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Application of logistic regression model in corporate financial decision making in the era of big data

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Abstract

In order to improve the prediction accuracy of financial decision risk early warning model (FEW), this paper firstly introduces five types of non-financial indicators, market price, management level, corporate reputation, governance structure and audit index, into the logistic regression (Logistic) financial risk decision early warning model on the basis of traditional financial indicators. Secondly, using the sample of A-share ST companies and paired non-ST companies in 2021, the probability of a company being ST after 3 years was predicted with 2018 data, and the robustness of the selected logistic financial risk decision early warning model was further tested by comparing the early warning accuracy of six logistic financial risk decision early warning models. The results of the study showed that adding three indicators, namely, market price, management level, and corporate reputation, to the logistic model was effective in improving the early warning accuracy of the model by 23.6%. In addition, by comparing the selected logistic financial risk early warning model with the Z-score model, it is found that the logistic model has the highest decision warning accuracy of 95.3%, which has a high robustness. Therefore, this paper introduces the logistic regression financial risk decision early warning model effectively helps enterprises to make financial decisions to issue timely warnings before the occurrence of unbearable crises and take appropriate measures in advance to avoid the enterprise delisting crisis.

Keywords: *financial decision making; risk warning; non-financial indicators; logistic model; z-score model*

Introduction

Due to the frequent occurrence of financial crises in recent years, the number and average size of bankrupt companies have increased dramatically, causing great concern among governments, financial institutions and regulatory bodies. During the Asian financial crisis in 1997 and the international financial crisis in 2008, many companies around the world found that their financial indicators had deteriorated significantly before taking remedial measures, and were often caught off guard and went into bankruptcy (Giordani, Jacobson, Von Schedvin, & Villani, 2014) (Mansouri, Nazari, & Ramazani, 2016) (Ciampi & Gordini, 2013). . In addition, the sudden 2020 Newcastle pneumonia epidemic posed a huge challenge to many companies worldwide, and the external environment deteriorated dramatically, with both listed companies and small and medium-sized enterprises bearing financial risks such as cash flow shortage, inability to repay debts, and delinquent employee wages (Jones, Johnstone, & Wilson, 2017) (Sun & Lei, 2021).

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There is a growing awareness that the production and operation of companies need to be based on a sound early warning system for financial crisis decision making in order to identify impending financial crises so that action can be taken at the beginning of the crisis to prevent further deterioration (Chang, Lan, & Lan, 2022; A. Wang & Yu, 2022).

Research on early warning for financial decisions originated in the 1930s, initially using a single variable to predict financial conditions, and then gradually expanded to traditional econometric models such as comprehensive multivariate models, and then further expanded to generalized linear regressions such as Logistic regression and Probit regression (AHMED et al., 2021). In (Trabelsi, He, He, & Kusy, 2015), an empirical study was conducted on 105 companies with financial crises and 2058 companies without financial crises, and the first logistic financial risk early warning (FEW) model was constructed, and it was confirmed that the accuracy of logistic regression was higher than that of multivariate discriminant analysis (MDA).

The literature (Siegrist, Bowman, Mervine, & Southam, 2020) first selected 58 distressed banks out of more than 5000 banks, and extracted data on eight indicators from these some distressed banks separately, and effectively predicted the probability of bank failure after two years using logistic model.

The literature (Jabeur, 2017) proposed a method to directly estimate the probability of corporate default using financial and non-financial variables in developing an early warning signal model for corporate default in emerging market economies such as India, thereby predicting corporate bond default in India. The literature (Gu, Wang, & Li, 2018) used a logistic regression model to directly estimate the probability of default and found that the model significantly outperformed the other two competing models.

