Finance Research Letters 85 (2025) 107758

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

The impact of financial statement indicators on bank credit ratings: Insights from machine learning and SHAP techniques☆

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ARTICLE INFO

Keywords:
Bank credit rating
Financial statement indicators
Machine Learning
SHAP

ABSTRACT

This study investigates the influence of financial statement indicators on bank credit ratings. We construct a dataset encompassing 53 banks and 28 key financial indicators and employ two machine learning models, GBR and LightGBM, to predict credit ratings based on these indicators. To understand the contributions of the individual indicators, we apply SHapley Additive exPlanations (SHAP) to interpret the forecasting results. The analysis reveals that indicators pertaining to a bank's revenue structure, particularly net interest income, have a significant impact on credit assessments. This finding underscores the critical role of a bank's debt repayment capacity and income stream diversification.

1. Introduction

The banking industry generates profits through its essential function of extending loans to individuals and businesses. As a result, banks are inherently exposed to the risk of their own default. Moreover, the credit risk arising from potential bank failures constitutes a significant threat to overall financial stability. The substantial losses experienced by banks and other entities caught up in the global credit crunch triggered by the collapse of the U.S. subprime mortgage market in 2007–2008 highlight the significant impact of credit risk on corporate profitability and underscore the importance of effective credit risk management. Therefore, managing default risk is a critical consideration not only within the banking industry itself but also for all market participants. Notably, recent banking disruptions, such as the collapse of Silicon Valley Bank, UBS's acquisition of Credit Suisse, and the bankruptcy of Citizens Bank, further underscore the renewed importance of robust credit risk management in the banking sector.

According to existing literature, a bank's credit risk is identified as a key determinant of its financial stability and profitability. Research by Ghenimi et al. (2017), Imbierowicz and Rauch (2014), and Abbas et al. (2019) highlights the negative effect of credit risk on banks, both individually and within the entire financial system. Consequently, several studies have examined the bank-specific fundamentals that influence credit risk. Factors such as loan provisions, asset quality, interest rate fluctuations, bank size, profitability, diversification, and market concentration are considered significant (Ahmad and Ariff, 2008; Lin, 2009; Chaibi and Ftiti, 2015; Gulati et al., 2019).

In particular, prior studies have examined the relationship between financial indicators derived from financial statements and the credit risk of banks. Poon et al. (1999) conducted a study aimed at explaining the credit ratings of banks across the globe using banking-specific financial data. Specifically, they employed a logistic regression model to assess the explanatory power of variables

☆ The work of S.-Y. Choi was supported by a National Research Foundation of Korea (NRF), South Korea grant funded by the Korean government (MSIT) (No. 2021R1F1A1046138) and the Gachon University Research Fund of 2023 (GCU-202303990001).

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https://doi.org/10.1016/j.frl.2025.107758
Received 3 May 2024; Received in revised form 11 June 2025; Accepted 11 June 2025
Available online 26 June 2025
1544-6123/

such as net interest income, debt, total equity, and pretax income in determining bank credit ratings. Similarly, Shen et al. (2012) investigated the relationship between commercial banks' credit ratings and selected financial indicators, including net income, total assets, and net interest revenues. Their findings indicate that these variables have a statistically significant impact on commercial bank credit ratings. Furthermore, Meriläinen and Junttila (2020) analyzed the relationship between credit rating adjustments and various financial factors, including liquidity, return on assets (ROA), total assets, and total equity, for Western European banks. Their results suggest that banks with greater asset liquidity tend to receive more favorable credit rating outcomes.

In addition, several studies have modeled the impact of depreciation on banks' capital conditions. For example, Meh and Moran (2010) developed a framework that incorporates depreciation into the assessment of bank capital. Likewise, Golbeck and Linetsky (2013) proposed a credit risk model that accounts for depreciation, emphasizing its role in determining the value of collateral assets. On the corporate side, depreciation is also recognized for its role in reducing the cost of investment and lowering tax liabilities, thereby encouraging capital expenditures. This investment-stimulating effect of depreciation is supported by empirical findings in Ohrn (2019) and Zwick and Mahon (2017).

This study examines the key financial statement components that influence a bank's inherent credit risk. We achieve this by analyzing credit rating data from a sample of 53 banks along with 28 corresponding financial indicators. We apply machine learning (ML) algorithms to predict credit ratings and the SHapley Additive exPlanations (SHAP) methodology, a prominent Explainable Artificial Intelligence (XAI) technique.

