Improvement of Traditional Bond Default Identification Model Based on ESG Score

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Abstract: The most important problem in the bond default field is whether the traditional model meets theoretical expectations well. To accurately identify bond default risk, this paper establishes a theory which introduces ESG scores into the traditional model of bond default identification based on some economic theory and tests the feasibility of the theory through empirical study methods. Has there been an improvement after incorporating ESG scores? After proving that incorporating ESG can truly predict reality well and have consistent practice by using the logistic regression method, this paper uses the CatBoost method in machine learning to solve an accurate prediction model. In the end, it was found that there is a significant positive relationship between ESG and bond default risk. After analysis, this paper draws the following results. First, ESG can help us better identify bond default risk. Second, when the company judges that its operating status is not good, it will whitewash the company through earnings management and public opinion to improve its ESG score. Third, the company will also default on bonds due to improper earnings management. To sum up, the establishment of ESG theory provides investors with a more precise method to assess the risk of corporate bonds.

Keywords: Corporate Bonds, Default Rate, ESG Evaluation, Multiple Linear Regression, Stepwise Regression.

1 INTRODUCTION

Nowadays, the rapid development of China's economic level has a certain negative effect on the environment and society. To continuously coordinate economic development with the environment and society, relevant laws and regulations have been introduced, and ESG concept has started to enter the vision of investors, enterprises, and the whole society. ESG evaluation system focuses on the performance of three non-financial indicators, namely environmental impact (E), social responsibility (S) and corporate governance structure (G), to measure the economic sustainability of enterprises.

From the existing research and practice around the world, many international organizations and investment institutions have introduced ESG concept into their original systems. At the same time, ESG has some connection with corporate credit risk. Three major credit rating agencies, Fitch, Moody's, and S&P have announced to the public the inclusion of ESG indicators into credit rating management. As the method gradually matures and practice

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advances, the application of ESG indicators on the impact of credit risk rating deserves attention.

Before 2014, China's bank wealth management products, trust wealth management products, and even fund subsidiary capital management products all had the feature of "rigid payment", which means that when the funds are at risk or the products fail to achieve the expected return, the issuer or channel party, for the purpose of interest and reputation maintenance, will guarantee the payment of the principal and return of the wealth management products by seeking third-party institutions to take over and using its own funds to advance the money first.

However, in 2014, the number of bond defaults in China exploded. In March, “11 Chaori Bond” became the first defaulted bond in the Chinese market, breaking the myth of “rigid payment”, as it could not pay the interest in full on time and reached the substantial default standard. “12 Jintai Bond” became the first bond to default on its principal. In recent years, bond default rate has gradually increased, which not only reflects the maturity of the China’s bond market, but also reveals that there is still a considerable credit risk in the market. As of 2021, there are 243 defaulting entities in China’s bond market, involving a total of 631 maturity defaulted bonds with a total maturity default amount of about 539.901 billion yuan. Analyzing the types of defaulted bonds, this paper finds that corporate bonds account for the largest proportion of the total number of defaulted bonds, which also illustrates that corporate bond credit risk deserves more attention and research.

As a bond variety with a high number of defaulted bonds, corporate bonds are representative in analyzing their specific default causes. Therefore, this paper combines ESG indicators and internal management ability with traditional corporate bond default impact indicators and constructs a system with a total of 11 variables at two levels: external to the company (macroeconomic), and internal to the company (financial indicators, ESG, and bond-related indicators), forming a more complete theoretical logic system through qualitative analysis. Moreover, with the consideration of data availability, 21 defaulted corporate bonds and 17 normal corporate maturity bonds from 2018-2021 are selected as the samples for constructing the corporate bond default risk identification model. Multiple linear regression and stepwise regression are applied to design the corporate bond default risk identification scheme, using the t-1 year data as prediction basis. Then, the results of whether ESG indicators are included are compared to determine the role of ESG information for corporate bond default risk identification.