The literature (Yang & Li, 2017) predicted corporate risk by logistic model and he used 35 variables from 3200 companies to build logistic regression and linear regression models. The literature (G. Wang, Wang, Zhou, Mo, & Xiao, 2020) developed a logistic model for predicting bankruptcy in the hospitality industry. By combining financial data from 16 U.S. hospitality firms and 16 non-bankruptcy matched firms, the logit model that can predict bankruptcy two years in advance was established. The literature (Wan, 2020) combines spline functions in order to consider the highly nonlinear relationship between bankruptcy and leverage, earnings, and liquidity in a logistics firm bankruptcy model.

The industry was found to model excessive nonlinearity to obtain bankruptcy predictions with 70%-90% accuracy compared to standard logistic models.

This paper first summarizes the current financial crisis prediction methods that are well known to domestic and foreign scholars. It contains linear regression (univariate model and multivariate discriminant analysis), nonlinear regression (Logistic regression and Probit model), and the application of machine learning in financial risk early warning.

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Next, we describe in detail the theory of financial risk (including classification, causes, identification and determination), the theory of financial decision risk prediction (including meaning, function and foundation), the form and characteristics of logistic regression models and the rationality of applying them to predict decision risk.

Finally, an empirical study of the six established logistic regression models for early warning of financial decision risk is carried out.

The constructed logistic financial decision risk early warning models are applied to ST company, and the financial decision risk early warning values ZP(y)1 and ZP(y)2 of ST company are calculated, and the effectiveness of the risk early warning models is determined by combining with the actual situation of the company.

Early warning of financial decision risks

For enterprises, the implementation of different financial decisions will face different consequences, and at the same time, the effectiveness of the implementation of financial decisions will be reflected in the company's financial position, and thus financial risk arises. Many scholars define the risk of not being able to repay debts after the expiration of the enterprise's term as the narrow financial risk, which mainly focuses on the rights and interests of creditors and shareholders and ignores the daily operation of the enterprise.

Financial risk in a broader sense involves a broader scope, mainly referring to the deviation between the actual financial situation of the company and the predicted business results due to the joint influence of many factors such as the complex natural environment, economic policy changes and business decisions in the company's production and operation.

In turn, the risk of falling into a financial crisis, including the risk of debt service, operational risk, the risk of capital recovery, investment and financing risk of the enterprise.

Early warning mechanism for decision risk

Enterprise group financial decision risk early warning mechanism as shown in Figure 1, the product of organic combination of traditional financial early warning system, enterprise's risk management mechanism and enterprise group internal control.

On the one hand, the financial early warning system is constructed through the risk management of the capital chain within the group enterprise, specifying the financial risks arising from the use of capital flow, preventing the progressive financial risks through capital supervision, and setting early warning points to prevent the sudden financial risks while making good risk warnings.

On the other hand, the combination of indicators and models early warning and internal control decision-making process early warning, the management of the risk of the group's internal capital market, and finally the formation of a group enterprise financial decision-making risk early warning mechanism that can be continuously and dynamically monitored.

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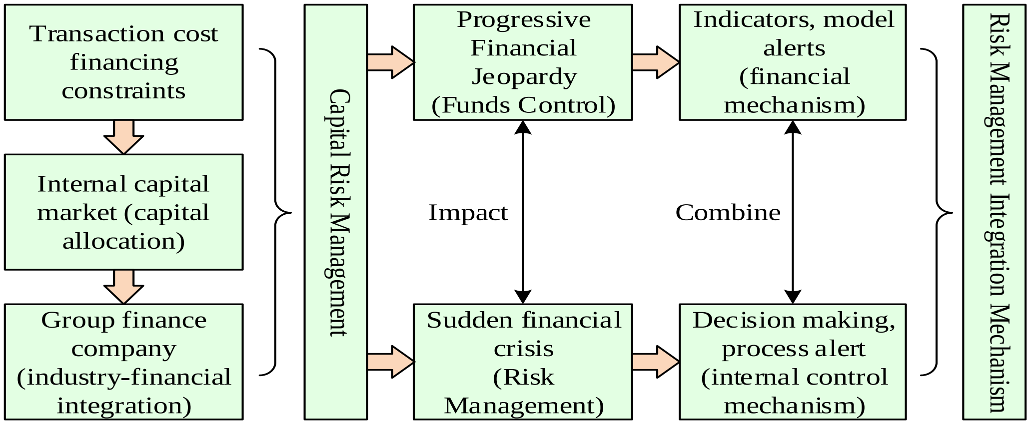

