capture more nuanced relationships, thereby enhancing the accuracy of predictions [4].

Solving the problem of bankruptcy prediction can provide decision support for regulators and ensure the stability of financial markets. For example, during the global financial crisis, many banks suffered huge losses and even went bankrupt due to their failure to identify and manage risks in a timely manner [5]. If these risks can be predicted in advance, banks can enhance their anti-risk ability by adjusting their balance sheets and increasing capital reserves [6].

1.2 Data

The data used in this study came from the Taiwan Economic Journal and covered the data period from 1999 to 2009. These variables cover multiple aspects of financial and operating metrics and can be broadly grouped into the following categories: Financial structure and solvency; Operating efficiency and profitability; Asset liability management and investment efficiency; Cash flow and operating activities.

2. Literature Review

Bankruptcy prediction remains a pivotal subject in financial risk management. An accurate model for predicting bankruptcy can provide bank managers with the tools necessary to identify and mitigate potential risks proactively. Over the past several decades, the academic and financial communities have developed various methods for bankruptcy prediction. These can be broadly categorized into traditional statistical methods and contemporary machine learning approaches.

Some traditional statistical methods. (1) Multiple Discriminant Analysis (MDA): MDA is the method used in the Z-score model proposed by Altman in 1968 [1]. (2) Logistic Regression: Logistic regression is a widely used statistical method for bankruptcy prediction [2]. (3) Probit Regression: Probit regression is similar to Logistic regression, with the main difference being that it adopts normal cumulative distribution function (CDF) to model [3].

Some modern machine learning methods. (1) Support Vector Machine (SVM)[7]. (2) Neural Networks [8]. (3) Decision Trees and Random Forests [9]. (4) Gradient Boosting Machines (GBM) [10].

The four methods used in this article:

(1) Lasso (Least Absolute Shrinkage and Selection Operator) [11]

Its optimization objective function is shown as follows:

$$minimize\left(\sum_{i=1}^{n}\left(y_i-\sum_{j=1}^{p}\beta_j x_{ij}\right)^2+\lambda\sum_{j=1}^{p}\left|\beta_j\right|\right)$$

Where, y_i is the observed value, x_{ij} is the independent variable, β_j is the coefficient, p is the number of independent variables, n is the number of samples, and λ is the regulating parameter controlling sparsity.

(2) Ridge Regression[12]

Its optimization objective function is shown as follows:

$$minimize\left(\sum_{i=1}^{n}\left(y_i-\sum_{j=1}^{p}\beta_j x_{ij}\right)^2+\lambda\sum_{j=1}^{p}\beta_j^2\right)$$

(3) Elastic-Net Regression[13]

Its optimization objective function is shown as follows:

$$minimize\left(\sum_{i=1}^{n}\left(y_i-\sum_{j=1}^{p}\beta_j x_{ij}\right)^2+\lambda_1\sum_{j=1}^{p}\left|\beta_j\right|+\lambda_2\sum_{j=1}^{p}\beta_j^2\right)$$

(4) Stepwise regression

Stepwise regression is appropriate for handling high-dimensional data and collinearity issues; however, it might be computationally burdensome on large datasets [14].

3. Methods

In this section, we will cover data processing, model fitting, and result analysis in detail. First, we divide the data into a training set and a test set in a 7:3 ratio, and fit four models on the training set. Subsequently, we will tune the parameters of the model for optimal performance and compare the mean square error (MSE):

$$MSE=\frac{1}{n}\sum_{i=1}^{n}\left(y_i-\hat{y}_i\right)^2$$

3.1 Model building

Lasso regression is a linear regression method based on penalty. The solution path is as follows.

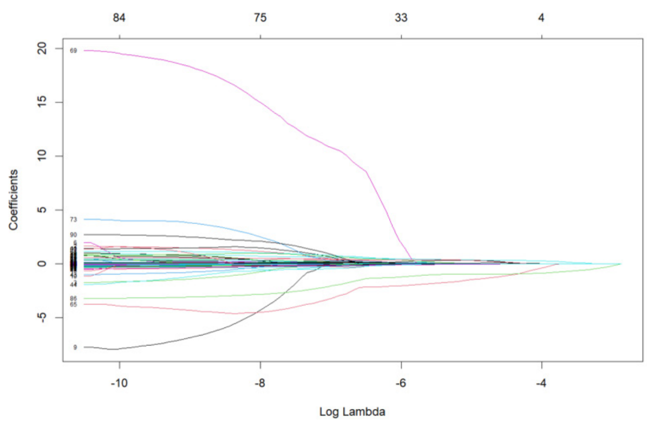

Figure 1. solution path of Lasso

The resulting model is:

$$\begin{aligned}\widehat{y_i} &= 1.71 - 0.009 \times Tax + 0.36 \times Debt + 0.34 \times Borrowing \\ &-0.32 \times Total.Asset.Turnover - 1.47 \times Working.capital.Equity \\ &+0.33 \times Equity.to.Long.term.Liability \\ &+0.079 \times Current.Liability.to.current.Asset \\ &+0.32 \times Liability.Asset.Flag - 0.95 \times Net.Income.to.Total.Assets\end{aligned}$$

The MSE of Lasso method is 0.02305698.

