Incorporating Asset Depreciation in SME Leasing Default Prediction: An XGBoost Approach

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Abstract

This study develops an XGBoost approach to forecast default risk in small and medium-sized enterprise (SME) equipment leasing, with a particular focus on asset depreciation patterns. The model was trained and tested on a dataset of 6,218 contracts from a Chinese leasing company. Beyond conventional predictors, it incorporates key depreciation metrics: residual value ratio, asset age, and remaining useful life. The proposed XGBoost model achieved an AUC of 0.813, outperforming all benchmark models. SHAP analysis identified the residual value ratio as the second most important predictor, underscoring the critical role of asset-specific factors in leasing defaults. Crucially, the SHAP dependence plot revealed a pronounced negative correlation between the residual value ratio and default probability. This finding aligns with the economic intuition underpinning leasing: equipment with a higher projected residual value strengthens the lessor's collateral position and reduces the lessee's incentive to default, as the asset retains significant recoverable value.

Keywords

SME financing, leasing default prediction, asset depreciation, XGBoost, SHAP.

1. Introduction

SMEs face finance-related problems due to poor collateral and creditworthiness. Leasing has proved to be a major source of finance for SMEs, where assets can be acquired without requiring significant capital [1]. However, default risk is considered a major challenge for financial institutions regarding leasing contracts. Therefore, it is important to create prediction models that can accurately determine default risks for leasing contracts.

Although many studies have improved the prediction of credit risk in banking institutions, studies on predicting credit risk in leasing contracts remain limited. According to Kozina et al. [2], most studies have focused on predicting credit risk in bank loans, but few have explored predicting credit risk in leasing contracts. Leasing contracts differ significantly from bank loans. There is a gap in the literature because no studies have explored the characteristics of asset depreciation in predicting credit risk in leasing contracts. Asset depreciation characteristics are vital in forecasting credit risk in leasing agreements since they affect asset residual values and hence the quality of the assets as collateral. Importantly, previous studies did not use asset depreciation characteristics in forecasting credit risk for leasing agreements.

This study aims to fill the gap by proposing a prediction model based on XGBoost with the inclusion of asset depreciation characteristics in the prediction of credit risk in leasing contracts. This study makes three contributions: (1) the inclusion of asset depreciation characteristics in the prediction of credit risk in leasing contracts, (2) the investigation of the importance of the characteristics in predicting credit risk in leasing contracts, and (3) the provision of interpretable results to support risk assessment in leasing organizations.

2. Related Work

Machine learning techniques have been found to have higher predictive accuracy in credit risk assessment compared to traditional statistical approaches. In a recent study by Barbaglia et al. [3], machine learning techniques were utilized to assess 12 million European mortgages. The results showed that the machine learning techniques had higher predictive accuracy compared to the traditional logistic regression method. In addition, interest rates and economic conditions were the key determinants identified in the model. In the field of SME finance, Bitetto et al. [4] showed that machine learning approaches possess higher predictive capabilities, especially in cases of low lender information. In a recent study by Cheraghali and Molnár [5], an exhaustive literature survey of 145 studies on default risk prediction for SMEs was carried out. The literature survey covered five decades and included more than 80 distinct estimation methods. Additionally, more than 54 different feature selection approaches were employed in these studies. The authors suggest that feature selection approaches ought to be incorporated as a normal part of default risk prediction.

In another recent study, Hernes et al. [6] used ceteris paribus plots, SHAP values, and feature importance analysis along with the XGBoost algorithm to predict credit risk. The results indicate the potential use of machine learning in credit decision-making by providing interpretable risk predictions. In addition, Hlongwane et al. [7] proposed a new framework to build a credit scorecard using Shapley values. The study suggests that it achieves a level of transparency comparable to that of logistic regression, while also maintaining the predictive effectiveness inherent in ensemble methods.

However, the problem of forecasting defaults within leasing contracts has not been sufficiently explored. Most studies of forecasting default risk focus primarily on bank loans and credit cards, without adequately examining the characteristics of default risk for leasing. The systematic depreciation of equipment represents a unique feature of leasing contracts and suggests that default risk cannot be entirely explained by standard credit risk models.

3. Methodology

3.1. Data

The dataset for this study consists of data from a Chinese equipment leasing company, which includes information on the contracts issued from January 2020 to December 2024. The dataset includes 6,218 SME leasing contracts, out of which 524 have defaulted, yielding a default rate of 8.4%. The data includes variables such as the characteristics of the lessee, the contract details, and the equipment.

To mimic real-world prediction scenarios, time-based data splitting was utilized to separate the data into sets for training and testing. The contracts issued in the period from 2020 to 2023 were used to train the model (4,856 contracts), while those issued in 2024 were set aside for testing (1,362 contracts). This ensured that the model did not have any information about the future during the test process.

3.2. Feature Engineering

Three categories of predictor variables are defined in this study. Borrower characteristics involve the credit information of the lessee enterprises. Enterprise age is used as a proxy measure of business operational experience, and registered capital and the number of employees represent the scale of the enterprise.

