An ESG-Modified Credit Risk Assessment Model Based on Decision Tree Model

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ABSTRACT

How to accurately assess corporate credit risk is a very important issue for financial institutions such as banks. Especially after the 2008 financial crisis, the discussion of credit ratings has gained more and more attention, and various evaluation models have been proposed to predict credit risk for enterprises. This paper is different from the traditional evaluation system, relying only on financial indicators. In this research, the ESG performance that reflects the sustainable development ability of the enterprise is included in the company's evaluation system for analysis. In addition, considering the inherent differences in ESG performance between different industries, a new indicator—relative ESG scoring is created to eliminate industry impact and obtain a more fair ESG evaluation. Then, this paper collects the data of 51 companies in different industries, establishes three decision tree models for comparison, adds ESG performance and relative ESG scoring in turn, and finally gets the model prediction accuracy rates: 71.43%, 80.95%, and 85.71%, respectively. After analyzing the results, it is proved that the addition of ESG performance and the newly created indicator can significantly improve the prediction accuracy of the credit risk assessment model, which provides a new idea for improving the index system of the credit risk assessment model.

Keywords: *Credit risk assessment, ESG scoring, Relative ESG scoring, Decision tree model.*

1. INTRODUCTION

1.1 Background

Credit risk is the possibility that the borrower (e.g. a listed company) is unwilling or unable to repay the lenders due to financial crisis, bankruptcy, or other reasons, resulting in losses to the bank, investor, or counterparty. Once credit risk occurs, corporate defaults can have a knock-on effect on banks and other related entities[1]. The assessment of credit risk is a matter of great concern to banks around the world since imprudent approval of the loans can have dire consequences, like the devastating financial crisis in 2008. Therefore, credit risk assessment has attracted great attention from many researchers, financial institutions, and the government in recent years. To accurately measure the credit risk of an enterprise, the core problem is to make a reasonable prediction of the default of the companies that may occur in the future. Up to now, the majority of scholars have made judgments only from the financial performance based on the indicators and data in the financial statements, without taking other factors that may affect credit risk into consideration.

Meanwhile, ESG ratings are showing an increasingly crucial impact on measuring the overall performance and potential of companies. With the promotion of sustainability and low-carbon awareness, governments and financial institutions are paying more attention to the ESG performance of enterprises. Companies with excellent ESG performance tend to get more policy privileges and investor preferences, which will furthermore have a non-negligible indirect impact on the financial situation of these enterprises. Therefore, ESG performance is included in the credit risk assessment to predict the default more accurately, which can significantly reduce the credit loss of the banks.

1.2 Related Research

In the selection of evaluation indicators, most of the research is only based on the financial indicators in the public financial statements of enterprises. However, the concept of sustainability has become more and more important, especially in today's world. Weber et al. analyzed the role that criteria pertaining to sustainability and environmental orientation play in the commercial credit risk management process based on data from

Y. Jiang et al. (Eds.): ICEDBC 2022, AEBMR 225, pp. 15–21, 2022.
https://doi.org/10.2991/978-94-6463-036-7_4

Bangladeshi banks and proposed that the company's sustainability performance may affect its creditworthiness as part of its financial performance [2]. Nevertheless, only a small number of studies have added the indicators of ESG performance so far and the existing research on ESG performance only depicted the indicators roughly.

To accurately assess the credit risk of different companies, much research has been conducted to build an effective assessment system. The credit risk assessment is essentially analyzing relevant data such as financial indicators to predict the default probability of the enterprise. Most mainstream research uses the credit scoring model to score each enterprise of their credit risk and sets risk warning lines to divide enterprises into two categories: defaulting enterprises and non-defaulting enterprises. The existing risk evaluation methods can be categorized into two types, the univariate analysis method, and the multivariate analysis method. The univariate analysis method is first proposed by Beaver, using only a single financial indicator, which is relatively simple to calculate but less accurate [3]. This is because a single indicator is not possible to comprehensively reflect the complex business conditions of the company. So the multivariate analysis method is better on this issue, and it is also more often used by researchers.