Our study involves two key steps. First, we leverage machine learning models to predict banks' credit ratings based on their financial characteristics. We then evaluate and refine these models to identify those with the strongest predictive capabilities. Following the prediction phase, we use SHAP analysis to elucidate the primary financial factors driving the model's predictions. Section 2 describes the research methodology in detail.

Our study makes a significant contribution by exploring the importance of financial factors in banking credit risk using ML techniques, which has advantages over traditional regression analyses. We address the black-box problem of ML models by employing the SHAP methodology, which enhances interpretability. By incorporating various financial indicators, we identify key metrics for investor attention and propose strategies to enhance bank operations and credit rating management.

The rest of the paper is structured as follows. Section 2 describes the financial data collection process, research workflow, and SHAP methodology. Section 3 presents the forecasting results and the SHAP analysis. Finally, Section 4 discusses the findings and offers concluding remarks.

2. Data description and methods

2.1. Data set

We conducted a comprehensive data extraction process from S&P Global Ratings,[1] focusing on the banking sector (Financial Institutions), resulting in a dataset encompassing 1971 companies. Subsequent refinement narrowed the selection to 227 companies with identifiable tickers on Yahoo Finance.

To further enrich our dataset, we employed Python for dynamic web scraping, targeting "Foreign Currency LT" data from S&P Global Ratings. This extraction collected crucial information, including "RATING", "RATING DATE", and "LAST REVIEW DATE", which ultimately reduced our dataset to 210 companies.

In the subsequent phase, we leveraged the "YahooFinancials" Python package for systematic ticker-based searches and streamlined data collection. We obtained financial metrics including income statements, cash flow statements, and balance sheets for 210 companies. This meticulous process yielded a dataset comprising 207 companies.

For financial data, we adopted a strategic approach by aligning the "Search Date" with the "LAST REVIEW DATE" to ensure that we select financial data corresponding to the nearest quarter. For example, we matched "JPMorgan Chase & Co." with a "LAST REVIEW DATE" of "2023-06-23" and "Search Date" set to "2023-03-31" to effectively capture the financial landscape for that specific period.

In our analysis, we converted credit ratings into credit scores, transforming categorical data into quantitative data to enhance prediction accuracy. We based this conversion process on the FICO score developed by the Fair Isaac Corporation. The FICO score classifies individuals into five tiers: "Exceptional" (800–850), "Very Good" (740–799), "Good" (670–739), "Fair" (580–669), and "Poor" (300–579). Moreover, numerous studies employed this score to gauge credit risk (Courchane et al., 2008; Smith, 2011; Arya et al., 2013; Bubb and Kaufman, 2014).

We applied the following transformation process. Initially, we categorized credit ratings into five distinct groups (AAA, AA, A, BBB, and BB-C) according to the S&P Global Ratings.[2] Subsequently, we matched these categories with their corresponding FICO score tiers of Exceptional, Very Good, Good, Fair, and Poor, respectively. Finally, each credit rating within a category was assigned an evenly divided FICO score corresponding to that category. For example, the credit ratings [BBB+, BBB, BBB-] are categorized as Fair, with scores ranging from 669 to 580, evenly distributed. We assigned BBB+, BBB, and BBB- a score of 669, 624.5, and 580, respectively.

