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Original Paper

Study on ESG Performance and Financial Distress Prediction of Listed Companies: Based on Logistic Regression and Artificial Neural Network

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Abstract

A reliable financial distress prediction model is an effective means to prevent financial risks, and the selection of predictors is the key to improve the prediction accuracy of the model. To test whether the ESG performance of listed companies can be used to predict financial distress, two prediction models of logistic regression and artificial neural network were used to predict the financial distress of some listed companies from 2022 to 2024. The results show that the prediction accuracy of both models decreases after ESG ratings are added to the commonly used predictors. It proves that the ESG performance of listed companies cannot be used to predict financial distress, and this conclusion is valid after the robustness test.

Keywords

ESG, Financial distress prediction, Logistic regression, Artificial Neural Network

1. Introduction

As China's economy enters a stage of high-quality development, Solidly promoting green and low-carbon development has become the goal of current economic and social development, and the demand for green finance continues to expand. Since 2018, China has begun to deploy ESG-themed wealth management products. Nowadays, ESG has become an important indicator to evaluate the green environmental protection of enterprises, and has received extensive attention from the whole society. Many rating agencies use the three aspects of environmental protection, social responsibility, and corporate governance to help enterprises score ESG. Investors can use ESG scores as a consideration for stock selection, which is known as ESG investing or perpetual investing. ESG investing is an investment philosophy that focuses more on sustainable development and long-term value. After experiencing various black swans such as the COVID-19 epidemic, people have pinned their hopes on ESG to get rid of uncertainty, so that institutional investors in China's securities market have already had ESG preferences (Zhou, 2020).

The Third Plenary Session of the 20th Central Committee of the Communist Party of China pointed out that it is necessary to coordinate development and security, and guard against financial risks. The development of enterprise financial distress prediction models is an effective means to prevent financial risks (Zhu, 2023). By accurately predicting whether an enterprise may fall into financial distress, investors and creditors can take measures in advance to reduce potential losses, corporate managers can timely discover potential problems to prevent the occurrence of financial crises, and government management departments can timely monitor the quality of listed companies and the risk status of the securities market, so improving the accuracy and reliability of financial distress prediction models is of great significance for maintaining the stability of the financial market. Forecasting a company's financial distress has always been a hot topic in academic research. The researchers considered various aspects of the company and continuously introduced different variables to improve the explanatory power of the predictive models, but the accuracy of these models has not been significantly improved (Zhang, 2020). Due to the increasing focus of investors and stakeholders on corporate sustainability, a company's ESG performance has become an important consideration in investment decisions. Can ESG performance be used to predict a company's financial distress?

There is little research on this issue. Existing research has focused on the economic returns of companies' ESG practices. Despite the results of these studies are mixed, we are all encouraging companies to improve their ESG performance. In the current context of financial risk prevention, we should also pay attention to the role of corporate ESG performance in predicting financial distress. Yang Song et al., integrated textual analysis of ESG reports of energy companies into the CatBoost algorithm to predict financial distress, and proved that Energy companies' financial distress can be effectively predicted by using text words, topics and sentiments derived from ESG reports (Song Y, 2024). Although this study fills a gap in the field of ESG and distress prediction research, it also has limitations. If textual variables are used to predict financial distress, companies can manipulate the results of the forecasts by changing the rhetoric in their ESG reports. This study will use the scores of Chinese ESG rating agencies to explore the impact of adding ESG variables to the financial distress prediction model, and continue to perfect the theory and methodology of financial distress forecasting.