2 LITERATURE REVIEW

Many domestic studies on ESG indicators on bond defaults and corporate ratings involve the analysis of environmental aspects, and environmental indicators should be particularly extensive in the rating of heavy industrial corporate bonds. Based on SynTao Green rating system, Zhang (2022) [1] selects credit bond issuers with defaults from 2014 to 2020 as sample data, establishes regression model analysis, and proposes that the evaluation indexes of environmental dimension mainly focus on whether enterprises have a clear environmental management system and whether they have a clear low-carbon and green plan. Using the Chinese bond ESG evaluation system as an indicator, Zhang et al. (2021) [2] analyzes ESG situation of 52 public bond issuers that defaulted in 2017-2020 and finds that ESG scores of companies decreased year by year in the three years before default, and representative deterioration indicators in environmental subordinate indicators were the ability of companies to meet environmental requirements and prevention and control of waste gas pollution.

The social perspective in ESG covers social responsibility elements such as employee relations, supplier management, investor protection, and community and social contributions. Ruan et al. (2019) [3] shows that corporate fulfilment of social responsibility enhances capital market recognition, improves corporate reputation, and reduces financing constraints and default possibilities through various ways such as charitable donations. Zhang et al. (2021) [4] shows that corporate fulfilment of social responsibility can improve moral evaluation, reputation, and access to policy support, enhance corporate development space, and reduce the possibility of bond default in terms of the endogenous dynamics of corporate growth.

The corporate governance component of ESG indicators, as the core of sound operation and development of companies, occupies a relatively important position. Leon et al. (2020) [5] uses empirical research to show the likelihood of bond default is highly correlated with four perspectives: highly concentrated ownership, inefficient board mechanisms, low disclosure of financial indicators, and high shareholder power. Li et al. (2017) [6], on the other hand, analyzes the relationship between concurrent independent directorship and bond default risk using data from listed companies issuing bonds in the Chinese bond market between 2010 and 2013. They conclude that the board payment, as one of the cores of corporate governance, has a correlation between bond default risk and the proportion of concurrent independent directors. The greater the proportion of concurrent independent directors, the less efficient their supervision, and the greater the default risk of the company. Sun (2022) [7] constructs a bond default risk assessment index system on the correlation between corporate governance and bond default, subdivides the corporate governance risk into three secondary indicators: corporate governance competitiveness, the shareholding ratio of the largest shareholder, and the amount of funds appropriated by related parties, and checks whether the corporate governance structure and board structure are reasonable.

There are many academic approaches to evaluate bond defaults. Incomplete contract theory argues for the possibility of evaluating the default risk of a company's debt through its financial status. Debt maturity structure theory points out that the duration of debt is also an important factor affecting default. Company competitiveness evaluation theory shows that the ESG rating system can be used to make an evaluation of a company's credit risk. Rao (2020) [8] summarizes several common models, such as GBDT algorithm, AdaBoost algorithm, support vector machine, BP neural net, and CatBoost model. Combined with the findings of Chang et al. (2019) [9] that ESG scores of domestic companies drop significantly before the occurrence of credit events, and the relationship between ESG and bond defaults is well justified by using above models.

3 RESEARCH DESIGN

In recent years, bond financing, as an important means of financing in China's capital market, has grown much faster than equity financing in the same period. Since March 2014, “11 Chaori Bond” broke the “rigid payment” of China's bond market. Since then, bond defaults have emerged one after another, and bond defaults may become “normal” in the future. Corporate bonds, as a bond with many defaults, have a certain degree of representativeness when analyzing the specific causes of default. Therefore, this paper combines ESG indicators reflecting corporate environmental responsibility, social responsibility and internal management ability with traditional corporate bond default impact indicators and constructs a system with 11 variables at two levels: external (macroeconomic) and internal (financial variables, ESG, bond-related variables), forming a more complete theoretical logic system through qualitative analysis. In addition, considering data availability, this paper selects 21 defaulted corporate bonds and 17 normal corporate maturity bonds from 2018-2021 as the samples for constructing the corporate bond default risk identification model, and applies multiple linear regression to design the corporate bond default risk identification scheme and verify the reasonableness, using t-1 year data as the prediction basis. Then, the results of whether ESG indicators are included are compared to determine the role of ESG information for corporate bond default risk identification.

3.1 Variable Selection

When selecting variables that affect corporate bond defaults, both extra-company and intra-company variables should be considered. The most significant of the extra-company variables are macroeconomic factors, while the intra-company variables cover mainly the company's finance and the bond itself.

