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Research article

The impact of ESG performance on the credit risk of listed companies in Shanghai and Shenzhen stock exchanges

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Abstract: A more precise and rigorous assessment of the impact of environmental, social, and governance (ESG) performance in business necessitates evaluating various firm characteristics. This study, focused on the ESG impact on enterprise credit risk, employed logistic models that incorporated the ESG rating index alongside other financial-related factors, including organizational structure, risk, and performance. The data were selected from all related listing companies in the Shanghai and Shenzhen stock exchanges. The results affirmed that (1) the risk of default decreased with improved ESG performance; (2) the return on assets, asset turnover ratio, leverage ratio, and operating income growth rate were the main financial factors affecting the default probability of enterprises; and (3) including ESG variables in the prediction model significantly improved the prediction accuracy of the model. The potential policy implications are presented in three perspectives. Businesses should prioritize developing good governance, fulfilling social obligations, and protecting the environment. Second, investors should integrate ESG ratings when making investment strategies. Third, the regulatory authorities are recommended to rapidly harmonize the ESG rating criteria and gradually develop the enterprise ESG information disclosure framework.

Keywords: ESG performance; enterprise credit risk; default risk; risk management; logistic model; financial indicators

JEL Codes: C52, G32, Q01

Abbreviations: (1) Roa: return on asset; (2) Liq: liquidity ratio; (3) Debt: debt-to-equity ratio; (4) Lev: leverage ratio; (5) Tat: total asset turnover rate; (6) Oig: operating income growth rate; (7) Qu: quartile

1. Introduction

The ESG (environment, society, and governance) index, a critical non-financial evaluation factor of enterprise value, is a more accurate and objective measurement of a firm's sustainability, making up for the deficiency of traditional financial information (Huang, 2021). S&P (2017) reports that more than 1,000 credit rating decisions related to ESG considerations have been made since 2015. According to Yang and Li (2023), the ESG concept is highly compatible with China's five development concepts: "innovation, coordination, green, open, and inclusiveness".

The vital turning point for the ESG industry is the onslaught of Covid-19, as the global health crisis has contributed to heightened attention in the ESG industry. Similarly, the increasing attention given to public debates on corporate social responsibility due to negligent behaviors of enterprises and major ESG-related scandals illustrates the importance of sustainability in credit markets (Mutamimah et al., 2021). In this regard, the materiality analysis of ESG extended from the perspective of investors to creditors, and a connection between higher effectiveness of overall risk management and better management of ESG criteria, has been demonstrated in the important academic, private sector, and multi-sector analysis (Henisz & Mcglinch, 2019). Among various firm risks, credit risk is defined as a measurement of the ability of firms to fulfill their contractual obligations related to several characteristics of firms, including leverage, earnings, collateral, reputation, and management competency (Altman & Hotchkiss, 2010). According to Barth et al. (2022), ceteris paribus, a lower probability of default, in other words, a lower credit risk, should arise from the higher ESG performance of firms with a more stable cash flow. After signing UNEP's Statement by Banks on the Environment and Sustainable Development, an increasing number of institutions have begun to recognize this connection and incorporate ESG information into risk assessments (Eliwa et al., 2021). Therefore, incorporating ESG into credit risk models will improve the efficiency of risk management and potential performance benefits.

However, the disclosure of ESG information is still in its early stages in China, and promotion is needed because of the paucity of literature on the metrological analysis of ESG development (Pan et al., 2022). While numerous studies focused on the financial influence of ESG in equity markets and the mutual fund industry, the prime question of interest is whether ESG performance is linked to credit risk (Pu, 2022; Gillan et al., 2021). In order to incorporate ESG performance into enterprise credit risk analysis, this article uses the ESG rating as the core variable and builds a logistic model to examine the credit risk of listed enterprises in the Shanghai and Shenzhen stock exchanges.

Specifically, this paper attempts to investigate whether a negative relationship exists between an enterprise's ESG scores and its credit risk. Additionally, the effects of other significant financial indices on credit risk are explored. Furthermore, various models are compared to assess how the ESG index may effectively predict credit risk. An essential contribution of this study is the provided strategies for business owners, investors, or governments to mitigate enterprise credit risk based on the negative relational correlations between ESG performance and credit risk. The remaining sections of this paper include a literature review, methodology, results, discussions, conclusions, and recommendations.

2. Literature review

Previous literature has discussed the impact of ESG performance on credit risk in two opposing views. The first stream of opinions believes that ESG decreases credit risk. According to the risk mitigation viewpoint, encouraging ESG performance will generate stronger cash flows that are less volatile, lowering the credit risk (Goss & Roberts, 2011). The first claim made in support of this position is that ESG activities benefit intangible assets such as reputation capital, moral capital, and policy support, in the long run enhancing shareholder wealth (Jang et al., 2020). For instance, high-reputation businesses' clients might be willing to pay a premium for their goods, suppliers may accept longer terms of payments, and reduced hiring expenses might be possible (Albuquerque et al., 2018). The moral capital derived from ESG activities also provides enterprises with an additional buffer during the strike of unfavorable events (Ghoul et al., 2017). The company's ESG activities signal its willingness to help other social actors and increase transparency to avoid information asymmetry, despite the expected high expenses, thereby reducing the perceived default risks by the investors (Jang et al., 2020). Put differently, as stated by Godfrey et al. (2009), "CSR-based (more general ESG) moral capital creates value if it helps stakeholders attribute the negative event to managerial maladroitness rather than malevolence and temper their reactions accordingly".