[1] https://disclosure.spglobal.com/ratings/en/regulatory/entity-browse

[2] "S&P Global Ratings Definitions", S&P Global

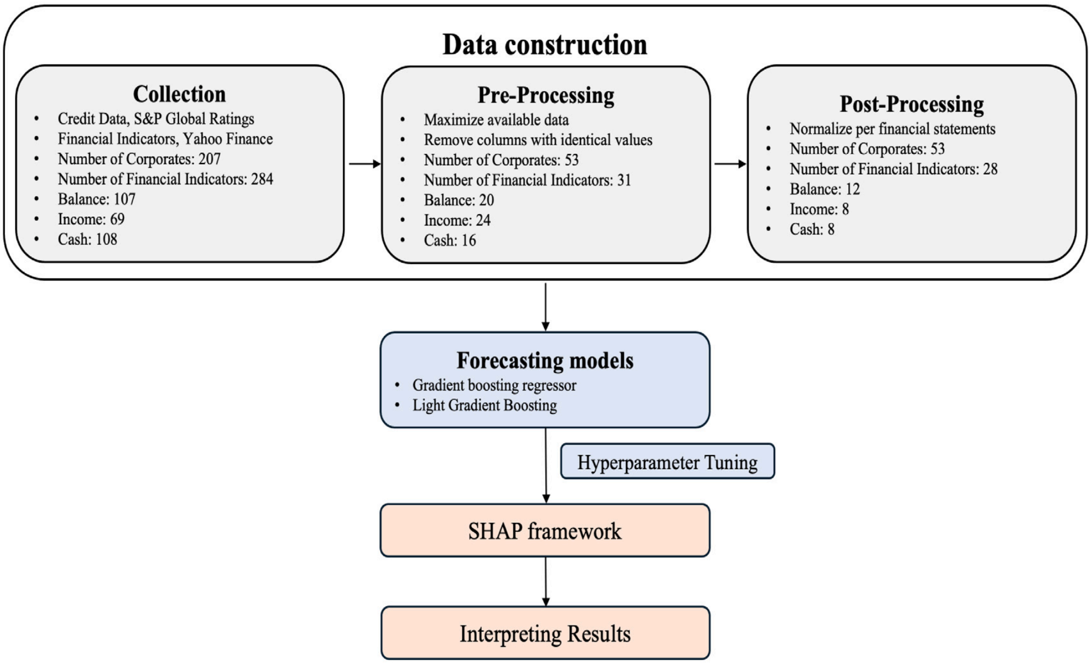


Fig. 2.1. Research framework flowchart.

Table 2.1
Descriptive statistics: Credit score (FICO score).

Mean	Max.	Min.	Std.Dev.	Skewness	Kurtosis	JB-test
623.372	739	419.5714	59.5878	−0.6475	1.1683	6.717

2.2. Research workflow

The data composition process encompasses three essential stages: data collection, pre-processing, and post-processing. These stages collectively form an overarching workflow, where each stage contributes to maintaining data quality and integrity. We also illustrate the workflow in Fig. 2.1. The key steps are as follows.

1. **Collection:** Gather credit and financial data from S&P Global Ratings and Yahoo Finance. This resulted in a dataset (207 × 285) containing Credit Ratings and 107, 69, and 108 financial variables from balance, income, and cash reports, respectively.
2. **Pre-Processing:** Focus on 61 key financial indicators per row and remove columns with duplicate values. This resulted in a dataset (53 × 32) that includes Credit Score.
3. **Post-Processing:** For effective analysis, categorize the financial variables according to their corresponding reports (balance, income, cash), and calculate the ratios with "Total Assets", "Total Revenue", and "Beginning Cash Position". Subsequently, remove these three columns to create the final dataset (53 × 29).[3]
4. **Modeling and Hyperparameter Tuning:** Apply the gradient boosting regression (GBR) and light-gradient boosting machine (LightGBM) models to predict credit scores using financial data, with fine-tuning conducted.
5. **Interpreting Results:** Employ SHAP to clarify the prediction mechanisms of our models, which improves the comparability of the results.

Fig. 2.2 illustrates the distribution of credit ratings for the 53 banks. We transformed these ratings into corresponding FICO scores (Table 2.1). The scores range from 739 (A+) to 419.5714 (CCC-), representing the transformation of credit ratings into numerical credit scores that effectively capture the spectrum of credit risk from low to high. The distribution is positively skewed, with a longer tail toward higher scores and an average score of 623.372, which aligns closely with the Fair BBB rating category.

Methodologically, we employed the GBR and LightGBM models to predict credit scores. These models garnered recognition for their strong predictive performance in studies such as those by Ma et al. (2018), Nguyen et al. (2021), Rathakrishnan et al. (2022).

[3] We provide details on this dataset in appendix.