3.1.1 Macroeconomic factors

As a result of assuming the default risk of the invested bonds, bond investors receive compensation for the risk premium, and in the bond market, the default risk of a certain bond is generally measured by comparing the difference between the interest rate of that bond and the interest rate of treasury bonds (risk-free rate) in the same period, which is also known as the credit spread. Since the macroeconomic development directly affects the Treasury rate, the credit spread associated with the Treasury rate is also directly affected, which in turn affects the company's financing costs. The indicator of annual GDP growth rate fully reflects the current macroeconomy. When annual GDP growth rate slows down or even becomes negative and the macroeconomy is in a downward cycle, investors tend to increase the weight of the Treasury rate in their portfolios, and companies can only attract investors by raising the interest rate of corporate bonds, which leads to high financing costs and can easily cause a break in the company's capital chain, which in turn increases the risk of default.

3.1.2 Company Financial Factors

Financial information is the most direct information to judge the company's operating condition, and investors can judge the company's solvency, profitability, operating capacity, and growth capacity from the published financial information.

Specifically, solvency indicators visually reflect a company's ability to repay its debts and indicate whether the company has sufficient cash flow to repay its short-term and long-term debts. If a company has a low solvency ratio, it is more likely to default on its debts. Profitability indicators visually reflect a company's ability to generate earnings, and are representative of return on assets, return on net assets and earnings per share. If a company's earnings are volatile and unstable, it is likely to default on its bonds. Operating capacity indicators visually reflect a company's ability to operate its assets, and a representative indicator is accounting receivable turnover. If a company is slow to recycle funds and its working capital flow is easily disturbed by various external factors and thus unstable, the company has a high risk of default. The growth ability indicator intuitively reflects the company's potential for sustainable operation, and the representative indicator is the growth rate of operating income. If a company's operating income is stagnant and business growth is slow, the company has a higher risk of default.

3.1.3 Factors of bond itself

The indicators related to the bonds themselves also reflect the risk of bond default to a certain extent. The higher the coupon rate of the bond

and the larger the actual issue volume, the greater the pressure on the company's operating cash, the greater the pressure to repay the bond, and thus the higher the possibility of bond default

3.2 Data Introduction

This paper collates all the bonds issued by enterprises with bond defaults in

China's real estate industry from 2018-2021 and obtains 38 relevant bonds. Since there are many industries involved in bond defaults and large differences between different industries, it is difficult to compare them, thus this paper selects real estate enterprises with defaults after 2018, and a total of four enterprises with bond defaults are selected from Huaxia Happiness Foundation Co, Beijing Huaye Capital Holdings Co, Zhonghong Holdings Co, and Taihe Group Co. The data on the firm characteristics variables in this paper are obtained from the Guotaian database and Bloomberg.

3.3 Data processing

3.3.1 Assign values to special data

Examining the data, this paper finds that bonds are classified according to either “default” or “normal” status. To facilitate the data processing, if the bond status is "default", it is assigned a value of 1, which means the default probability is 100%; if the bond status is "normal", it is assigned a value of 0, which means the default probability is 0%.

3.3.2 Processing of missing values

By checking the data, this paper finds that there is no ESG rating for Zhonghong Holdings Co. in ESG rating data queried by Bloomberg, and randomly checking ESG ratings given by Shang Dao Rong Green, this paper find that Zhonghong Holdings Co. and Taihe Group Co. have the same

Table 1: Definition of Variables

Type	Variables and Unit	Symbol	Explanation
Dependent Variable	Default rate	Y	Probability of default on bonds
Independent Variable	Actual issue volume (1/10 billion)	X_1	Total number of bonds issued

	Coupon rate (%)	$\boldsymbol{X_2}$	The ratio of interest paid by the bond issuer to investors each year to the face amount
	Balance sheet ratio	alr	Total liabilities divided by total assets as a percentage
	Earnings per share	eps	Ratio of profit after tax to total equity
	Return on Total Assets	roa	Ratio of total enterprise net profit to average total enterprise assets
	Return on Net Assets	roe	Net income attributable to owners of the parent divided by average net assets
	Operating income growth rate	oig	Ratio of the increase in operating income of the enterprise for the current year to the total operating income of the previous year
	Accounts Receivable Turnover Ratio	tar	The relationship between the net profit achieved by the enterprise and the sales revenue
	GDP annual growth rate	gdp	Rate of increase of GDP in year T relative to year T-1
	Bloomberg ESG Score	esg	Combined environmental, social, and corporate governance score

ESG rating in 2018, and had similar ratings in the E, S, and G subscales, so it can be inferred that these two companies had similar ESG status in 2018, so the ESG rating of Taihe Group Co. in Bloomberg in 2018 was used instead of Zhonghong Holdings Co. for analysis.