Multivariate models can be subdivided into three categories: statistical, operational research, and data mining. Statistical methods include option pricing theory, such as the EDF model developed by KMV, which combines real-time data from the stock market to measure the company's expected default frequency to determine credit risk. Durand established a reliable discriminant function under the structure of the discriminant analysis method and imported the company's data for classification to make credit decisions [4]. Methods of operational research include linear programming, integer programming, and the analytic hierarchy process. Freed et al. developed a linear discriminant algorithm eliminating the complexities of conventional statistical approaches[5]. Bajgier et al. compared the results of three linear programming approaches for the discriminant problem which included two formulations from Freed and Glover and indicated that each method was statistically preferable [6]. Besides, some models based on data mining are prevalent in recent research, such as the decision tree method, neural network, genetic algorithm, and nearest-neighbor interpolation [7-9]. With these methods, it is feasible to find the correlations between indicators and identify data features to make the right predictions through computer programs.

1.3 Objective

According to the related research above, it is obvious that detailed and accurate measurement of ESG performance hasn't been taken into the assessment model, which is also the problem that this paper tended to solve.

This paper aims to select ESG scores and add these indicators into the credit risk assessment procedure to reflect a company's sustainability, instead of only analyzing the financial variables. The ESG scoring is used to reflect the ESG performance of the enterprise, which is also the authoritative ESG evaluation method common to listed companies. In this essay, the ESG scores are gathered from SynTao Green Finance ESG ratings and RANKINS CSR Ratings, two authoritative ESG scoring institutions. Additionally, a new indicator called Relative ESG Performance is created to reduce the impact caused by the difference between various industries. In this way, the assessment model can not only depict the ESG performance well but also effectively reduce the bias due to the intrinsic differences between different industries.

This paper also meticulously portrays the financial performance of the enterprise and selects 18 different indicators from different aspects of the financial performance for analysis, which enables a comprehensive evaluation of the company's default probability by considering both financial performance and ESG performance.

Based on the decision tree model, our goal is to figure out whether ESG performance can help better predict the probability of credit defaults of companies and enhance the prediction accuracy of the credit assessment system using financial and ESG indicators.

2. METHOD

2.1 Data Collection

This article collected the financial and ESG performance data of 51 Chinese listed companies from various industries, (retail, manufacturing, insurance, transportation, real estate, finance, etc.) to ensure that this assessment model can be widely applicable. According to the provisions of the stock exchange, ST stock refers to the stock of enterprises that are given special treatment since they have been operating for two consecutive years of financial loss. Similarly, *ST stock refers to the stock of enterprises that receive delisting warnings since having operated for three consecutive years of loss. Such enterprises are often in unhealthy financial conditions or even bankruptcy, which means they are very likely not to repay their debts. For this reason, this article chose ST and *ST enterprises as defaulting enterprises. Through the CSMAR database, a total of 17 defaulting enterprises and 34 non-defaulting enterprises are selected, which are matched following the principle of similar size in the same industry.

In general, the data disclosure is relatively comprehensive, only a very small amount of data is missing. Noticing this, the missing-value filling is conducted to continue the next steps. In addition, a sample equalization process was carried out to improve the accuracy of the prediction, expanding the number of default samples to 34. The enriched sample data is then divided into two categories: train set and test set. Since the decision tree model requires enough data to learn and train to ensure a high accuracy rate, 24 non-defaulting companies and 24 defaulting companies are selected as train sets, and 10 non-default companies and 10 default companies are used as test sets.

2.2 Indicator System

In terms of indicators, two major types of data are collected: financial indicators and ESG indicators.

Financial indicators are mainly divided into four aspects: Solvency, Profitability, Operating Capacity, and Development Ability. It includes 18 indicators of Class A financial statements (shown in Table 1) including current ratio, quick ratio, cash ratio, cash flow-based interest coverage ratio, debt to assets ratio, return on assets, return on equity, gross operating margin, accounts receivable turnover, the growth rate of net profit and so on.