2. Theoretical Basis

2.1 Definition of Financial Distress

Enterprise getting into financial trouble is a gradual and continuous process. Usually, there is no clear demarcation point from financial normalcy to financial distress, so experts and scholars at home and abroad have a variety of different definitions and judgment criteria for financial distress. The first to propose a financial distress prediction model was Beaver. The Z-Score discriminant model proposed by Beaver and Altman has had a profound impact on subsequent research. Altman believes that a public declaration of bankruptcy is the only criterion for financial distress (Wu, 2022), and most studies abroad follow this approach. Because the act of filing a bankruptcy petition occurs objectively and is highly measurable, it is relatively easy to determine the research sample. The research in this paper focuses on listed companies, which rarely have bankruptcy cases. Because listing qualification is a precious "shell" resource, even if a listed company meets the bankruptcy conditions, other entities will restructure it. From the perspective of the development and evolution of financial difficulties, the company's financial distress is first cash-strapped, and then there are credit risks, crisis warnings and other processes (Zhang, 2020). Bankruptcy is the end of financial distress, that is, financial distress occurs before bankruptcy. Therefore, many studies argue that financial distress should be defined before a company goes bankrupt. Ross et al. define financial distress as a company's inability to meet its obligations, and this inability is determined by two criteria: stock-based bankruptcy and liquidity-based bankruptcy (Maulidine, 2014). A stock-based bankruptcy is a situation where the company has negative net assets, while a liquidity-based bankruptcy is a situation where the company's operating cash flow cannot meet the company's current liabilities. Ross's definition is based on the theory that if a company has negative net income for 3 consecutive years, the company's financial performance is poor, and if the company does not make improvements, the company may face bankruptcy. In China, ST companies are often defined as financially failed companies in academic circles, which is also in line with Ross's theory. ST is a special treatment of the Shenzhen and Shanghai Stock Exchange for the stock trading of listed companies with abnormal financial status or other conditions. If a listed company has a negative net profit for two consecutive fiscal years, or if the audit result of the most recent fiscal year shows that its shareholders' equity is less than the registered capital, the company will be subject to special treatment, and these financial anomalies are an important sign that the company is in financial distress. There are many other ways to define financial distress in existing studies, such as a liquidity ratio of less than 1 (Zhu, 2023), arrears of dividends, insolvency, etc. The choice of definition method should be based on the needs of the users of the predictive model. Forecasting ST companies in advance will help financial institutions, investors and regulators identify potential risks in a timely manner and take appropriate measures to avoid or reduce losses. In this study, "ST" is also used as a criterion for judging the financial distress of a listed company.

2.2 The Relationship between Corporate ESG Performance and Financial Distress

There are three different views in academia on the impact of corporate ESG performance on financial performance. Most studies agree that ESG performance has a positive impact on financial performance, mainly for the following reasons: (1) environmental protection and resource conservation measures can reduce energy and resource costs and improve resource efficiency (Yang, 2023); (2) Good ESG performance sends a signal to the market that companies are healthy and healthy, making consumers, suppliers, investors, governments and other stakeholders more willing to cooperate with them to help companies achieve excess returns (Zhang, 2023); (3) Enterprises with good ESG performance have a higher level of management, which helps enterprises improve financial governance benefits (Lin, 2014). The opposite view is that the better the ESG performance, the lower the company's financial performance (He, 2023). This is because fulfilling ESG responsibilities requires a large amount of unnecessary investment, which increases the company's operating costs. There is also an argument that there is no relationship between ESG performance and financial performance. A plausible explanation is that there are so many intermediate variables between ESG performance and financial performance that there is no compelling reason to predict any relationship between the two (Liu, 2024). Most of these studies use return on assets (ROA, = net profit / total assets) to measure financial performance. When a company's ROA continues to decline or is negative, it is a sign that the company may be facing financial distress. Therefore, three relationships between ESG performance and corporate financial distress can be inferred from the above perspectives: the first is that the better the ESG performance, the less likely a company is to fall into financial distress; The second is that companies with better ESG performance are more likely to be in financial distress; The third is that there is no relationship between ESG performance and corporate financial distress.