Variable	L_1	L_2	L_3	L_4	L_5	L_6	X_1	X_2	P_1
VIF	7.34	7.69	17.67	10.96	21.24	7.21	1.64	3.70	3.16

3.4 Model Construction

3.4.1 Variable definition

There are one dependent variable and eleven independent variables in the regression model in this paper. Please see table 1.

3.4.2 Model building

This paper explains the effect of ESG on bond default probability by constructing the following multiple linear regression model without ESG factors.

$$Y = \alpha_1 X_1 + \alpha_2 X_2 + \beta_1 alr + \beta_2 eps + \beta_3 roa + \beta_4 roe + \beta_5 oig + \beta_6 tar + \gamma_1 gdp + \varepsilon$$

The model with ESG is as follows.

$$Y = \alpha_1 X_1 + \alpha_2 X_2 + \beta_1 alr + \beta_2 eps + \beta_3 roa + \beta_4 roe + \beta_5 oig + \beta_6 tar + \gamma_1 gdp + \emptyset_1 esg + \varepsilon$$

4 EMPIRICAL ANALYSIS

4.1 Multiple linear regression analysis

Multiple linear regression is a statistical analysis method that examines the linear relationship between a continuous response variable and multiple explanatory variables. Like simple linear regression, multiple linear regression examines the regression coefficients, the R-squared, the test and the conditions for holding.

Regression analysis was first done on all independent variables without the ESG score model and default rates, with the following results：

Table 2: VIF of Each Variable

R-squared	0.8499
Mean VIF	8.95
White test	0.0984

The table 2 shows that although the fit has improved slightly after the inclusion of the ESG scores, the VIF values have also increased significantly compared to before the inclusion, and several variables still have VIF values greater than 10, and there is multicollinearity, which still does not satisfy the conditions for multiple linear regression analysis.

Therefore, with or without the inclusion of ESG scores as a factor, trying to use multiple linear regression to explore the relationship between the dependent and independent variables requires trying new methods for improvement.

4.2 Stepwise regression-based model improvement

As the variables did not satisfy the conditions for multiple linear regression, this paper used stepwise regression to remove variables with co-linearity. The basic idea is to reduce the degree of multicollinearity by removing variables that are less important and highly correlated with other variables. The explanatory variables other than ESG scores were first regressed stepwise against the default rate, with the results in table 3.

Table 3: Regression Result

	Non standardized coefficient		Standardized coefficient	t	p	VIF	R^2	Adjusted R^2	F
	B	S.E.	Beta						
Constant	0.782	0.090	-	8.698	0.000**	-	0.306	0.287	F(1,36)=15.873 p=0.000
EPS	-0.178	0.045	-0.553	-3.984	0.000**	1.000			

The actual issue volume, coupon rate, gearing ratio, return on net assets, earnings per share, return on assets (ROA), operating income growth rate, accounts receivable turnover rate and annual GDP growth rate were used as independent variables, while the default rate was used as the dependent variable in the stepwise regression analysis. And the R2 = 0.306, which can explain 30.6% of the variation in the default rate. Furthermore, the model passed the F-test (F=15.873, p=0.000<0.05), indicating that the model is valid.

To test the normality of earnings per share, the P-P diagram test is then applied, which reflects the extent to which the actual cumulative probability of the variable matches the theoretical cumulative probability and can be used to examine whether the data obeys a certain type of distribution. If the data obeys a normal distribution, the data points should largely coincide with the theoretical straight line. As shown, the image is found to be approximately diagonal and the data points largely coincide with the theoretical straight line, indicating some normality.

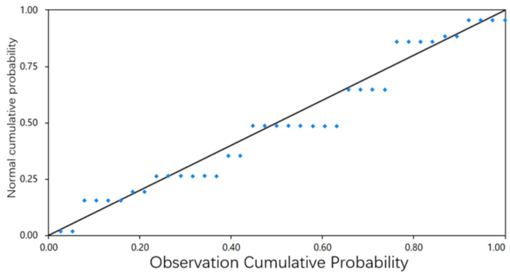

Figure 1: EPS Normal P-P plot

The model formula is:

Default rate = 0.782 - 0.178 * eps

The regression coefficient value for earnings per share is -0.178 (t=-3.984, p=0.000<0.01), implying that earnings per share can have a significant negative relationship on the default rate.