In terms of ESG performance, this article uses ESG scorings issued by professional rating agencies-- SynTao Green Finance ESG Ratings and RANKINS CSR Ratings to reflect the overall ESG performance of the company. ESG rating agencies collect public information on the company's environmental, social and corporate governance aspects and self-disclosure information, quantitatively evaluate the ESG situation and finally convert the ESG information into a sustainable development performance score that investors can easily use. This score has also become a necessary disclosure content for listed companies stipulated in many exchanges so it can better reflect the true ESG performance of the enterprise.

Apart from the above, when collecting ESG rating data from companies in different industries, the phenomenon that the ESG scores of listed companies in different industries vary greatly is noticed. Some enterprises such as integrated financial services, telecommunications services, medical services, banking, insurance, and other service industries score between 2.4-4.7, while other manufacturing industries, such as the power production industry, textile, garment industry, and paper industry score only in the range of 0.4-1.5, which shows that there are likely to exist inherent differences between different industries, resulting in a large gap in the ESG rating results of companies in different industries.

Table 1. Indicator System

Facets	Indicators	
Financial Performance	Solvency	Current Ratio; Quick Ratio; Cash Ratio; Times Interest Earned; Cash Flow-based Interest Coverage Ratio; Debt to Assets Ratio
	Profitability	Return on Total Assets; Return on Assets; Return on Equity; Gross Operating Margin; Return on Investment
	Operating Capacity	Accounts Receivable Turnover; Inventories Turnover; Total Assets Turnover
	Development Ability	Growth Rate of Total Assets; Growth Rate of Net Profit; Growth Rate of Operating Profit; Growth Rate of Total Operating Revenue
ESG Performance	ESG scoring	
	Relative ESG scoring	

For further discussion, it is because some industries have their inevitable problems that are unfavorable to ESG ratings, which makes it difficult for listed companies in these industries to obtain higher ESG ratings. The electricity production and paper industries, for example, inevitably produce a lot of pollution and emissions in their production processes, resulting in negative ratings of environmental-level scores in ESG ratings. It is unfair and biased to score uniformly in the presence of such industry gaps. In response to this problem, this paper created a new ESG performance indicator based on the authoritative ESG score, which can not only describe ESG performance well but also eliminate this unfair problem caused by the inherent differences between different industries. This article created the indicator "Relative ESG Scoring", defined as follows:

$$\text{Relative ESG Scoring} = \frac{\text{ESG scoring of the company}}{\text{Average ESG scoring of the industry to which the company belongs}}$$

Finally, the whole indicator system is described in Table 1.

2.3 Decision Tree Model

The decision tree is essentially a graph structure and classifier that can analyze decision rules from a series of samples with features and labels, complete the classification and regression of samples, and present the classification results in the form of a dendrogram. This paper chooses the decision tree model in the machine learning field to conduct the research. It is because credit risk assessment is a relatively complex process, many independent variables are difficult to guarantee that the default risk is acted in the form of linear regression and it is often difficult to meet the assumption of normal distribution. So this paper does not use linear regression models such as logistic model and probit model used by many scholars[10-11].

The amount of data on defaulting enterprises in this article is small, only half of that of non-defaulting enterprises, so there is an imbalance problem in the data, which would cause biased predictions. Therefore, the SMOTE algorithm is used to equalize the positive and negative samples, so that the proportion of defaulting companies and non-defaulting companies can reach a 1:1 equilibrium state. After the sample equalization process is completed, the stratified sampling of 68 samples is carried out to complete the division of the train set and the test set. This paper selects a commonly used 7:3 ratio to let the train set contain 48 samples: 24 defaulting companies and 24 non-defaulting companies. And the test set contains 20 samples in total, 10 companies for each category. Besides, due to the relatively large number of indicators, several indicators are appropriately deleted during the actual model operation to avoid overfitting problems.