Additionally, ESG performance directly impacts financial gains, particularly when it comes to decreased capital costs (Godfrey et al., 2009). The implications of investor preferences for ESG attributes on firms' costs of capital have been examined by a variety of recent theoretical models, typically showing that high ESG enterprises will have reduced costs of capital (Pedersen et al., 2021). According to the initial theoretical model developed by Heinkel et al. (2001), negative screening reduces investor ownership of organizations that perform poorly in terms of environmental, social, and governance factors, which decreases stock prices and increases capital expenditures for these businesses. Moreover, information asymmetry between the firm and the external investors is explicitly reckoned as the main cause of financing constraints. As indicated by Xu and Cheng (2020), the more the ESG performance alleviates the information asymmetry in the market, the better the firm is recognized by investors. However, credit ratings of banks are also adjustable due to Cov-19 for example, as shown by Chodnicka-Jaworska (2021).

On the opposite end, the overinvestment perspective views ESG as a waste of companies' resources. The appropriation of scarce resources may contribute to a rise in cash flow volatility and, thus, higher firm credit risk (Goss & Roberts, 2011). The high performance of ESG tightens resource constraints on businesses, necessitating more attention to environmental protection and social responsibility when allocating resources to maintain a multitude of relationships with stakeholders (Peterson, 2009). As a result of less investment in projects with the potential for positive net present values or development, firms' core competitiveness may suffer (Zhang et al., 2021).

Moreover, investing substantially in ESG may lead to conflicts between management, who stand to gain from overinvestment, and the shareholders, who bear the associated expense (Shiu & Yang, 2017). Unnecessary expenditures on charitable donations and aiding social services locally, nationally, and worldwide could increase the fluctuation of firms (Bhardwaj et al., 2018). In this sense, excessive investments in ESG tie up financial resources and reduce the business value, which explains the positive association between ESG performance and credit risk (Goss & Roberts, 2011).

In summary of the literature discussion and response to the debate, this study hypothesizes that firms with better ESG performance may experience lower default probability due to stable cash flows and loosened capital limitations. The mitigating effect of ESG improvement on credit risk is expected to be detected with other financial indicators reflecting the operation status of enterprises included in the prediction models.

3. Methodology and variables

The logistic modeling proposed by Theil (1969) is applied to incorporate ESG performance into the credit risk analysis and explore whether a comparatively excellent ESG performance decreases an enterprise's credit risk. Previous studies across various domains have extensively utilized logistic regression. Its effectiveness in modeling categorical outcomes has been validated in many previous studies such as the modeling of extreme weather events or understanding farmers' intention and willingness to install renewable energy technology, etc. It is especially well-suited for ESG research due to its ability to model the relationship between predictor variables and a categorical response variable. Unlike linear regression, which predicts continuous outcomes, logistic regression is tailored for categorical responses (e.g., "high ESG" versus "low ESG"). One of the model's strengths lies in its flexibility to combine with other financial indicators. By integrating ESG metrics with traditional financial ratios (e.g., debt-to-equity ratio and profitability), we expect to gain a comprehensive view of a company's overall financial health and performance. In summary, a logistic regression model is chosen, hoping that it will empower the research to explore the intricate interplay between ESG practices and company performance. The basic form of a binary logistic regression model is the following:

$$\pi(X) = \frac{\exp(\beta_0+\beta_1 X_1+\cdots+\beta_k X_k)}{1+\exp(\beta_0+\beta_1 X_1+\cdots+\beta_k X_k)} \tag{1}$$

Estimates of the regression coefficients $\tilde{\beta}$ can be found using the log-likelihood functions. To integrate ESG performance in the enterprise credit risk warning model, first, we specify the output as follows:

$$E(\mathrm{def}_i) = P(\mathrm{def} = 1|x) = \frac{1}{1+\exp\left[-(\alpha+\beta_1 \mathrm{ESG}+\sum_{i=2}^{n} \beta_i X_i)\right]} \tag{2}$$

where

• P is the probability of the categorical response variable def, describing the predicted default probability of the i-th enterprise. If the firm defaults, its def value should be 1, otherwise the corresponding def value should be 0.

• β_0 is the main coefficient, capturing the marginal effect of ESG on the probability of default. If high ESG performance reduces the credit risk happening probability, it should be significantly negative, and vice versa.

• ESG is the core predictor variable, ranging from 1–9 according to the nine levels of ESG rating from excellent to inferior.

• X_i represents financial-related predictor variables.

From the current research perspective, there are basically two major approaches to incorporate ESG into the prediction models: ESG index from rating agencies in practice and ESC scoring based on firm information by experts or researchers, although the former also largely relies on the firm information in their rating metrics. For the first approach, ratings institutions may provide comprehensive, transparent, and standardized benchmarks for ESG performance. These indices aggregate data from various sources, ensuring consistency and comparability across companies. On the other hand, expert ESG scoring relies on company disclosures and external assessments. Experts evaluate ESG practices based on their knowledge and expertise, considering factors possibly beyond what companies self-report. Although expert-driven ESG scoring complements self-reported data by providing an external perspective, it may vary in quality and depth depending on the expertise of the evaluators, in addition to its high cost in time and other aspects. Given such concerns, the current study takes the first approach of focusing on the ESG index, especially considering its consistency, transparency, and wide coverage.