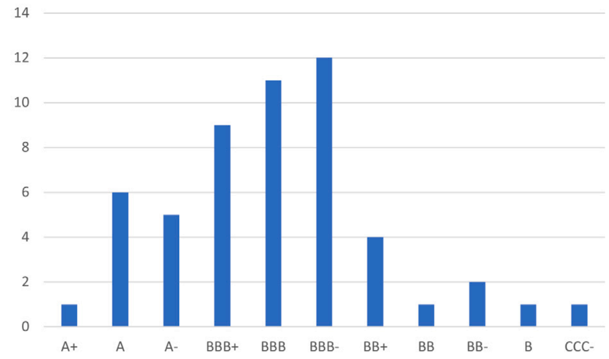


Fig. 2.2. Histogram of the Sample Banks' Credit Ratings.

Table 3.1
Tuned ML model prediction results.

Model	Metric	FICO score	
		Original	Tuned
GBR	MAE	45.7967	20.6499
	MSE	4455.1102	780.0732
	RMSE	58.1084	27.9298
	R^2	−1.0803	0.4264
LightGBM	MAE	47.5969	23.7511
	MSE	3695.8687	930.5977
	RMSE	56.1047	30.5057
	R^2	−0.1504	0.3157

Our selection of these two models is driven by the desire to ensure the robustness of both the predicted credit scores and the subsequent SHAP analysis results.

2.3. SHAP framework

The SHAP framework introduced by Lundberg and Lee (2017) is a powerful tool used in machine learning to explain the output of any model by attributing the prediction outcome to its individual features.

Developed based on the Shapley value in cooperative game theory principles (Shapley, 1953), the SHAP assigns an importance value to each feature, indicating its impact on a model's prediction. This value quantifies the influence of the feature on the difference between the actual and average predictions when considering the current set of feature values. Furthermore, it offers a unified approach for interpretability across various models, including complex models such as deep neural networks, boosting models, and support vector machines.

The SHAP framework is currently being used in various fields (Futagami et al., 2021; De Lange et al., 2022; Guliyev and Mustafayev, 2022; Deng et al., 2023; Goodell et al., 2023; Kim et al., 2024). These studies found that incorporating the SHAP methodology with machine learning can enhance both the interpretability and reliability of the machine learning model. Additionally, SHAP analysis facilitates the identification of novel features and provides clarity regarding their influence on the prediction outcomes.

3. Forecasting credit score and SHAP analysis

Table 3.1 compares the performance metrics of the GBR and LightGBM models before and after hyperparameter tuning. Both models show notable improvements in performance after tuning, with a substantial decreases in MAE, MSE, and RMSE. This result indicates fewer prediction errors. Additionally, the R^2 value shifts from negative to positive, signifying a significant increase in explanatory power.

We present a scatter plot matrix of the actual and predicted data values (credit scores) generated by the two models in Fig. 3.1. This matrix shows the correlation between variable pairs with histograms along the diagonal displaying variable distributions. The correlation coefficient between the predicted values is 0.98, which is significantly higher than the 0.76 and 0.7 correlation coefficients between the actual and predicted values. This result indicates an accurate pattern capture by the models, ensuring consistent predictions and high reliability.

We utilize the SHAP framework to analyze credit score predictions produced by the GBR and LightGBM models to gain a more granular understanding of how individual financial indicators influence credit score predictions. We summarize the results in Fig. 3.2, which illustrates the feature importance for each model. Additionally, Fig. 3.3 presents the SHAP summary plots to visualize how each feature value in a specific data point (represented by color) influences the credit score prediction.