In this paper, the C4.5 decision tree algorithm is used to construct a decision tree recursively from top to bottom based on the selection rule that the indicator with the maximum information gain rate would be selected as the decision attribute. After the decision tree is generated, the decision tree is pruned to reduce the size of the tree structure, alleviate the overfitting problem, and finally obtain the decision tree classification result graph and model accuracy.

$$\text{Classification accuracy} = \frac{\text{number of correctly classified samples}}{\text{total number of test samples}} \times 100\%$$

To explore whether ESG indicators have an impact on the accuracy of credit risk assessment models and whether the newly constructed Renewable ESG scoring can solve the problem of industry differences and improve model accuracy, three different decision tree models are constructed for analysis.

3. RESULTS AND DISCUSSION

In this paper, a credit evaluation model is established based on the decision tree method. Through the analysis and learning of enterprise-related indicators, enterprises are classified into two categories: defaulting companies and non-defaulting companies. A total of 18 classic financial indicators in four aspects: Solidity, Profitability, Operating Capacity, and Development Ability are considered in the indicator system of the decision tree model. First of all, only financial indicators are considered in Model 1, Model 2 is added ESG scoring to see the impact of ESG scoring on the accuracy of the model. Model 3 includes Relative ESG scoring, which is the newly created indicator in this paper, to study whether excluding industry factors can improve the model prediction ability. After processing the data and model settings, the classifier is trained with a training set. When the classifier is formed, the test set data is tested to output the accuracy.

The results of the output accuracy of the three models are as follows:

Table 2. Accuracy Result

	Model 1	Model 2	Model 3
Accuracy	71.43%	80.95%	85.71%

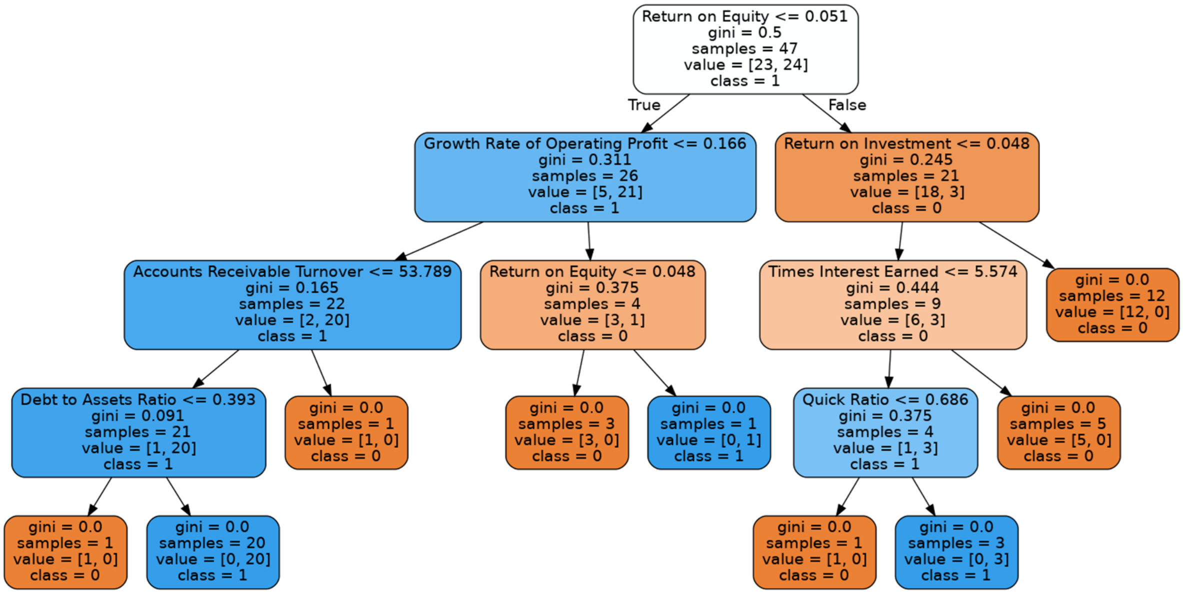

Figure 1 Decision Tree in Model 1

From the accuracy of the classification model, it is obvious that the accuracy rate of the three models is over 70% and increases in turn. The maximum can reach nearly 86%, indicating that the prediction ability of the model is accurate and the prediction results are also reliable. Besides, according to the results of the ROC curve, the deviation from the X-axis indicates that the probability of misjudgment is low and the AUC value is about 0.86, which can both evince that the decision tree classifier in this paper is effective.