The core predictor variable is based on the Huazheng ESG rating, covering the quarterly ESG performance of the A-share listed companies through Q3 2018 to Q3 2022. The dataset used for the study was available at the WIND database at the library of the first author' affiliated university when the current study was carried out. The database categorized rating levels together with explanations and indicators such as the standard of information disclosure and regulatory compliance to the regulations. The ESG ratings of the firms can be denoted by AAA, AA, A, BBB, BB, B, CCC, CC, and C from excellent to inferior. We assign a score from 9 to 1 to the collected ESG ratings, with a higher score indicating better performance.

With respect to the predictor variables, six financial-related indicators, as presented in Table 1, are selected to measure the operating status of firms in five respects: profitability, solvency, capital structure, operation, and growth. It is well-known and a common practice that assessing a company's financial health involves examining several critical indicators. Profitability stands out as a fundamental measure, reflecting a firm's ability to generate earnings relative to costs and investments. Key ratios like return on assets (Roa) and return on equity (Roe) provide insights into operational efficiency and shareholder value. Meanwhile, solvency, as emphasized by Graham and Harvey (2001), gauges a company's capacity to meet long-term obligations. Solvency ratios, such as debt-to-equity and interest coverage, ensure financial stability and creditor confidence. Capital structure, as stressed by Graham and Harvey (2001), influences risk, cost of capital, and flexibility. Striking the right balance between debt and equity financing is crucial for maximizing firm value. Operational effectiveness, encompassing metrics like inventory turnover and asset utilization, directly impacts profitability. Lastly, growth, as an indicator, reflects a company's expansion over time. Sustainable growth, supported by revenue growth rates and customer acquisition, attracts investors and ensures competitiveness.

Table 1. Definitions of financial-related indicators.

Financial respect	Index	Abbreviation	Formula
Profitability	Return on asset	Roa	Net profit / Average total assets
Solvency	Liquidity ratio	Liq	Current asset / Current debt*100
	Debt-to-equity ratio	Debt	Total liabilities / Shareholders' equity *100%
Capital structure	Leverage	Lev	Debt / Asset*100
Operation	Total asset turnover	Tat	Total sales revenue / Average total assets*100
Growth	Operating income growth rate	Oig	(Current operating income - Previous operating income) / Previous operating income*100

This study divided the selected 292 listed enterprises into two categories as samples. The default group comprised 126 enterprises, omitting two companies that were delisted by March 2023. All enterprises marked as "*ST" or "ST" in the collected database of the ESG grading system were included in the default group. Another group of 166 companies was selected from the same or a closely related industry with corresponding "ST" enterprises with normal operating performance. Listed enterprises with "ST" and "*ST" were generally enterprises given "special treatment" by Shanghai and Shenzhen Stock Exchanges due to their abnormal financial conditions, which mainly refered to situations of financial deficits or poor management for 2 to 3 consecutive years and, thus, with higher credit risk. The samples were made up of the normal group and the default group. For the purpose of examining the relationship between ESG performance and the degree of credit risk, logistic models were built using the data of the ESG index and other predictor variables of each enterprise.

The predictor variables of the ESG ratings were available at WIND at the library of the first author's affiliated university when the research was done, which provided transparent underlying data and scores combining the policies and status quo of ESG disclosures of the selected companies. Other financial-related variables were compiled from the Third Quarter Fiscal 2022 Results report, the most recent financial statement for each company that was available by February 2023, according the database for the study.

4. Results

4.1. Descriptive statistics and correlation analysis

The sample descriptive statistical results for the variables are displayed in Table 2. The mean value of the ESG index is 5.11, whose ESG rating is between BB and BBB, greater than the median value of 5, whose ESG rating is BB. The ESG index ranges from 2 to 9, with the standard deviation being 1.29, indicating that the sampled enterprises vary widely in their ESG performance. Even though the greatest Roa is 22.07%, the mean and median of its values are close to zero, and the third quartile is under 5%, demonstrating that the sample's overall profitability is poor, ranging from 0% to 5%. A degree of short-term solvency against emergencies is guaranteed by the mean and median liquidity ratios being 196.26% and 135.45%, respectively, with the first quartile being 83.89%. This indicates that nearly 75% of the included firms have more considerable current assets than current liabilities. Moreover, the wide range and high standard deviation of the included financial indicators, particularly the debt-to-equity ratio and liquidity ratio, show apparent differences in the operation, growth, and solvency among various enterprises.

Table 2. Sample descriptive statistics.

Variable	Observations	Mean	Std	Min	1^{st} Qu	Median	3^{rd} Qu	Max
Def	292	0.43	0.50	0	0	0	1	1
Esg	292	5.11	1.29	3	4	5.00	6	9
Roa	292	0.67	6.78	−22.11	−2.90	0.78	4.79	22.07
Liq	292	196.26	198.55	11.04	83.89	135.45	224.27	1700.25
Lev	292	55.93	32.32	1.04	30.97	53.16	55.93	179.55
Tat	292	40.62	44.07	0.50	13.60	32.49	40.62	357.70
Oig	292	56.89	40.06	−7.44	40.09	50.00	60.67	341.42
Debt	292	441.75	2265.72	−4063.46	34.46	85.00	223.78	24765.00

Table 3. Default group descriptive statistics.

Variable	Observations	Mean	Std	Min	1^{st} Qu	Median	3^{rd} Qu	Max
Def	126	1	0	1	1	1	1	1
Esg	126	4.325	0.76	3	4	4	5	7
Roa	126	−2.59	7.41	−22.11	−6.32	−2.73	0.60	22.07
Liq	126	128.76	113.96	12.02	58.49	89.10	154.73	518.83
Lev	126	72.57	36.63	6.94	42.41	75.83	94.12	179.55
Tat	126	29.03	25.76	0.50	8.69	17.98	45.64	151.60
Oig	126	63.17	53.64	−7.44	39.62	50.68	69.19	341.42
Debt	126	862.21	3412.45	−4063.46	33.43	128.64	627.68	24765.00

Table 4. Normal group descriptive statistics.