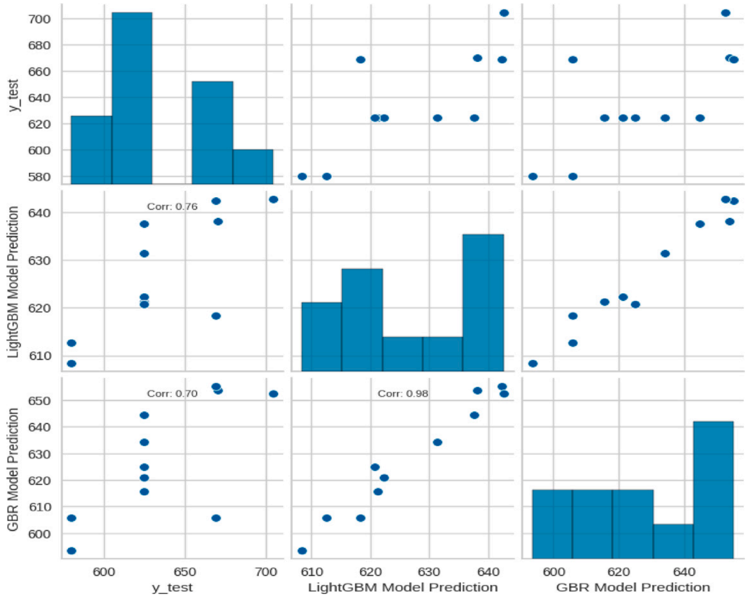
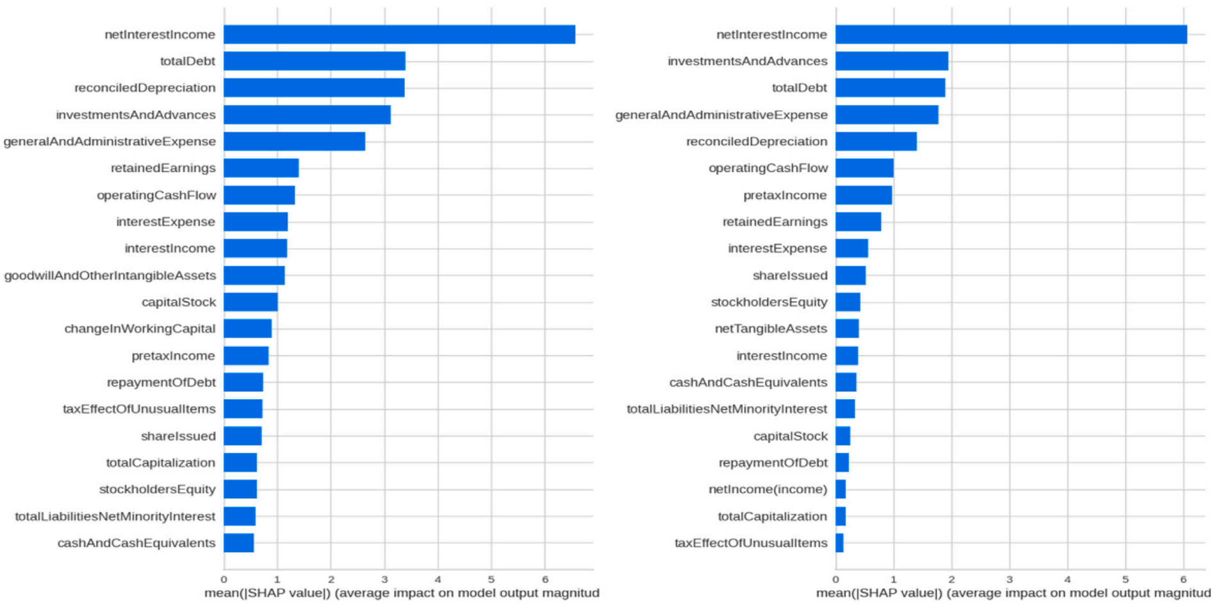


Fig. 3.1. Pairwise Scatter Plot of Actual vs. Predicted Credit Scores.