The heat map plots the correlation coefficients between the explanatory variables without ESG, with darker red indicating a stronger positive correlation and darker blue indicating a stronger negative correlation (fig. 2).

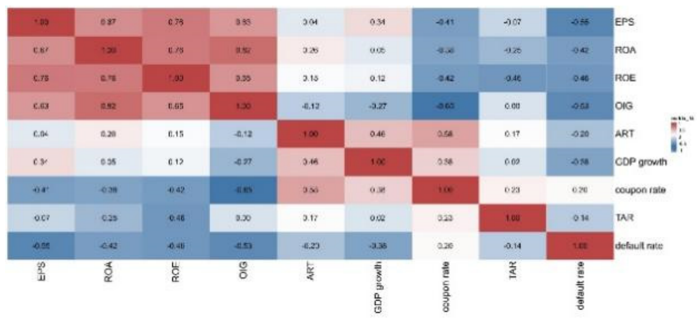

Figure 2: Heat map of correlation coefficients between explanatory variables without ESG

The higher calorific values in the upper left and middle regions were observed to be more relevant.

Through the above analysis, the performance of bond defaults over the period 2018-2021 does not fit with bond default theory through empirical analysis tests, this paper next proceeds to add ESG to the model for testing. The results are as follows：

Table 4: Regression Result Including Confidence Interval and VIF Value

Indicators	Regression coefficients	95% CI	VIF
Constant	-2.574** (-8.554)	-3.164~-1.985	-
EPS	-0.415** （-10.722）	-0.491～-0.339	4.24
ROE	2.316** （8.948）	1.809～2.823	5.13
OIG	-0.315** (-11.331)	-0.370~-0.261	3.40
TAR	0.020** (4.195)	0.010~0.029	1.85
ESG	0.189** (11.771)	0.158~0.221	4.22
Sample size	38		
R^2	0.891		
Adjusted R^2	0.874		
F value	F(5,32)=52.441,p=0.000		

The actual issue volume, coupon rate, Balance sheet ratio, eps, roe, Operating income growth rate, accounts receivable turnover, GDP growth rate, esg as independent variables, and default rate as dependent variable were used in the stepwise regression analysis, and after automatic identification by the model, the remaining NAV, EPS, operating income growth rate, accounts receivable turnover, and ESG were identified. A total of five items were included in the model, with an R-squared value of 0.891, implying that ROE, EPS, operating income growth rate, accounts receivable turnover rate and ESG could explain 89.1% of the variation in the default rate. Moreover, the model passed the F-test (F=52.441, p=0.000<0.05), indicating that the model is valid. The normality of earnings per share was then tested by a P-P diagram (as shown), and the images of the selected independent variables were found to be approximately diagonal, indicating some normality.

The model equation is：

Default rate = -2.574 + 2.316*roe - 0.415*eps - 0.315*oig + 0.020*tar + 0.189*ESG

In addition, a retrospective test for multicollinearity in the model revealed that the VIF values of several variables in the model were greater than 5 but less than 10, implying that there may be some cointegration problems, so the closely correlated independent variables were checked and the analysis was re-run after eliminating the closely correlated independent variables. The final specific analysis revealed that：

(a) The value of the regression coefficient of roe is 2.316 (t=8.948, p=0.000<0.01), implying that NPA will have a significant positive relationship on the default rate.

(b) The regression coefficient value for earnings per share is -0.415 (t=-10.722, p=0.000<0.01), implying that earnings per share can have a significant negative relationship on the default rate.

(c) The regression coefficient value for Operating income growth rate is -0.315 (t=-11.331, p=0.000<0.01), implying that the growth rate of operating income will have a significant negative relationship on the default rate.

(d) The regression coefficient value for accounts receivable turnover is 0.020 (t=4.195, p=0.000<0.01), implying that accounts receivable turnover will have a significant positive relationship on default rate.

The value of the regression coefficient for ESG is 0.189 (t=11.771, p=0.000<0.01), implying that ESG will have a significant positive relationship on the default rate.

A heat map of the correlation coefficients between the explanatory variables for the inclusion of ESG is plotted in fig.3.