Figure 1 Theoretical construction of enterprise group financial early warning

Commonly used financial decision risk warning models

Univariate model

Univariate models are models in which a single variable is selected for prediction. The advantage of this method is that it is relatively simple, but the disadvantage is that the basis for selecting a single variable is subjectively influenced, and the accuracy of judgment is doubtful. In addition, the prediction effect of univariate model is greatly reduced by complex factors, and the possibility of error is higher. Enterprises based on a single indicator for risk response are prone to corresponding management loopholes.

Advantages and limitations of the univariate model and factors that should be concerned in its practical application:

(1) Only single financial ratios are analyzed and examined in order of their impact on the financial crisis, and trends in the development of the enterprise are observed. This is a simple way to determine the financial situation of a company, and does not require complex calculations.

(2) Factors that may cause misjudgment based on the selection of financial indicators, emphasizing the impact of current asset items on the financial crisis of the enterprise. The total debt in the debt coverage ratio treats the impact of all liabilities on the enterprise as the same, and does not consider the difference between short-term and long-term liabilities.

(3) Indicators are easily affected by inflationary factors when taking values, which can lead to analysis results.

(4) Different financial ratios often have a wide range of guessing objectives and capabilities, which can lead to different financial reflections for the same financial situation.

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(5) Univariate ratio analysis conducted over a longer period of time may indicate that a firm is in distress or may be in distress in the future, but it does not provide concrete evidence of the likelihood and timing of the firm's insolvency.

Companies applying different ratios to the same situation may yield different judgment results, so the entire set of financial ratios should be used as indicators for early warning analysis to make comprehensive judgments and avoid the pitfalls of using a single ratio.

Multivariate model

The multivariate model is formed after adding variables to the univariate model. The multivariate model is characterized by the selection of different indicator weights, which is more subjective in assigning weights to the indicators, and the workload is larger, and the early warning effect of different enterprises is not consistent, so it is difficult to promote the use within the industry.

The advantages and limitations of multivariate model and the factors that should be paid attention to in practical application:

(1) It is more scientific than the univariate early warning model to predict the risk of an enterprise after a comprehensive analysis by linking the indicators of solvency, profitability and operating capacity through five variables.

(2) Less consideration is given to the present value factor of future cash flows. And it is precisely the indicator that really reflects the ability to repay the debt.

(3) The accuracy of the predictive power of multivariate models depends mainly on the reasonableness of the choice of weights. The weights of each model are generally derived from empirical data or regression analysis of historical data, and the statistical conclusions are limited by the sample selection.

(4) Companies fine-tune the applicability of the weights in response to changes in the external environment that affect business operations. And consider adding cash recovery rate indicators.

Early warning model design for financial risk decision based on logistic regression

Decision risk warning logistic regression model for financial indicators

In the logistic regression model, P represents the probability of something happening. Conversely, by combining the linear regression equation and the Sigmoid function, the equation expression of the logistic regression model is shown in Equation (1):

$$LogitP = \beta_0 + \beta_1 A_1 + \ldots + \beta_n A_n \tag{1}$$

where $A_1, A_2, \ldots A_n$ denotes the explanatory variable in the equation and $\beta_0, \beta_1 \ldots \beta_n$ is the coefficient of the linear regression equation, and after transformation, the expression of P can be calculated as shown in equation (2):