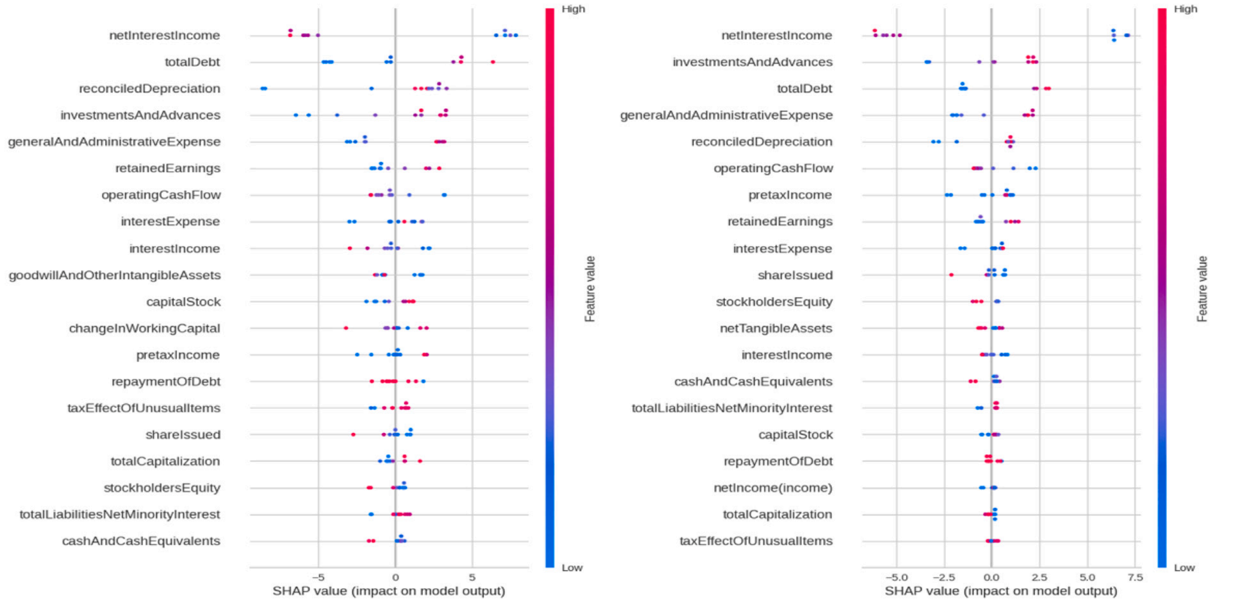


(a) GBR (b) LightGBM

Fig. 3.2. Feature importance based on SHAP values for the two forecasting results. Note. The y-axis indicates the mean absolute SHAP values, which are depicted in descending order.

Features with high contributions to credit score prediction by the two models are displayed in order on the y-axis in Fig. 3.2. Accordingly, we identify the top five factors in common: net interest income (NII), total debt, investments and advances, reconciled depreciation, and general and administrative expenses.

First, NII has the most contribution in both models. The NII, represents the revenue generated from interest on loans or deposits minus the interest expenses paid to depositors, making it a crucial financial metric, especially in banking. This metric reflects a bank's ability to attract funds, extend loans, and generate interest income as well as its reliance on interest income in relation to overall revenue.



(a) GBR (b) LightGBM

Fig. 3.3. SHAP summary of the forecasts.
Note. Feature importance, ranked on the *y*-axis, correlates with SHAP values on the *x*-axis. Negative SHAP values indicate that the feature contributes to a lower credit score at the given value, whereas positive SHAP values suggest that the feature contributes to a higher credit score. Each point is colored by feature value: blue for low and red for high.

Another high-ranking factor is Total Debt, which relates directly to credit rating. Total Debt represents the total liabilities of a corporation or institution, including its loans and corporate bonds. The Total Debt/Total Asset ratio indicates the proportion of a bank's debt to its total assets, which is crucial for assessing debt obligations and financial stability. Elevated ratios often raise concerns about the bank's repayment capacity.

Furthermore, "Investments and Advances" pertaining to the bank's investment income is another significant contributor. This measure encompasses the total value of investments, loans, and mortgages held by institutions. The Investments and Advances/Total Asset ratio indicates the percentage of a bank's assets allocated to these activities, reflecting the extent of asset allocation for revenue optimization.

The remaining factors for banks are cost related. The reconciled depreciation indicates the adjusted asset depreciation over time. The Reconciled Depreciation/Total Revenue ratio indicates the proportion of revenue attributed to depreciation, higher ratios suggesting significant expenses. General and administrative expenses include operational overhead, salaries, and legal/accounting fees. The General and Administrative Expense/Total Revenue ratio reflects spending efficiency, with lower ratios indicating better management.

Moreover, we analyze the impact of financial indicators on credit scores using the SHAP framework (see Fig. 3.3).

In Fig. 3.3, we can see that for NII, lower ratios positively affect credit scores. A low NII/Total Revenue ratio suggests that the bank does not rely solely on loans and deposits, emphasizing high-quality service and offering diverse financial solutions. This implies significant revenue from sources such as investment products, insurance, and asset management services (Smith et al., 2003; Lee et al., 2014; Köhler, 2014). In particular, Köhler (2014) emphasized the importance of bank structure in revenue diversification.

The findings reveal a positive impact of higher Total Debt/Total Assets on credit scores, indicating the use of strategic debt for efficient fund deployment and growth capital (Saona Hoffmann, 2011). Despite high levels of debt, stable cash flows, robust asset structures, and trustworthy financial strategies can positively influence credit rating. Consequently, these elements may lead to a higher credit score.