Variable	Observations	Mean	Std	Min	1^{st} Qu	Median	3^{rd} Qu	Max
Def	166	0	0	0	0	0	0	0
Esg	166	5.70	1.30	3	5	6	7	9
Roa	166	3.07	5.15	−10.63	0.27	2.29	5.89	20.32
Liq	166	247.89	231.84	11.04	117.39	168.52	280.9	1700.25
Lev	166	43.46	21.25	1.04	26.39	42.80	59.11	92.23
Tat	166	49.44	52.46	2.07	22.33	35.99	55.47	357.70
Oig	166	51.67	23.89	0.85	41.33	49.45	58.38	224.05
Debt	166	122.87	159.19	6.75	35.97	72.52	143.68	1187.35

The descriptive statistical results for variables in the default and normal groups are presented separately in Table 3 and Table 4. We can see that the profitability of businesses with reduced default potential is noticeably better by comparing the return on asset (Roa) performance between different groups, where the third quartile of the default group Roa is slightly over 0, and, on the contrary, over 75% of the Roas of the normal group are above 0. Apart from that, the non-default group's mean and median total asset turnover ratio (Tat) and liquidity ratio (Liq) values are roughly twice as high as those of the default group, explaining the normal group's superior capacity for operation efficiency and debt repayment.

However, it is discernible that the default group exhibits a higher overall leverage ratio and debt-to-equity ratio than the normal group, which reflects the default group's higher borrowing propensity and the normal group's lower debt ratio in the capital structure. As for the operating income growth rate (Oig), it has shown obvious differences between different groups due to their close mean and median values plus the relatively large ranges, with the exception of the significantly lower volatility and the absence of negative observations for the Oig rate in the normal group.

The mean and median of ESG for the default group are about 4 (ESG rating B), whereas they are around 6 (ESG rating A) for the normal group. The majority of the businesses with a higher likelihood of default have low ESG ratings, ranging from CCC to BB levels, which is explained by the considerably lower standard deviation of the ESG index of the default group. It has been discovered that a warning index for enterprise default risk could be an ESG grade that is lower than A. Nevertheless, a more thorough investigation is needed to determine whether ESG can be utilized as the primary predictor variable to assess the credit risk of enterprises.

Table 5. Pearson correlation coefficient matrix.

	P	Roa	Liq	Lev	Tat	Oig	Debt	ESG
p	1							
Roa	−0.42***	1						
Liq	−0.30***	0.29***	1					
Lev	0.45***	−0.53***	−0.06	1				
Tat	−0.23***	0.02	−0.01	−0.05	1			
Oig	0.14**	−0.01	−0.04	0.04	−0.03	1		
Debt	0.16**	−0.06	−0.11 *	0.19**	−0.05	0.02	1	
ESG	−0.53***	0.39***	0.24***	−0.3***	0.26***	−0.06	−0.08	1

Table 5 lists the Pearson correlation coefficient matrix of the variables, and the symbols ***, **, and * denote correlation coefficients that are significant at the levels of 1%, 5%, and 10%, respectively. The fact that there is a strong negative correlation between the default possibility P and the rates of return on assets (Roa), liquidity (Liq), and total asset turnover (Tat) suggests that improvements in these financial indexes may bring about a fall in the default probability. Simultaneously, P has a 5% level significant positive relationship with the operating income growth rate (Oig) and debt-to-equity ratio (Debt), as well as a 10% level significant positive relationship with the leverage ratio, which reveals that high debt and high operating income growth rates in an enterprise's capital structure will likely aggravate its credit risk. We can roughly infer that, without taking into account other variables, the better the corporate ESG performance, the lower the likelihood of enterprise default or rating decline because the correlation coefficient between the occurrence of credit risk events of enterprises and their ESG performance is significantly negative. Nevertheless, further empirical research is necessary for more precise conclusions. Noting that the majority of the absolute values of the correlation coefficients among the seven explanatory variables are below 0.2, it is evident that the multicollinearity issue in the model is not severe. As a result, a further regression analysis is appropriate.

4.2. Regression result

In order to further test the variables affecting the credit risk of listed enterprises, a logistic model for the empirical analysis was built.

Table 6. Regression using only ESG.

	Estimate	Std. Error
(Intercept)	6.0045***	0.7984
ESG	−1.2800***	0.1659

Table 6 presents the regression result of ESG alone with no other control variables. The coefficient is considerably negative at the level of 1%, confirming the conclusion that the better a company's ESG performance, the less probable that credit risk events would occur.

Table 7. Regression using only financial indicators.

	Estimate	Std. Error
(Intercept)	−1.2211*	0.6131
Roa	−0.0941***	0.0276
Liq	−0.0013	0.0012
Lev	0.0209**	0.0071
Tat	−0.0132**	0.0050
Oig	0.0084*	0.0037
Debt	0.0003	0.0002

When the core explanatory variable ESG is absent, the regression model assesses how other financial-related factors affect an enterprise's likelihood of default. As exhibited in Table 7, while the coefficient of the leverage ratio is significantly positive at the 5% level, the return on assets ratio (Roa) and total asset turnover ratio (Tat) are significantly inversely correlated with the default rate, suggesting that optimizing profitability, enhancing operational effectiveness, and reducing leverage can significantly lower corporate credit risk.