Obviously, these three relationships are contradictory. Based on this, this paper argues that it is not possible to predict financial distress with ESG performance because the relationship between ESG performance and financial performance is not unique. Of course, whether this judgment can be established still needs more rigorous empirical testing. While Chen (Chen, 2005) and Wang et al. (Wang, 2007) concluded that corporate governance is an important predictor of financial distress, Zheng et al. (Zheng, 2019) also found that corporate social responsibility also affects the probability of a company falling into financial distress. But ESG is a combination of "environmental", "social" and "governance". Companies with the same overall performance may vary greatly in different dimensions (Luo Jinghua, 2022). And users of ESG information don't think about just a part of it. Therefore, this paper uses the comprehensive ESG performance of companies to conduct an empirical study.

3. Study Design

3.1 Model

At present, the most commonly used models for predicting the financial distress of enterprises are discriminant analysis, logistic regression and artificial neural networks. Among them, the discriminant analysis method has great limitations, so logistic regression and artificial neural network are used to predict financial distress in the following paper (Zhang, 2001; Ni, 2014; Ji, 2018).

3.1.1 Logistic Regression Model

Logistic regression is a analysis method for qualitative data. The dependent variable is a binary variable that takes only two values, 0 and 1. The objects of logistic regression study are the magnitude of the probability that the dependent variable is equal to 1, P (y=1), and the influencing factors of the magnitude of P. The factor that affects the value of y is the independent variable, which is denoted as x_1, x_2, …, x_k. When predicting whether a company will be in financial distress, y=1 indicates that it will be financially distressed, and y=0 indicates that it will not be financially distressed. Establish a binary logistic regression model:

$$logit(P) = \ln\frac{P}{1-P} = \beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k$$

From the above equation we can calculate that

$$P = \frac{e^{\beta_0+\beta_1 x_1+\ldots+\beta_k x_k}}{1+ e^{\beta_0+\beta_1 x_1+\ldots+\beta_k x_k}}$$

where P is the probability of y=1; logit(P) is a logical transformation of P, which is used to overcome the difficulties in processing P directly (He Xiaoqun, 2016). β_0 is a constant term; β_1, β_2, …, β_k is the regression coefficient of x_1, x_2, ..., x_k.

3.1.2 Artificial Neural Networks

Artificial neural networks (ANN) are an important machine learning technique that is commonly used to complete some discrete nonlinear fitting tasks. There are various types of artificial neural network models, such as multilayer perceptron (MLP) and radial basis function (RBF), and MLP are commonly used. Figure 1 shows a schematic diagram of a three-layer MLP-ANN, the basic principle of which is as follows: the input layer is operated linearly to the hidden layer, the result is a non-linear operation in the hidden layer, and the hidden layer to the output layer is linearly again. There are two parameters in a linear operation, “a” and “b” of “ax+b”, and what the artificial neural network needs to do is to determine the parameters of these linear operations, so that their output is the least wrong with the real result. The nonlinear function in the hidden layer, also known as the activation function, is responsible for providing a universal nonlinear feature. In general, nonlinear functions are better fitted than linear functions. If you use a linear activation function, then the result will be the translation, scaling, and addition of the linear function. No matter how you do these three things, the end result is still a linear function, which is no different from doing a linear fit. Therefore, the activation function must be nonlinear in order for the function of the artificial neural network to be effective.