Contract characteristics include terms that describe the relationship between lessors and lessees. The literature shows that interest rate is a significant determinant that predicts default risk in a mortgage contract [3]. The lease term, down payment ratio, and monthly payment amount also play a role in determining lessee default risk.

Asset depreciation characteristics represent a key innovation in the prediction of default risk. The asset type is described based on the classification of the asset in terms of its depreciation pattern. The asset age at contract initiation and the remaining useful life of the asset provide information about the remaining value of the asset. The depreciation method indicates whether it uses straight-line or accelerated patterns. The residual value ratio is calculated as a measure of collateral quality, with lessees showing less incentive to make payments when the estimated residual values are below their debt amounts, a concept in mortgage default risk that is called negative equity.

In categorical variables like industry type, equipment type, and depreciation method, one-hot encoding is applied to transform them into numerical inputs. Table 1 shows the definitions and descriptions of these variables.

Table 1. Variable Definitions and Descriptive Statistics

Category	Variable	Description	Mean	Std. Dev.
Borrower	firm_age	Years since registration	7.2	4.8
Borrower	registered_capital	Registered capital (million CNY)	12.4	18.6
Borrower	industry	Industry sector (8 categories)	—	—
Borrower	employees	Number of employees	86	124
Contract	lease_term	Duration (months)	36.4	12.2
Contract	down_payment	Down payment ratio (%)	18.6	8.4
Contract	monthly_payment	Monthly payment (thousand CNY)	42.8	35.6
Contract	interest_rate	Annual interest rate (%)	7.2	1.8
Asset	equipment_type	Equipment category (6 types)	—	—
Asset	asset_age	Equipment age at start (years)	1.4	1.2
Asset	useful_life	Estimated useful life (years)	8.6	3.2
Asset	depreciation_method	Straight-line or accelerated	—	—
Asset	residual_ratio	Residual value / original cost (%)	24.2	12.8
Target	default	Default occurrence (1=yes, 0=no)	0.084	0.277

3.3. Model and Evaluation

The primary predictive model applied is XGBoost, which is a gradient-boosting algorithm that combines an ensemble of decision trees. Decision trees are learned iteratively to correct errors from previous iterations [8]. The objective function optimized within this framework is:

$$\mathcal{L} = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{1}$$

where $l(y_i, \hat{y}_i)$ represents the loss function that measures the difference between the actual label y_i and the predicted value $\hat{y}_i$, and $\Omega(f_k)$ denotes the regularization term that controls the complexity of the tree f_k. This formulation is effective in dealing with non-linear relationships and interactions, as well as overfitting issues at the same time.

For the comparative analyses, two baseline models were adopted: a logistic regression model, which is in line with the statistical approach, and a random forest model, which is an alternative methodological framework. For both XGBoost and Random Forest, five-fold cross-validation was performed on the training data to optimize the hyperparameters of these two machine learning models. The scale_pos_weight parameter was also utilized in the XGBoost model to deal with class imbalance issues.

Model performance was evaluated using four key metrics. The AUC assessed overall discriminative power. Precision and recall were used to measure the accuracy of positive predictions and the model's ability to identify all true defaults, respectively. Their balance was summarized by the F1-score, which is the harmonic mean of precision and recall. In addition, SHAP (Shapley Additive Explanations) was used to interpret the output of the model. Based on cooperative game theory, SHAP quantifies the contribution of a feature to a specific prediction made by the model. SHAP dependence plots were generated to determine the relative importance of the features used by the model.

4. Results

4.1. Model Performance Comparison

Table 2 shows the results of the performance of the three models, measured by their ability to predict the outcomes on the hold-out test set. The XGBoost model had the best AUC of 0.813, which was higher than that of the Random Forest model (0.786) and the Logistic Regression model (0.742). In terms of the classification metrics, the XGBoost model had a precision of 0.724 and a recall of 0.763, which resulted in an F1-score of 0.743. The Random Forest model had a similar recall of 0.751 but a lower precision of 0.698, which resulted in an F1-score of 0.723. The Logistic Regression model had the worst performance among all the models, with a precision of 0.651, a recall of 0.673, and an F1-score of 0.662.

Table 2. Model Performance Comparison on Test Set

Model	AUC	Precision	Recall	F1-score
Logistic Regression	0.742	0.651	0.673	0.662
Random Forest	0.786	0.698	0.751	0.723
XGBoost	0.813	0.724	0.763	0.743

The moderate values of recall that are obtained for all models reflect the difficulty involved in the prediction of rare cases of default, which constitute 8.4% of the total sample. The XGBoost model was able to classify over 76% of actual defaults with a precision higher than 72%.