Based on the results above, the decision tree model is effective in predicting corporate default risk, which can assist banks and other financial institutions to make more rational credit decisions and reduce credit risk.

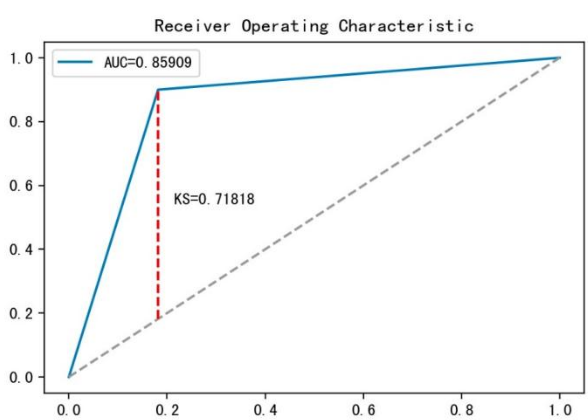

Figure 2 Receiver Operating Characteristic

For further analysis, from the comparison between model 1 and model 2, it can be found that after adding ESG scoring, the prediction accuracy has increased significantly, from 71.43% to 80.95%, which greatly improves the accuracy of the model prediction. This can also prove that the ESG performance of enterprises can be added to the credit risk evaluation system to measure the strength of enterprises from a richer and more comprehensive dimension, output more accurate prediction results, and reduce credit risks. This also provides new ideas for banks to credit ratings of enterprises.

Comparing Model 2 and Model 3, it can be found that the addition of a new relative ESG indicator can improve the accuracy rate by nearly 5 percent. This shows that in the specific process of ESG rating, the inherent differences between different industries hurt the objective measurement of the company's environmental performance, which reduces the accuracy of model discrimination. The newly created relative ESG scoring eliminates the industry gap, reduces this bias, and allows banks and investors to evaluate the overall performance of enterprises more wisely.

4. CONCLUSION

This paper collects the financial and ESG data of 51 listed companies in different industries and establishes three decision tree models to assess their credit risk based on different indicator settings. Through the models' prediction accuracy, the answer to whether ESG performance can help improve the credit risk assessment is clear. Finally, the models' accuracy rates are 71.43%, 80.95%, and 85.71%, respectively, which verifies that the addition of ESG performance can attribute to predicting the default risk of enterprises more accurately, which will help improve the current measurement of credit risk. The addition of ESG performance means that sustainability can have a beneficial effect on assessing the overall performance of a company. Moreover, the increasing emphasis on ESG is also a signal for the development direction of industries, indicating that publicly listed companies should attach more attention to their environmental, social and government performance. After adding the ESG indicators into the evaluation system, the companies with outstanding sustainability can get higher scores and then receive the investment and loans more easily, which concurs with the trend of "responsible investment"(investors are inclined to invest in a morally acceptable way).

In addition, by providing insight into ESG's industry rating distribution data, this paper identifies the potential drawbacks of using ESG scores solely to reflect sustainability. To tackle this problem, this paper creates a new ESG indicator, Relative ESG Scoring, to eliminate industry differences and obtain a more fair ESG performance. With this indicator, investors and governments can eliminate this inherent industry gap when making investment decisions and assessing companies in these industries, rather than just judging by the absolute size of the ESG score. Rational decision-makers can consider the company's relative ESG performance in the specific industry (i.e. whether the company's ESG performance is comparatively better than that of other competitors in the industry), to make investment choices, credit decisions, and strategies. This indicator also significantly improved the accuracy of the model and proved its value for properly measuring ESG performance and credit risk assessment.

Regarding the research on credit risk assessment, a large number of scholars have invested energy and got fruitful results. There are dozens of evaluation models, and this paper only chooses the decision tree model for analysis and obtains the results considering the data characteristics. Subsequent research can be conducted by trying more models to improve generalization ability.

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