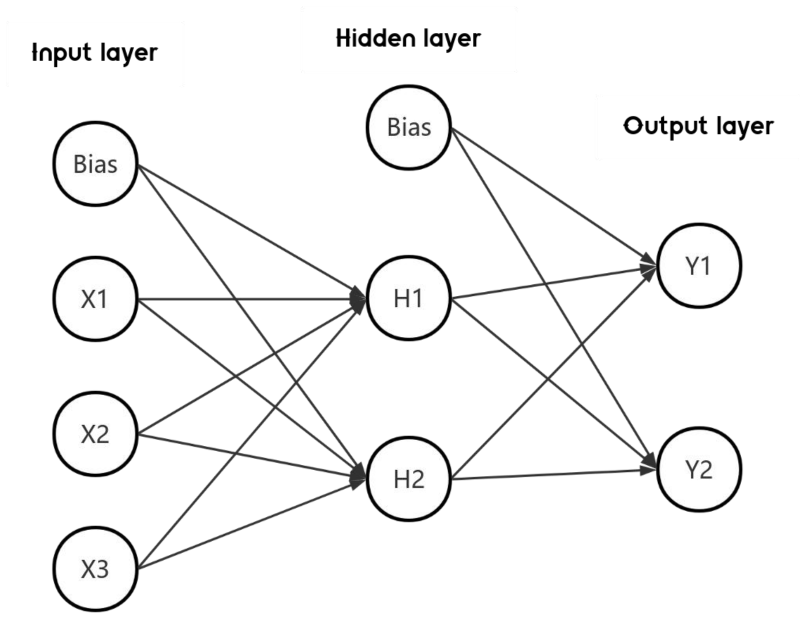

Figure 1. Structure Diagram of Artificial Neural Network

To minimize the error between the output of these parameters and the true result, we first need to construct a loss function, $z=\Sigma(y_i-\hat{y}_i)^2/n$, to quantify the error. The output of an artificial neural network can be written directly as an expression for each input, $\hat{y}=f(x)$. By using the chain derivative, you can find the partial derivative of the error for each parameter, $\partial z/\partial a$. If the partial derivative is positive, moving a little in the direction of decreasing the parameter will make the error smaller, and the larger the partial derivative, the greater the tendency of the error to decrease, and vice versa. After many iterations of this method, the error becomes very small. When the loss function converges to 0, the artificial neural network is successfully trained. This method is called gradient descent, and the disadvantage is that it converges slowly because its path is orthogonal at each step. Hestenes and Stiefle proposed a conjugate gradient method (Hestenes, 1952), in which each search direction is a combination of the negative gradient direction (the direction in which the function value drops the fastest) and the search direction of the previous iteration. This method avoids repeated searches in the same direction and overcomes the shortcomings of the slow convergence of the gradient descent method.

In this study, the financial distress prediction using artificial neural network is divided into two steps: training and prediction. First, we divide the dataset into a training set and a test set, and use the data in the training set to train the artificial neural network. After finding the optimal parameters, we use the explanatory variables in the test set to calculate the results of their financial distress predictions.

3.2 Variable

Summarizing the predictors of financial distress used in previous studies, they can be broadly divided into the following categories: (1) Profitability. Including operating profit margin, return on equity, operating net profit margin, return on total assets, net profit margin on total assets, return on investment, etc. (2) Business ability. Including total asset turnover, accounts receivable turnover, inventory turnover, fixed assets turnover, etc. (3) solvency. Including debt-to-asset ratio, current ratio, quick ratio, interest coverage ratio, cash ratio, equity ratio, etc. (4) Ability to grow. Including the growth rate of operating income, the growth rate of net profit, the growth rate of total assets, the growth rate of net assets, etc. (5) Cash flow. Including net cash flow per share, total cash recovery rate, net cash content of operating income, net cash content of net profit, etc. (6) Market performance. Including earnings per share, price-to-earnings ratio, price-to-book ratio, total assets, net assets per share, etc. (7) Corporate governance. Including the total number of shareholders, the proportion of shares held by the chairman, the proportion of shares held by the largest shareholder, and the correlation between shareholders, etc.

Due to the high correlation between homogeneous variables, principal component analysis (PCA) has been used in many studies to convert a large amount of potentially relevant data into a small amount of unrelated data. But PCA also has its limitations: first, PCA is only suitable for linear data; Second, PCA is a simple mathematical transformation, and there is no economic logic behind it. Third, PCA may lose some important information because it retains only the main components of the data and discards some of the minor components. In order to ensure the generalizability of the research results, this paper decided to retain the original data and select only one of the variables in each category. There is no consensus on what metrics are most appropriate. We selected the following variables for analysis based on the frequency used in previous studies: return on equity (X_1), total asset turnover (X_2), debt-to-asset ratio (X_3), growth rate of operating income (X_4), net cash content of operating income (X_5), net assets per share (X_6) and the shareholding ratio of the largest shareholder (X_7). In addition, the ESG score of the company is used as the core explanatory variable in this study.