Ridge regression is a linear regression method based on two norm penalty. However, we observed an unusually high MSE for ridge regression, which may suggest overfitting.

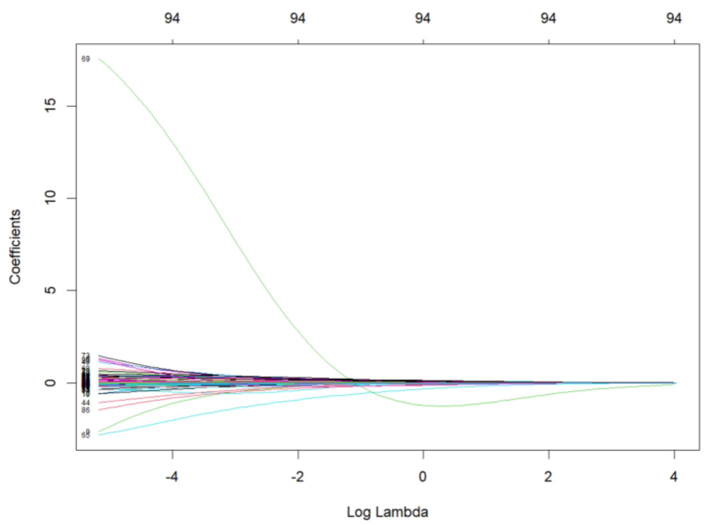

Figure 2. solution path of Ridge regression

Elastic net regression is a linear regression method that uses both one-norm and two-norm penalties. The solution path is as follows:

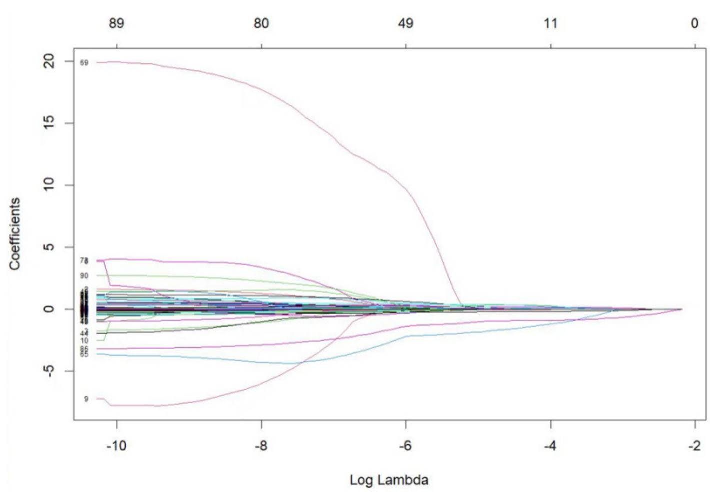

Figure 3. solution path of elastic net regression

The resulting model is

$$\hat{y}_i = 0.3996822 + 0.026 \times Debt.ratio - 0.026 \times Net.worth.Assets - 0.43 \times Net.Income.to.Total.Assets$$

The MSE of elastic mesh method is 0.025728.

Stepwise regression is an algorithm that gradually adds or removes independent variables. We use a stepwise regression algorithm on the training set and calculate the MSE on the test set. In our dataset, the MSE for stepwise regression is 0.198991028045842.

4. Result Analysis

From above results, we can clearly see that Lasso and elastic net model regression have the best performance with the lowest MSE value, while Ridge regression model has the worst

performance with an abnormally high MSE value. The performance of stepwise regression model is slightly worse than Lasso and elastic net regression model, but still better than ridge regression model.

Ultimately, the selection of a predictive model for bank bankruptcy should be guided by both its empirical performance and its theoretical robustness. This involves continuous testing and validation against emerging data, ensuring that the model remains relevant and effective in a dynamic economic landscape. Our study contributes to this ongoing endeavor by highlighting the strengths and limitations of various models and suggesting pathways for future research and application in the banking sector.

5. Conclusion and prospect

This study compares Lasso, Ridge regression, elastic net regression and stepwise regression to evaluate the problem of bank failure prediction. Lasso and elastic net regression models perform best on the test set and have low mean square error (MSE), which is suitable for bank failure prediction problems. The stepwise regression model is not so good in feature selection, and its predictive performance is slightly worse than Lasso and elastic network regression model.

In summary, Lasso and elastic net regression model are recommended models for bank bankruptcy prediction, which can achieve variable selection and model sparsity while maintaining prediction accuracy.

Based on the results of the bank bankruptcy prediction model, targeted policy suggestions are put forward to promote the formulation and adjustment of financial supervision policies and ensure the stability and healthy development of the financial system. For example, according to the forecast results of the model, formulate targeted regulatory policies, strengthen the supervision of high-risk banks, timely detect and deal with potential risks, and maintain the stability and healthy development of the financial market.

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