$$P=\frac{1}{1+e^{-(\beta_0+\beta_1A_1+\ldots+\beta_2A_n)}} \tag{2}$$

In this paper, the P value represents the probability of judging whether an enterprise is in financial crisis or not, and the probability of financial risk of an enterprise is judged with the help of the magnitude of P value for the purpose of risk early warning. Logistic regression model, as a continuous type probability distribution model, can be seen through its function image that the value range of P is [0,1]. When the logistic regression model is applied to financial decision risk early warning, a company in financial crisis is defined as the value 0, and a company in financial normalcy is defined as the value 1, with 0.5 as the cut-off point. After substituting the company's financial data into the logistic regression model, the value of P can be taken as the probability of the company's financial risk. When the value of P is less than 0.5, it indicates a higher probability of the company falling into financial crisis, and when the value of P is greater than 0.5, it indicates a higher probability of the company's financial normalcy. The logistic regression model is shown in Figure 2.

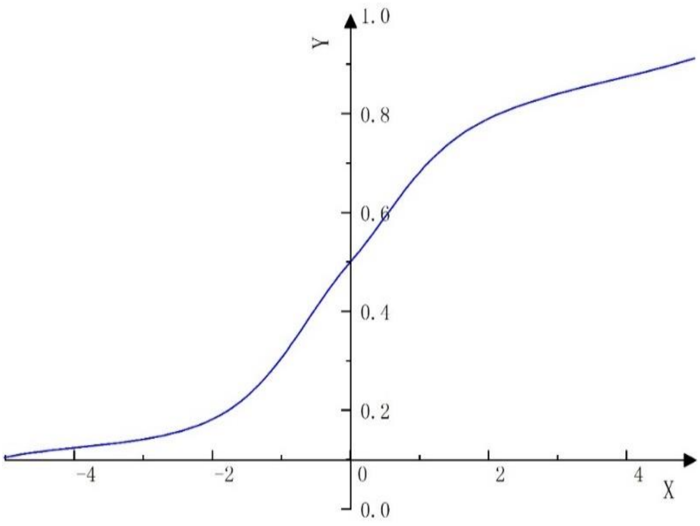

Figure 2 Logistic function image

Dichotomous logistic regression model

After using the Mann-Whitney U nonparametric test, 19 indicators were obtained that could be used for modeling. Together with the four indicators that passed the independent sample t-test, a total of 23 indicators were obtained (Pan et al., 2021). Finally, 23 indicators were selected from 52

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indicators for modeling, and they are: total asset turnover, total asset growth rate, administrative expense growth rate, equity concentration 4%, current ratio, quick ratio, total asset net profit margin, fixed asset net profit margin, selling expense ratio, administrative expense ratio, financial expense ratio, accounts receivable turnover, fixed asset turnover, capital intensity, shareholders' equity turnover ratio, net cash flow to creditors from financing activities, net cash flow to shareholders from financing activities, equity cash flow, fixed assets growth rate, operating income growth rate, total operating cost growth rate, cost of sales growth rate, and equity concentration index 1%. Therefore, the final logistic regression modeling is performed using the data of these 23 indicators.

The 0mnibus test is commonly used to test the overall significance level of the constructed model, and the null hypothesis of this test is that there is no significant linear relationship between the independent and dependent variables. The output results are shown in Table 1 below. The chi-square value is 80.336 with a p-value less than 0.1, which rejects the null hypothesis and indicates that the constructed model is significant as a whole.

The test results indicate that there is a more significant linear relationship between each explanatory variable and the explanatory variable, and this result also verifies the validity of the early warning model from a statistical point of view.

Table 1 Omnibus test of model coefficients

		Cardinality	Degrees of freedom	Significance
Step 1	Step	83.338	21	0.000
	Block	81.125	21	0.002
	Model	80.356	21	0.000

The companies in financial crisis ("ST" companies) were recorded as 0 and non-financial crisis ("non-ST") companies were recorded as 1 as the dependent variable. For each sample company, 23 indicators extracted from the normality and variance tests in the previous section were used as covariates to construct a logistic regression model using stepwise regression. As shown in Table 2 below, through stepwise regression, five indicators were finally extracted as A variables in the model, namely, total asset turnover, total asset growth rate, total asset net profit margin, cost of sales ratio, and shareholders' equity turnover ratio, and the excluded indicators are listed in the Appendix.