3.3 Samples and Data

Since macroeconomic instability and institutional factors in different years have an important impact on the probability of distress of enterprises (Arnab, 2014), samples should be selected at the same time to control the temporal bias. This study selected samples of A-share listed companies on the Shenzhen and Shanghai Stock Exchanges, and only select the new companies from normal to ST in the past three years as the y=1 sample, which is considered to be in financial trouble, and these samples have no special treatment records in the previous three years. Considering the industry differences, the accounting measurement and governance system of the financial industry is different from that of other industries, so the financial industry is excluded from this study. Previous studies have found that social performance has little impact on manufacturing firms (Chung, 2018), and the impact of manufacturing on the environment is more significant, so manufacturing and non-manufacturing should be studied separately. This paper only examines the impact of non-manufacturing companies. For manufacturing, it will be carried out in a future study. After excluding the financial industry and the manufacturing industry, a total of 39 listed companies will be ST for the first time in 2022-2024. Referring to the existing literature, we use a one-to-one matching method to select non-ST companies in the same period and industry as the matching sample. Since ST samples are small, in order to narrow down the selection of non-ST samples, we draw on the research of Huang and Li (2003) to select non-ST samples among companies with ROE less than 5% (Huang, 2003). The 78 samples selected were divided into two parts: the training group and the prediction group. The training group is composed of 53 companies, including 27 ST companies and 26 non-ST companies; The forecast group consists of 25 companies, of which 12 are ST companies and 13 are non-ST companies.

Data for the predictor were taken from the third year prior to the year in which the sample was located. The reason why the data for years T-1 and T-2 are not used to forecast the financial situation for year T is related to the decision mechanism of "ST". A company's being ST in year T is usually due to consecutive losses in years T-1 and T-2. If you know that a company is losing money in year T-1, then just know that it is also losing money in year T-2, you can be sure that it will be ST in year T. If a company does not lose money in year T-2, then it does not constitute a loss for two consecutive years, regardless of whether it loses money in year T-1. In this way, some companies can be 100% sure whether they will be ST in year t, which would overestimate the prediction accuracy of the model.

The data on whether each company is ST and X_1, X_2, X_3, X_4, X_5, X_6 and X_7 are all from China Stock Market & Accounting Research Database (CSMAR). The company's ESG performance data comes from Sino-Securities Index ESG Rating, which is denoted by ESG_1. It classifies ESG performance into nine levels, from highest to lowest, C, CC, CCC, B, BB, BBB, A, AA, and AAA. In this study, nine grades were assigned on a scale of 1 to 9. In addition, Wind ESG Rating was selected for robustness testing, which is denoted by ESG_2.

4. Empirical Analysis

4.1 Correlation Analysis

The risk information contained in different variables may overlap or conflict with each other, so it is necessary to test the correlation between the variables. The test results are shown in Table 1. In the selected sample, ESG1 was positively correlated with X1 and X6, but ESG2 had no significant correlation with them. Besides, Both types of ESG ratings have weak correlations with other variables. Therefore, the next step of the analysis can be carried out.