Table 8. Regression using both ESG and financial indicators.

	Estimate	Std. Error
(Intercept)	3.5864***	1.0340
ESG	−1.0422***	0.1796
Roa	−0.0633*	0.0293
Liq	−0.0007	0.0013
Lev	0.0201**	0.0077
Tat	−0.0069	0.0050
Oig	0.0084*	0.0040
Debt	0.00024	0.0002

Table 8 gives the regression outcomes with the ESG indicator and all the financial-related predictor variables included. The regression results show that ESG is significantly negative at the level of 1%, indicating that a high ESG index can significantly explain the low possibility of corporate credit risk events occurring. In general conformity with the findings shown in Table 7, the coefficients of leverage rate and operating income growth rate are considerably positive among the variables. In contrast, the coefficient of return on assets (Roa) is significantly negative.

4.3. Multicollinearity test

The generalized variance-inflation factors are calculated and examined to check whether any multicollinearity problem will affect the model's fitting effect between any of the seven variables. The variance-inflation factor (VIF), which can be interpreted as the inflation in size of the confidence ellipse or ellipsoid for the coefficients of the variables in comparison with what will be obtained for orthogonal data, quantifies the severity of multicollinearity through an ordinary least squares regression analysis gauging how much the variance of the estimated regression coefficient is raised as the result of collinearity (Yee, 2015). According to the collinearity diagnostic criteria of Hair (1994), we assume there is no collinearity problem between predictor variables, and no modification is required when the variance-inflation factors (VIF) are less than 10.

Table 9. Multicollinearity test.

ESG	Roa	Liq	Lev	Tat	Oig	Debt
1.0399	1.1629	1.6070	1.7836	1.0574	1.0152	1.0330

As can be seen from the data in Table 9, all of the variance-inflation factors (VIF) are around 1, far less than 10, so we may reckon that the collinearity problem is not serious.

4.4. Stepwise AIC backward regression

Intending to elect the optimal predictor variables influencing the default risk of enterprises for the accuracy improvement of the predicting model, stepwise AIC backward regression is then adopted. The optimal regression model is constructed using variables drawn from all of the seven candidate predictor variables by eliminating predictors stepwise according to the Akaike information criterion until no more variables are left to remove. The Akaike information criterion is a benchmark for selecting models that achieves a trade-off between finding the best fit and parsimony in the model structure. The overfitting problem is avoided by the penalty in AIC statistics imposed on the overparameterized model, resulting in a more parsimonious model (Hsu et al., 1995). The optimal variable set is then obtained, and the variable liquidity ratio (Liq) is removed with a decrease from 263.89 to 262.18 in AIC.

Table 10. The regression results of the model with the selected variables.

	Estimate	Std. Error
(Intercept)	3.3564***	0.9360
ESG	−1.0486***	0.1792
Roa	−0.06187*	0.0292
Lev	0.0226***	0.0062
Tat	−0.0069	0.0050
Oig	0.0084*	0.0040
Debt	0.0002	0.0002

First, a better ESG rating performance will probably contribute to a lower enterprise credit risk, as it is obvious that the core predictor variable ESG plays a positive role in identifying default risk, given that its correlation coefficient is significantly negative at the 1% level. Second, the relationship between the leverage ratio (Lev) and the operating income growth rate (Oig), and the likelihood of default, is positive, with coefficients of the two variables being positive and significant at 1% and 10%, respectively. On the other hand, the return on asset ratio (Roa) and total asset turnover ratio (Tat) are significantly negatively related to the default probability. Other indexes being equal, an enterprise with higher Roa and Tat ratios will be less likely to default. Finally, though not significant, the debt-to-equity ratio does affect the default probability in a positive direction.

The regression analysis is also conducted on the model without adding the core variable ESG but only optimal predictor variables are selected, and the result is displayed in Table 11 below:

Table 11. Regression without ESG.

	Estimate	Std. Error
(Intercept)	−1.7110***	0.4298
Roa	−0.0922***	0.0275
Lev	0.02572***	0.0058
Tat	−0.01314**	0.0050
Oig	0.0083*	0.0037
Debt	0.00026	0.00024

Compared to the results in Table 10, it can be noticed that neither the significance level nor the correlation coefficient of any given variable has dramatic changes, further demonstrating the trustworthiness of the best predictor variables that comprised the model. An enterprise's default risk can be reduced by optimizing capital structure, lowering its corporate debt ratio, and improving the management efficiency, turnover rate, and profitability of the income-producing assets. On the other hand, a higher income growth rate may not necessarily reflect that a corporation remains secure, and it can even raise credit risk to some degree. Although in Pu's (2022) research, the income growth rate representing development is found to have a negative correlation with the credit risk. This might be the result of the study's exclusive emphasis on the listed companies in the construction field.

4.5. Model diagnosis

Based on the above regression analyses, we can use the following formula to predict the default probability of enterprises:

$$\text{logit}(P) = \log(P/1\text{-}P) = 3.3564 - 1.0486ESG - 0.0619R + 0.0226L - 0.0069T + 0.0084O + 0.0002D \quad (3)$$

where R stands for the return on asset ratio, L for the leverage ratio, T for the total asset turnover ratio, O for the operating income growth rate, and D for the debt-to-equity rate for each enterprise in the sample. Since the intercept is 3.3564, the likelihood of defaulting could be predicted as follows:

$$P = \frac{\exp(3.3564 - 1.0486\text{ESG} - 0.0619\text{R} + 0.0226\text{L} - 0.0069\text{T} + 0.0084\text{O} + 0.0002\text{D})}{1 + \exp(3.3564 - 1.0486\text{ESG} - 0.0619\text{R} + 0.0226\text{L} - 0.0069\text{T} + 0.0084\text{O} + 0.0002\text{D})} \quad (4)$$

When the P is close to 0, it is indicated that the enterprise has little default probability and, on the contrary, when the P is approaching 1, the default probability and thus the credit risk for the enterprise is high. The expected P-values for the 292 enterprises are calculated according to the formula above, where an actual state of 0 signifies not being marked as an 'ST' enterprise with low credit risk, and a state of 1 indicates being marked as 'ST' or 'ST*' with high credit risk. The P is the default probability predicted by the model built for the enterprises.