Table 2 Step-by-step regulation step-by-step table

Model	Input variables	Divided variables	Method
1	Total asset turnover	0.048	Step (condition: probability of F to be entered <=0.050, probability of F to be removed >=0.100)
2	Total Assets Growth Rate	-0.276	
3	Total assets net profit margin(ROA)	0.875	
4	Cost of sales ratio	-0.315	
5	Shareholder Equity Turnover Ratio	0.243	
Dependent Variable: Sample Grouping			

The p-values of the five independent variables of the stepwise regression coefficients were less than 0.05, indicating that the model fit was good. Based on the above analysis, the regression equation was derived as:

$$\ln\left(\frac{p}{1-p}\right) = -0.036 + 0.72A_1 + 0.529A_2 - 2.199A_3 + 1.008A_4 - 0.034A_5 \tag{3}$$

Where A_1 is total asset turnover rate, A_2 is total asset growth rate, A_3 is total asset net profit margin, A_4 is cost of goods sold rate, and A_5 is shareholders' equity turnover rate. The equation is deformed as shown in equation (4), and then the equation is the logistic regression model to be constructed in this paper.

$$P = \frac{1}{1+e^{-(-0.036+0.72A_1+0.529A_2-2.199A_3+1.008A_4-0.034A_5)}} \tag{4}$$

Early Warning Model for Financial Indicator Decision Making

A logistic risk warning model (Model 1) containing only 13 financial indicators is constructed as:

$$p(s_t = 1) = \frac{e^{\beta_0 + \sum_{i=1}^{13} \beta_i x_i}}{1 + e^{\beta_0 + \sum_{i=1}^{13} \beta_i x_i}} \tag{5}$$

According to the regression results, three variables are retained in model 1, namely fixed asset turnover X_3, total asset turnover X_4, and capital preservation and appreciation X_{12}. The Omnibus test of significance of the model coefficients is <0.05, indicating that at least one of the variables included in the model for this fit has a statistically significant OR, i.e., the model is meaningful overall.

The R^2 of the model was 0.564, indicating that model 1 explained 56.4% of the causes. The Hosmer-Lemeshaw test was used to test the goodness of fit of the model, and when significance > 0.05 then the information in the current data was considered to have been adequately extracted, and model 1 had a significance of 0.741, which was a good fit.

The goodness-of-fit interval of the Hosmer-Lemeshaw test model is shown in Table 3, and the fitting results after adding the variable equations are shown in Table 4.

Table 3 Omnibus test of model 1 coefficients

		Cardinality	Degrees of freedom	Significance
Step 7	Step	0.003	0.047	1.364
	Block	0.012	0.741	1.051

Model	0.564	0.058	1.131

Table 4 Variables in model 1 equation

Step 7		B	Standard error	Wald	Significance	Exp(B)	95% confidence interval of Exp(B)	
							Lower limit	Upper limit
	X3	0.013	0.007	1.523	0.239	1.235	0.994	1.209
	X4	-4.578	1.342	9.375	0.004	0.174	0.004	0.173
	X12	1.935	1.376	1.021	0.389	4.051	0.385	59.351
	Constants	0.671	1.671	0.174	0.451	1.932		

Where model 1 regression equation is:

$$\ln \frac{p}{1-p} = 0656 + 0.011x_3 - 4.598x_4 + 1.376x_{12} \tag{6}$$

The probability of each company being ST after 3 years can be predicted based on the regression equation, and 22 of the ST companies are correctly predicted with an accuracy of 81.5%, and 21 of the non-ST companies are correctly predicted with an accuracy of 92.4%. Thus the accuracy of prediction within the sample of the Logistic Financial Indicator Decision Alert Model is 86.8%. The specific test results are shown in Table 5.