Table 1. Correlation Test

		X_1	X_2	X_3	X_4	X_5	X_6	X_7
ESG_1	Pearson correlation	0.310^{**}	0.167	-0.158	0.208	-0.015	0.347^{**}	0.136
	Significiance	0.006	0.143	0.168	0.067	0.895	0.002	0.236
	Number of cases	78	78	78	78	78	78	78
ESG_2	Pearson correlation	0.184	-0.104	-0.108	0.052	-0.037	0.049	-0.052
	Significiance	0.108	0.365	0.345	0.649	0.747	0.670	0.653
	Number of cases	78	78	78	78	78	78	78

4.2 Predict the Outcome

Table 2 shows the results of the logistic regression model predicting the financial distress of the sample of the prediction group without adding ESG variables. The model is 38.5% correct for companies with y=0 (not in financial distress), 75% for companies with y=1 (in financial distress), and 56% for the overall forecast. The prediction accuracy of the model for y=0 is very low, and the prediction effect is not good. After ESG_1 in the independent variable, the prediction accuracy of the model for y=0 has improved, and the overall accuracy rate reaches 68%. Compared with the absence of ESG variables, the inclusion of ESG_1 significantly improves the accuracy of financial distress prediction.

Table 2. Logistic Regression Prediction Results (1)

measurement		prediction		
		y=0	y=1	Correct percentage
no ESG variables	y=0	5	8	38.5
	y=1	3	9	75
	Overall percentage			56
ESG_1	y=0	8	5	61.5
	y=1	3	9	75
	Overall percentage			68

Since the results obtained by machine learning may be different each time, each experiment is repeated ten times in artificial neural network prediction, and the results are shown in Table 3.When ESG variables are not included, ANN's prediction accuracy is the highest 84%, the lowest is 68%, and the average is 74.4%. After joining ESG1, ANN has a prediction accuracy rate of 88% at the highest, 64% at the lowest, and an average of 74%. It can be seen that after the addition of ESG variables, the accuracy of financial distress prediction has not changed significantly, and the average accuracy rate has decreased slightly.

Table 3. The Percentage of ANN Predictions Correct (1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
no ESG variables	76	84	72	72	72	76	80	76	68	68
ESG_1	64	68	76	72	84	84	72	88	64	68
ESG_2	68	60	64	64	64	68	68	68	64	68

In the above, logistic regression and artificial neural networks give different results, which may be due to too few sample sizes and too many independent variables, resulting in more errors in logistic regression. After comparing the significance of the seven independent variables in the logistic regression equation, the two factors with the lowest significance, X3 and X6, were removed. The results of the logistic regression again are shown in Table 4.

Table 4. Logistic Regression Prediction Results (2)

measurement		prediction		
		y=0	y=1	Correct percentage
no ESG variables	y=0	7	6	53.8
	y=1	2	10	83.3
	Overall percentage			68
ESG_1	y=0	6	7	46.2
	y=1	2	10	83.3
	Overall percentage			64
ESG_2	y=0	6	7	46.2
	y=1	4	8	66.7
	Overall percentage			56

After adjusting the number of independent variables, the prediction accuracy of logistic regression was significantly improved. The same results were obtained as the neural network, the accuracy of financial distress prediction was not significantly improved after the addition of ESG variables, and even decreased slightly. This shows that ESG performance cannot be used to predict financial distress in multivariate models.

4.3 Robustness Test

To prevent coincidence in the experimental results and ANN trapping into local optimum, the robustness test was performed by substituting the variables and changing the sample size. After replacing ESG_1 with ESG_2 in the independent variables, the prediction results are shown in Tables 3 and 4. In the logistic regression prediction results, the prediction accuracy of ESG_2 was 56%, which was lower than that of ESG_1. After replacing ESG_1 with ESG_2 in ANN, the average accuracy of the model was 65.6%, which was also significantly lower than the 74.4% without ESG variables.

According to the above sample selection principle, 122 non-ST samples were selected to expand the total number of samples to 200, which were divided into 150 training group and 50 prediction group. There were 30 ST samples in the training group and 9 ST samples in the prediction group. The results predicted by the new sample using the two models are shown in Tables 5 and 6. After sample enlargement, there are much more non-ST samples than ST samples, which makes it easier for logistic regression to predict y=1 to y=0. In Table 5, all companies are predicted to be financially distressed, perhaps because the sample is not selected according to a one-to-one matching model (Huang He, 2003). In Table 6, the prediction accuracy of ANN is significantly higher than that of logistic regression, with an average prediction accuracy of 93.4% without ESG variables, 91% with ESG_1, and 91.6% with ESG_2. None of the above results supports the view that the addition of ESG variables can improve the accuracy of financial distress prediction, and they also showed that the addition of ESG variables makes the accuracy of financial distress prediction lower.