Higher ratios of Investments and Advances/Total Assets are associated with a favorable stance toward credit scores. A high ratio indicates effective asset management, conveying positive signals of the bank's stability and growth prospects (Sarkar et al., 2019).

We see a positive correlation between the Reconciled Depreciation/Total Revenue ratio and credit scores. A higher ratio suggests that the bank allocates more resources to depreciation, which not only stabilizes asset values but also generates tax savings and enhances cash flow. These advantages can be seen as contributing to improved liquidity and reduced financial risk for the bank, which ultimately support the attainment of higher credit ratings (Ohrn, 2019; Zwick and Mahon, 2017). Likewise, we find a positive correlation between the General and Administrative Expense/Total Revenue ratio and credit scores. This finding suggests the need for substantial investments in general and administrative expenses, potentially for enhanced services and technological innovation (Golec, 1996).

4. Discussion and concluding remarks

This study explores the main factors affecting banks' credit scores by combining credit ratings and financial indicators into a comprehensive dataset. We used two machine-learning methods, GBR and LightGBM, and optimized them through hyperparameter tuning to ensure robust results. We applied the SHAP framework to enhance model interpretability, allowing us to identify and compare the relative impacts of different financial variables on credit score predictions. The key findings are as follows.

First, the SHAP analysis identified five key factors that influence credit scores: NII, total debt, investments and advances, reconciled depreciation, and general and administrative expenses. These findings align with previous studies, suggesting a degree of commonality among the drivers of banks' credit risk. By analyzing the impact of these factors, we gain valuable insights into the underlying dynamics affecting credit scores. This knowledge can inform financial management and risk-assessment practices.

Second, NII emerged as the most significant contributor to credit scores. Notably, a lower NII ratio was the only factor among the top five with a positive impact on the score. This finding highlights the importance of diversifying revenue sources beyond traditional interest income for banks seeking to improve their credit ratings.

Third, the remaining four identified factors (total debt, investments and advances, reconciled depreciation, and general and administrative expenses) exhibited a positive correlation with credit scores when their values were higher. While the specific interpretations of each factor may differ, their collective influence suggests that credit scoring models reward proactive financial engagement. Additionally, these factors may indicate a bank's willingness to incur the costs associated with growth-oriented activities.

The NII and total debt are key factors in assessing banks' financial health (Abor, 2005; Menicucci and Paolucci, 2016). The NII signifies core income, and higher values imply better profitability, while total debt indicates stability; higher levels suggest increased bankruptcy risk. The finding that NII contributes more significantly to credit rating evaluations suggests that future profitability in banking outweighs loan considerations. This result underscores the importance of liquidity and future cash flows when assessing banks (Poon and Firth, 2005; Berger and Bouwman, 2009; Acharya et al., 2012).

Banks' profit is highly sensitive to interest rate fluctuations, affecting not only the NII but also overall revenue. When central banks increase interest rates, banks should consider reducing their reliance on the NII to enhance stability.[4] Generating additional revenue through diverse financial activities is crucial. Diversification stabilizes bank revenues and improves resilience during crises (Köhler, 2015; Gelman et al., 2023). Such diversification strategies can bolster banks' financial soundness and foster sustainable growth.

This study's findings emphasize the vital roles of revenue diversification and liquidity management in banking. Regular asset reassessment and evaluation using financial indicators are crucial for maintaining a balanced portfolio and reducing risk. Proactive financial strategies, including income source diversification and expansion efforts, are necessary to ensure stable revenue streams and prioritize customer satisfaction over cost.

Future research can build upon our findings by identifying the most influential financial statement components in determining credit ratings. Furthermore, employing more detailed classifications, such as distinguishing between Investments and Advances, could enable a more refined approach to predicting credit ratings. Lastly, we also recommend that subsequent studies explore the integration of both financial metrics and non-financial variables, including ESG factors, to enhance the predictive accuracy and practical applicability of credit risk models in the banking sector.

CRediT authorship contribution statement

Min-Jae Lee: Writing – original draft, Methodology, Formal analysis, Data curation. **Sun-Yong Choi:** Writing – original draft, Funding acquisition, Formal analysis, Conceptualization.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.frl.2025.107758.

Data availability

The authors do not have permission to share data.

[4] "European banks must look at fees, diversification as NII bonanza nears peak", S&P Global

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