The area under the receiver operating characteristic (ROC) curve, which plots the sensitivity (the probability that a default enterprise is predicted to be defaulted by the model) versus 1-specificity (the probability that a non-default enterprise is determined to default by the model), provides information on how well the model predicts outcomes. If it equals 0.5, the model is said to predict at random when the slope of the ROC curve is equal to 1. The model's predictive power increases with the value of the area under the curve approaching 1.

The ROC curve demonstrates that it deviates from the blunt curve, and the area under the curve (AUC) generated using R programming is 0.87904, confirming the prediction model's effective classification performance.

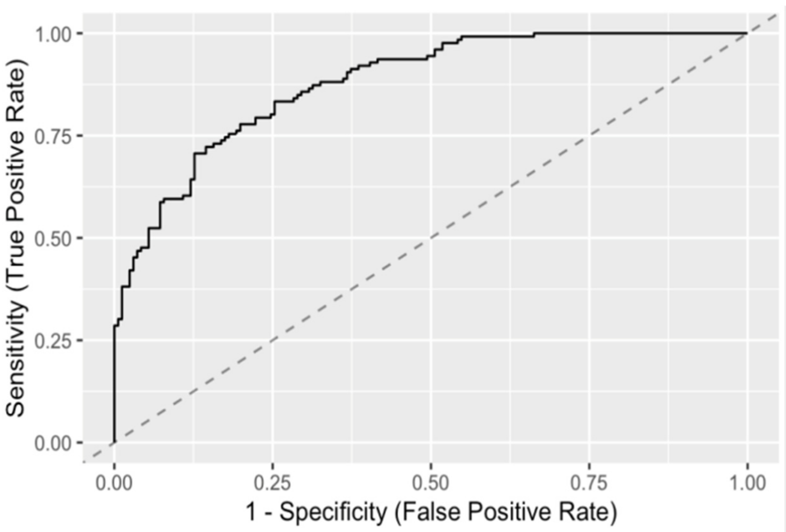

Figure 1. ROC of the model.

4.6. Robustness test

The robustness test is carried out by replacing the model variables to better illustrate the robustness of the regression results and the stability of the model. ESG2, a new rating criterion, is applied for the primary explanatory variable. A broader method for ESG2 is used instead of the original 1–9 scores for C–AAA, assigning A–AAA with 3, B–BBB with 2, and C–CCC with 1. With the new data set, logistic regression and stepwise backward AIC regression are performed. The results are shown in Table 12.

The results of the logistic regression of the model with all variables added appear in columns 1 and 2, while the results of the stepwise backward AIC regression are reported in columns 3 and 4. The coefficient of ESG is still significantly negative at the 1% level, pertaining to a comparison of column 1 and column 2 with the regression results in Table 8. The coefficient and significance level of the other variables are largely consistent with the full model described in part 2, except for the total asset turnover variable, which becomes significant at the 10% level.

Table 12. Robustness test.

	Estimate	Std. Error	Estimate	Std. Error
(Intercept)	3.03444*	1.2333	2.6976*	1.1709
ESG	−2.1506***	0.5447	−2.1771***	0.5459
Roa	−0.0824**	0.0286	−0.0804**	0.0285
Liq	−0.0010	0.0012		
Lev	0.0220**	0.0074	0.0258***	0.0060
Tat	−0.0111*	0.0051	−0.0112*	0.0051
Oig	0.0081*	0.0039	0.0081*	0.0039
Debt	0.0003	0.0002	0.0003	0.0002

Moreover, the results in columns 3 and 4 interpret that the optimal model is obtained after removing the liquidity ratio variable through the model selection, in accordance with the result obtained by the original data set, and the coefficient and significance results are similar to those presented in 4.2. Figure 2 provides the ROC curve of the model with the ESG2 variable, and the AUC calculated is 0.846768; though slightly lower than the original one, we can still tell that it has a strong ability for prediction. Consequently, the positive effect of ESG performance on reducing enterprise default probability and the reliability of the model built are validated through a robustness test.

Similarly, the robustness test's ROC curve illustrates that the AUC slightly decreases to 0.846768, confirming both the predictive validity of the robustness model and the dependability of the original model constructed with the selected variables. Due to the difference in the AUC values produced by employing ESG and ESG2, we may speculate that a more accurate ESG rating variable in the model will boost its predictive precision and capacity to identify defaulting organizations.