Table 5. Logistic Regression Prediction Results (3)

	y=1	y=0	Overall correctness
no ESG variables	0	100%	82%
ESG_1	0	100%	82%
ESG_2	0	100%	82%

Table 6. The Percentage of ANN Predictions Correct (2)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
no ESG variables	94	94	94	92	94	92	94	94	92	94
ESG_1	92	90	90	92	92	90	94	86	90	94
ESG_2	92	92	92	92	90	88	92	92	94	92

To test whether there may be an advanced or lagging impact on ESG performance, the ESG data of the T-3 year was replaced with the data of the T-4 and T-2 years. Since the prediction results of logistic regression with a sample size of 200 are not good, only the neural network test is used here, and the results are shown in Table 7. The average accuracy of financial distress predictions was 93.4% without ESG variables, 91.8% and 91.2% when the ESG variables of the previous period were added, and 92.4% and 91.6% when the ESG variables of the lagging period were added. The prediction accuracy of the model with ESG scoring is lower than that without ESG score, which still does not prove that ESG performance can improve the prediction accuracy of financial distress, indicating that ESG performance has no advanced or lagging impact on financial distress prediction.

Table 7. The Percentage of ANN Predictions Correct (3)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
no ESG variables	94	94	94	92	94	92	94	94	92	94
T-4 ESG_1	92	86	92	92	94	92	92	94	90	94
T-4 ESG_2	92	92	94	90	94	92	84	92	90	92
T-2 ESG_1	92	92	92	94	92	90	92	94	94	92
T-2 ESG_2	94	92	90	88	90	92	92	92	94	92

5. Conclusions and Discussions

This study used logistic regression and artificial neural networks to predict the financial distress of some A-share companies in the past three years. After adding ESG predictors, the accuracy of predicting the company's financial distress decreases, which proves that the ESG performance of listed companies cannot be used to predict financial distress. Comparing the two models, it can be found that the prediction accuracy of artificial neural networks is higher than that of logistic regression, because nonlinear regression is more flexible and can fit more complex data patterns; Logistic regression has higher requirements for sample selection and the number of variables, its use has some limitations. The study used the ESG ratings of Sino-Securities and Wind, and the prediction effect of the two institutions is not exactly same. In most experiments, the predictive accuracy of Sino-Securities Index ESG rating was slightly higher than that of Wind's ESG rating.

A company's financial distresses are influenced by a variety of factors. In general, the more information a model contains, the more predictive it is (Zhang, 2020), but this study has come to the contrary to this common sense. This paper believes that there may be several reasons for this phenomenon: (1) Although the particularities of the manufacturing and financial industries are considered in this study, the sample is still from many different industries. The role of ESG performance may be different in different industries, as not all ESG factors have a material impact on all industries. Due to the small sample size of this study, it is impossible to conduct the study by industry, so that industry differences are ignored. (2) Because there are unquantifiable parts in the composition of ESG, the current ESG measurement involves some subjective judgments, and it is difficult to determine whether the measurement results are reasonable. Different institutions have different ESG scoring systems, and the ESG scores they produce are also inconsistent, which adds to the confusion of using ESG data. (3) ESG practice in China is still in its infancy, and the company's managers attach different importance to ESG performance, which will also lead to the inability to use the company's ESG performance to predict financial distresses.

While there is a link between a company's ESG performance and financial information, the relationship is complex. Therefore, this paper suggests that stakeholders should be proactive when considering a company's ESG performance. Rather than focusing on the absolute ESG score, they should focus on the data sources behind the ESG ratings and the scoring methodology to predict the company's financial health based on facts.

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