4.2. Feature Importance Analysis

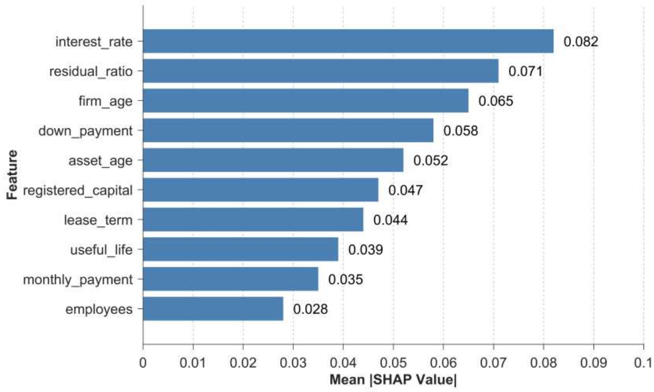

Figure 1. Global Feature Importance Ranking (Top 10 Variables)

Figure 1 displays the global feature importance ranking based on the average absolute SHAP values for the test set. Of the top ten predictors, three are associated with asset depreciation: residual_ratio ranks 2nd, asset_age ranks 5th, and useful_life ranks 8th. Interest rate is the most important feature, followed by residual_ratio. Borrower characteristics, including firm_age (3rd) and registered_capital (6th), demonstrate notable predictive power. Contract-level variables, including down_payment (4th) and lease_term (7th), occupy intermediate positions.

4.3. Feature Effect Analysis

Figure 2 presents SHAP dependence plots for three important variables, showing their directional effects on default probability. SHAP value analysis reveals key drivers of default risk across the panels. In panel (a), a higher residual_ratio is strongly associated with a lower default probability. Conversely, panel (b) shows that older equipment (asset_age) correlates with a higher risk of default. Finally, panel (c) confirms the expected positive impact of rising interest rates on default likelihood. These results demonstrate the significant economic impact of asset depreciation on default risk, strengthening confidence in the model's predictive power regarding these features.

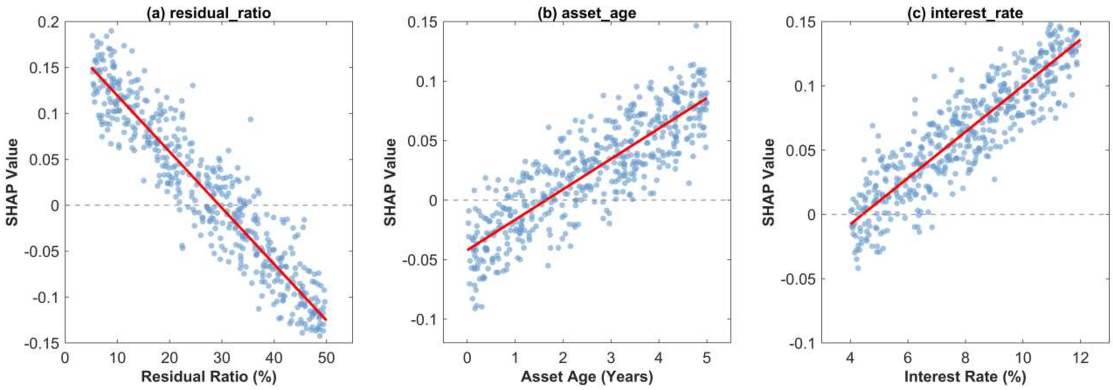

Figure 2. SHAP Dependence Plots for Key Variables

5. Discussion

The results substantially contribute to the prediction of leasing defaults. This performance hierarchy-with gradient boosting models leading-further validates prior evidence of their effectiveness in predicting SME defaults [9]. The large gap between XGBoost and logistic regression also highlights the need to use nonlinear models in predicting leasing defaults due to the nonlinear relationships involved.

Furthermore, the negative correlation between the residual value ratio and the probability of default is a collateral effect. This dual incentive system, which is the basis for the leasing framework, differentiates leasing from unsecured credit, in which incentives are entirely based on borrower characteristics. The positive relationship between asset age and default probability captures the effect of the dual incentive system, as the incentives for both parties are limited at the termination of the equipment's useful life.

Decomposing predictions into constituent parts makes it easier to formulate differentiated intervention strategies, allowing asset-related risk factors to be targeted with strategies such as collateralization and optimization of contract length. In addition, as has been identified in Lin and Wang [10], attribution instability in SHAP can create problems when moderately important features are involved. For operationalization purposes, leasing companies can include residual value projections in credit scoring models and regularly reassess residual ratios throughout the life of the contract to identify accounts with negative equity before payment problems arise.

Several limitations warrant acknowledgment. First, the sample is drawn from a single Chinese equipment leasing firm, which raises issues of generalizability to other markets. Second, the sample period from 2020 to 2024 overlaps with the pandemic-induced disruptions, which may have affected the usual patterns of defaults. Third, the accounting-based estimates of depreciation, as opposed to market-based valuations, raise issues of measurement. Additional research with a more comprehensive sample and market-based asset valuations would increase the confidence in the current findings.

6. Conclusion

This study shows that the characteristics of asset depreciation contribute significantly to the prediction of leasing defaults. The interpretable machine learning model indicates that the adequacy of collateral indeed operates as another channel of risk in addition to the standard risk factors related to borrowers and contractual agreements. By applying credit risk theory to leasing, this study offers financial institutions serving SMEs a novel perspective on default prediction.

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