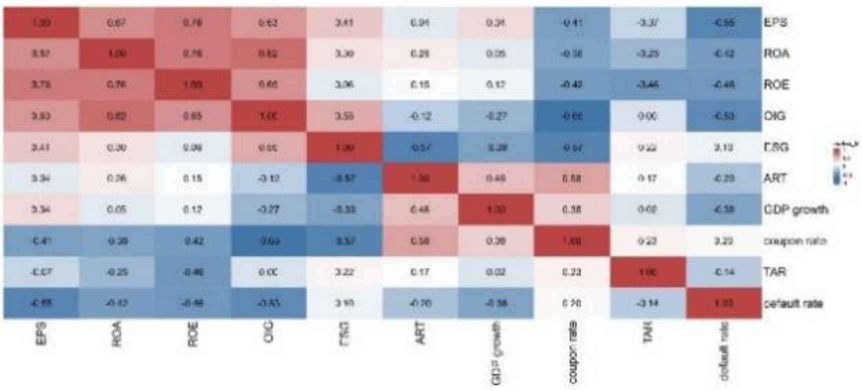

Figure 3: Heat map of correlation coefficients between explanatory variables including ESG

The heat map of correlation coefficients between explanatory variables relative to those that do not include ESG is less red as a proportion of the full plot, indicating that it has fewer multicollinearity variables than those that do not include ESG, consistent with the results of the stepwise regression method (only one variable remains after stepwise regression).

Thus, by incorporating ESG into the model, more of the independent variables pass the stepwise regression test, including the ESG score, which is partially in line with theoretical expectations.

However, as the bond default rate has a value of 0 or 1, like a dummy variable, it would be more natural to treat it as a dummy variable.

4.3 Model improvement based on machine learning CatBoost

The use of multiple linear regression cannot handle bond default models that incorporate or exclude ESG, and stepwise regression, while able to explain the effect of some variables on bond defaults after reducing some of them, still excludes factors that should theoretically be included. Now this paper uses CatBoost algorithm to construct a corporate bond default risk identification model as an improvement of the regression model, and thus designs a corporate bond default risk identification scheme incorporating ESG information based on the CatBoost algorithm.

Without considering ESG:

The parameters were first designed, and the specific values were selected as shown in the following table:

Table 5: Parameter Design Value Selection

Data Slicing	0.7
Data Shuffle	Yes
Cross-validation	No
Number of iterations	100
Learning Rate	0.1
L2 canonical term	1
Maximum depth of the tree	10
Overfitting detection threshold	0
Number of iterations to continue after reaching optimization	20

The training was carried out after the parameter settings were made and the following results were obtained:

Table 6: Results of Training Set and Test Set

	MSE	RMSE	MAE	MAPE	R^2
Training set	0	0.003	0.002	38.563	1
Test set	0.018	0.134	0.09	62.133	0.926

In summary, using the Catboost method can predict a sample fit of 0.926, which is a significant improvement over the previous one, but with a larger MAPE value.

A graph of the test data predictions is shown in fig.4, which shows a good trend and fit.

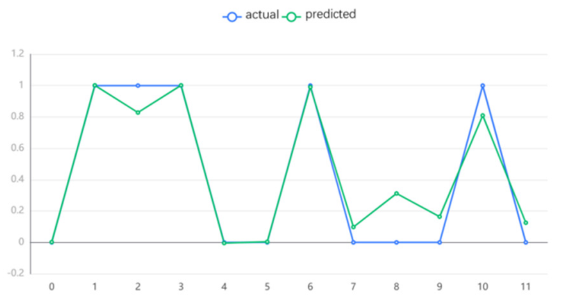

Figure 4: The graph of the test data predictions

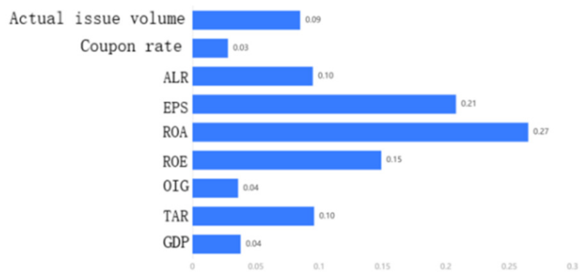

Figure 5: The importance of all features

Now consider the case where ESG scores are integrated into the model. The parameter design was the same as before. After performing the training with the parameter settings, the following results were obtained.