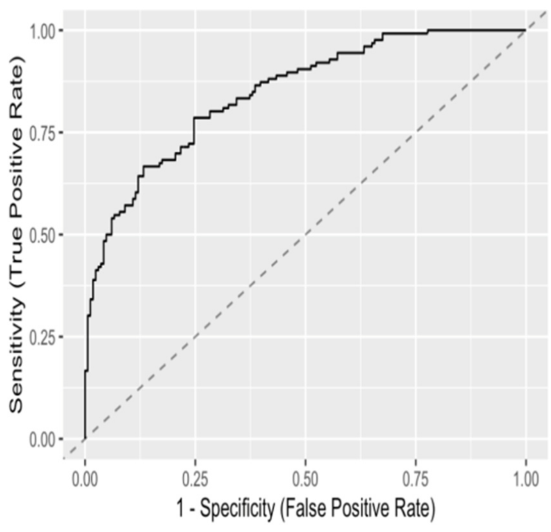

Figure 2. ROC for the robustness test.

5. Discussion

The default probability of each firm is derived after a back substitution is performed on the data set of the predictor variables in the sample into the prediction model to attempt to verify the prediction accuracy of the model. The predicted outcome of whether an enterprise defaults is determined and compared with its actual state according to a predetermined threshold value. The probability that a default enterprise will be projected to be in default by the model is balanced against the specificity and the probability that a non-default enterprise will be assessed to be normal when choosing a threshold value. The Youden index is used to select the best threshold point, where the Youden index is the sum of sensitivity and specificity minus 1, representing the logistic model's ability to distinguish between the real defaulting enterprises and normal enterprises. The performance of the model improves with increasing Youden index values.

Where the default probability P equals 0.5803213, the Youden index reaches its maximum. This intersection is thought to optimize the prediction accuracy; hence, the threshold value is set at 0.58. Enterprises are considered to have defaulted when the anticipated default probability exceeds 0.58; otherwise, they are considered in good standing. For the purpose of trying to determine whether the core predictor variable ESG should be included in the prediction model, the prediction accuracy of the entire model and the optimized model with and without the ESG index, which corresponds to the regression results in Table 7, Table 8, Table 10, and Table 11, are compared.

Table 13. Confusion matrix of the optimal model.

	With ESG				Without ESG		
Optimal model	Normal group	145	21	87.35%	149	17	89.76%
	Default group	39	87	69.05%	56	70	55.56%
				79.45%			75%

We first concentrate on the outcomes of the models that contain every predictor variable. When the core variable ESG factor is taken into account, relating to the regression result in Table 8, 87 out of 126 firms in the default group are expected to default, with a sensitivity of 69.05%. With a specificity of 87.35%, 145 out of 166 are predicted to be non-defaults in the comparable normal group. The model's overall prediction accuracy is 79.45%. When the core variable ESG factor is excluded, which corresponds to the model described in Table 7, 71 businesses in the default group are predicted to default, with a decrease in sensitivity to 56.35%, and the specificity for the normal group is 89.76%, or 17 out of 166 businesses in the normal group are predicted to default. Without the core variable, the model's total prediction accuracy decreases to 75.34%.

Second, the stepwise AIC backward regression results in Table 10 and Table 11 correlate to the regression results for the model's prediction accuracy employing only the variables chosen by this regression. The specificity is 89.76% and the sensitivity is 55.56% without the core variable ESG index. With a 75% overall prediction accuracy rate, 219 of the 292 firms' predictions align with the present situation. The specificity of the selected model marginally drops to 87.35%, the sensitivity climbs to 69.05%, and the overall prediction accuracy of the model hovers around 79.45% when the ESG component is taken into consideration. This also highlights the logistic model's capacity to quantify the credit risk of the listed enterprises.

Despite the fact that the sensitivity of the optimal variable model with the ESG variable is 2.41% lower than that without the ESG variable, it is discovered that the logistic model of enterprise default risk with ESG index is more accurate in terms of sensitivity, specificity, and overall prediction accuracy. Adding an ESG rating variable to the model without the liquidity ratio results in a 4.45% gain in prediction accuracy, and embedding an ESG rating index increases the total prediction accuracy of the model with all six financial variables by 4.11%. Thus, the positive influence of the inclusion of the ESG index on the prediction accuracy of corporate default risk is assessed.

With regard to each model, specificity is significantly higher than sensitivity, which implies that the model has a better performance at identifying non-defaulting businesses than defaulting ones. To be more precise, including an ESG variable in both the full and optimal models does not bring an obvious change in the specificity but improves the accuracy of predictions for defaulting enterprises by nearly 15%, which leads us to suppose that the ESG index has a more substantial impact on successfully predicting defaulting enterprises. Furthermore, there is no loss of accuracy in the logistic model with the ESG index after the liquidity ratio (Liq) variable is removed, which clarifies how the model chosen by the stepwise AIC backward regression achieves the same or even higher prediction accuracy of the full model with greater parsimony.

The hypothesis concerning the potential relationship between ESG performance and credit risk has been tested through multiple regression analyses. In effect, the results, which portrayed that the ESG factor plays a significant role in decreasing enterprise default probability, are consistent with the findings of Lins et al. (2017) and Bénabou and Tirole (2010), who observed that firms with more robust ESG profiles could have lower downside exposures due to better resilience during the financial crisis. In addition, the outcomes articulated that integrating the ESG index was evident to improve the precision of credit risk prediction. In alignment with Broadstock et al.'s (2021) analysis of cumulative returns taking advantage of the timely data during the COVID-19 crisis, it is possible for investors to systematically navigate away from adverse risk by viewing ESG performance as a valuable signal for future stock performance and risk mitigation in times of crisis. While empirical research in this field uses a variety of methodologies, such as dissecting ESG into its component parts and drawing diverse conclusions, this paper only takes ESG into account as one element. For instance, Ng and Rezaee (2015) discovered that while there was no association between social performance and credit risk, there was one between environmental and governance performance. Future research could be furthered by comparing the regression results based on whether ESG performance is measured by an aggregate measure or three specific sub-measures.