Table 7: Results of Training Set and Test Set

	MSE	RMSE	MAE	MAPE	R2
Training set	0	0.003	0.001	50.075	1
Test set	0.015	0.124	0.053	34.942	0.931

Seeing a significant reduction in the MAPE value from, while the fit is 0.931, another improvement from before, indicating a more accurate evaluation of bond defaults after incorporating the ESG score.

A graph of the test data predictions is shown below, which shows a good trend and fit.

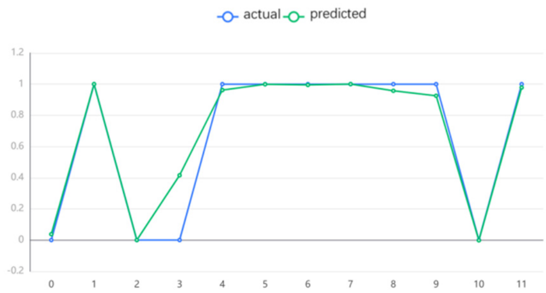

Figure 6: A graph of the test data prediction (ESG scores are integrated)

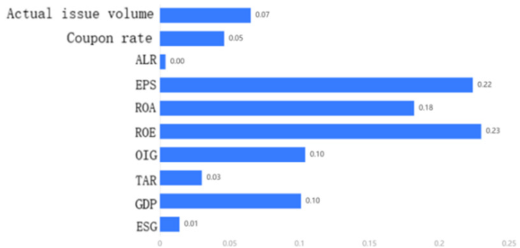

Figure 7: The importance of all features (ESG scores are integrated)

4.4 Improvement of CatBoost prediction model based on CatBoost classification

In line with the idea of using logit regression to improve multiple linear regression models, CatBoost regression is suitable for making predictions on continuous variables, but the default rates used in this paper are discrete variables, so this paper use the CatBoost classification model instead of the regression model.

This paper used the Catboost classification for each of the two cases with or without ESG, with the same parameter settings as in the Catboost regression, to produce the following results:

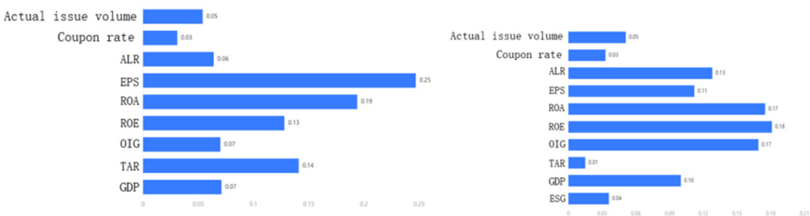

Figure 8: The importance of all features

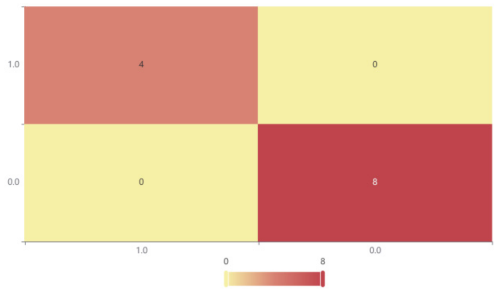

Figure 9: The Confusion Matrix

Table 8: Model Assessment Results

	Accuracy	Recall	Precision	F1
Training set	1	1	1	1
Test set	1	1	1	1

5 CONCLUSION

By comparing the two models in the linear regression and whether to include the variable ESG score, the precision of the judgement of the default rate of corporate bonds can be improved through the ESG score. Since there is a positive relationship between the ESG score of a company's T-1 year and the default rate of its bonds, which is not in line with previous expectations, this paper speculates that: firstly, companies improve their ESG scores through surplus management as well as through public opinion and whitewashing when they judge themselves to be in a poor state of operation; secondly, defaults on corporate bonds in the real estate sector are caused by prior mismanagement of surplus. Furthermore, the CatBoost approach still leads us to the same conclusion as the linear regression, namely that the incorporation of ESG will help companies to discriminate between bond default risk, but whether ESG has a positive or negative impact on this is more difficult to determine through the importance of the characteristics of ESG scores. This paper also finds that the inclusion of ESG in the explanatory variables is effective in reducing the multicollinearity between variables.

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