The financial factor regression results show a positive correlation between credit risk and the leverage ratio (Lev), operational income growth rate (Oig), and debt-to-equity rate, as well as a negative correlation with the return on asset ratio (Roa) and total asset turnover ratio (Tat). Similar findings are presented by previous studies of Zhang et al. (2021) and Pu (2022). However, disparities do exist. For example, in Tekić et al.'s (2021) credit risk research of 295 agricultural enterprises, no significant relationship was discovered between credit risk and the total asset turnover ratio (Tat), while the income ratio negatively correlated to the default probability. Apart from that, Chen et al.'s (2021) credit risk evaluation of small- and medium-sized listed enterprises of online supply chains came to the conclusion that the operating income growth rate (Oig), which measures an enterprise's asset scale growth and serves as the primary index for the analysis of the capacity for capital accumulation and development, had a favorable impact on credit risk reduction in the home appliance and construction industries. Concerning research on listed companies in various industries, there may be discrepancies in correlations between different financial indicators and credit risk.

Future research directions in the realm of credit ratings and their interplay with external factors may also include investigating the delayed reaction of credit ratings to extreme events, such as significant climate policy changes. Exploring the role of ESG factors in credit worthiness using new techniques such as AI algorithms remain a promising direction. Leveraging large-scale data-processing techniques, researchers can delve into sentiment analysis of social media data, where one may gain insights into how ESG-related news and events affect market perceptions of the company. Interdisciplinary collaborations between finance, data science, and sustainability experts may also yield innovative insights and provide a more comprehensive understanding of how the multifaceted factors jointly impact company performance. The present study does not further distinguish between different sorts of firms owing to the limited default sample size, and future advancement could be made in investigating the relationship between financial indices and enterprises in each field based on the updated ESG rating data.

6. Conclusions and suggestions

In order to provide guidance and policy implications for risk management and investment decisions by quantifying credit risk, this study used logistic regression to develop a credit risk prediction model of enterprises with the core predictor variable as the ESG rating index. The research was based on the samples of enterprises being treated specially, marked as "ST"or "ST*" by the Shanghai and Shenzhen Exchanges with higher probability to default, and corresponding enterprises under normal operation. There was a discernible inverse relationship between credit risk and ESG performance. Events related to credit risk were less likely to occur in companies with higher ESG ratings. Meanwhile, enterprises could effectively reduce the probability of default by improving profitability and operational efficiency and optimizing capital structure. The prediction effect of the model with the ESG index was better than the model without the ESG factor in sensitivity and overall prediction accuracy, which indicated that ESG can effectively identify the credit risk of enterprises and verified the reliability of the prediction model.

Our findings demonstrated that the inclusion of ESG factors in credit risk models significantly enhanced predictive accuracy. This outcome underscored the effectiveness of ESG metrics in identifying critical factors for financial management. Financial institutions can rely on ESG data to make informed lending decisions, safeguarding their portfolios, thus proving that ESG isn't just a buzzword—it's a practical tool for assessing credit risk. Companies that embrace ESG principles not only contribute to a sustainable future but also strengthen their financial standing. As investors and lenders increasingly recognize the value of ESG, integrating these factors into credit assessments becomes imperative. By doing so, companies can navigate the complex landscape of credit risk with greater confidence and resilience, including optimizing their capital structure, reducing the strain on financial resources, and enhancing their resilience against economic shocks.

Policy implications on predicting and preventing defaulting enterprises from three different perspectives are put forward according to the conclusions. First, enterprises ought to stop viewing environmental protection, social responsibility fulfillment, and governance improvement as time- and resource-consuming chores. Enterprises should be aware of the repercussions of poor ESG performance and aggressively incorporate ESG into their development strategies. Particular attention should be paid to the advancement of corporate governance, and investment should be increased in green technology and ecologically friendly goods and services. Examples of actions to enhance ESG performance include establishing ESG management divisions, hiring professionals, and actively disclosing high-quality ESG information.

Second, while making investment decisions, investors ought to weigh non-financial indicators, such as ESG ratings, and be conscious of their critical role in predicting a company's default risk. It is essential of course to also consider pertinent financial indicators, including the return on asset ratio (Roa), leverage ratio (Lev), and operating income growth rate (Oig).

Third, there is currently no uniform structure or guidelines established by ESG reporting frameworks to ensure consistency and comparability of ESG information disclosure, and listed companies are the main participants of ESG information disclosure. The environmental, social responsibility, and corporate governance (ESG) information reported by many businesses consists primarily of qualitative descriptions and lacks precise quantitative indicators, which weakens the quality of the ESG information. As such, the regulatory authorities are recommended to unify the ESG rating standards as soon as possible, gradually strengthen enterprise ESG information disclosure frameworks, and guide enterprises to prioritize ESG performance. In an effort to further lay the groundwork for the development of a comprehensive ESG rating system, regulators can also motivate businesses based on how well their ESG information disclosures are done. These initiatives could include increasing fines for false information regarding ESG as well as developing a negative list elicited from ESG performance.

However, taking into account the scarcity of corporate default data in China, this study only evaluates 292 businesses. Long-term data and comprehensive observations are few because ESG research is still in its initial stages. Complex models with time-related indicators are challenging to implement with only the early data. After a more developed ESG framework is constructed, future research could incorporate time-related factors into models to more accurately evaluate the relationship between the ESG index and enterprises' credit risk.

Use of AI tools declaration

The authors declare that they have not used artificial intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declare that there are no conflicts of interest.

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