Table 5 Model 1 Decision alert accuracy

	Actual test		0	1	Percent correct
Step 7	ST	0	27	7	81.5%
	Non- ST	1	5	23	92.4%
Overall percentage			81.5%	92.4%	86.8%

Non-financial indicators decision risk warning logistic regression model

Introduction of a decision risk warning model with market prices

On the basis of financial indicators, 2 non-financial indicators market price (P/E ratio X_{14}, book-to-market ratio X_{15}) are introduced into the Logistic Risk Warning Model (Model 2) as:

$$p(s_t = 1) = \frac{e^{\beta_0 + \sum_{i=1}^{15} \beta_i x_i}}{1 + e^{\beta_0 + \sum_{i=1}^{15} \beta_i x_i}} \tag{7}$$

Table 6 shows the regression test results. One variable is retained in model 2, the book-to-market ratio X_{15}. The Omnibus test of significance of the model coefficients is <0.05, indicating that the OR of the book-to-market ratio X_{15} is statistically significant, i.e., the model is meaningful overall, and the model has a R^2 of 0.269.

Table 6 Omnibus test for model 2 coefficients

Step 1		B	Standard error	Wald	Significance	Exp(B)	95% confidence interval of Exp(B)	
							Lower limit	Upper limit
	X6	-0.979	0.376	6.528	0.112	0.339	0.119	0.716
	X8	-1.356	0.415	4.376	0.027	2.748	1.235	3.142
	X15	1.748	0.525	5.103	0.005	0.151	0.026	0.856
	Constants	1.007	0.346	4.838	0.046	3.890		

Then the model 2 regression equation is:

$$\ln\frac{p}{1-p} = 3.89 + 0.339x_6 + 2.748x_8 + 0.151x_{15} \tag{8}$$

Table 7 shows the regression equation predicting the probability of each company being ST after 3 years. Among them, 23 ST companies have a correct prediction accuracy of 83.2% and 21 non-ST companies have a correct prediction with an accuracy of 78.4%. Collectively, the in-sample prediction accuracy of the logistic decision warning model with the introduction of market price indicators is 81.3%, which is higher than the accuracy of the financial indicator warning model of 76.8%.

Therefore, the introduction of market price indicators in the logistic early warning model helps to improve the accuracy of early warning.

Table 7 Model 2 Decision alert accuracy

	Actual test		0	1	Percent correct
Step 7	ST	0	21	6	83.2%
	Non- ST	1	3	23	78.4%
Overall percentage			83.2%	78.4%	81.3%

Introduction of a management-level decision risk warning model

Based on the introduction of market price indicators, 2 non-financial indicators management level (the ability to provide timely and accurate statements X_{16}, the sale of fixed assets X_{17}) were introduced into the logistic risk warning model (model 3) for:

$$p\left(s_t = 1\right) = \frac{e^{\beta_0 + \sum_{i=1}^{17} \beta_i x_i}}{1 + e^{\beta_0 + \sum_{i=1}^{17} \beta_i x_i}} \qquad (9)$$

Table 8 shows the regression results for model 3. Five of the variables are retained in model 3, being return on total assets X_8, capital preservation and appreciation rate X_{12}, net profit growth rate X_{13}, book-to-market ratio X_{15}, and ability to provide timely and accurate statements X_{16}.

Omnibus test for significance of model coefficients < 0.05 indicates that model 3 is significant overall. The R^2 of model 3 is 0.731, indicating that model 3 explains 73.1% of the causes.

Table 8 Omnibus test for model 3 coefficients

Step 1		B	Standard error	Wald	Significance	Exp(B)	95% confidence interval of Exp(B)	
							Lower limit	Upper limit
	X7	-37.03	13.223	7.952	0.005	0.000	0.000	0.000
	X10	1.116	0.841	2.333	0.121	0.058	0.024	0.945
	X13	1.172	0.516	9.315	0.025	3.276	1.203	5.155
	X16	-0.025	0.008	2.873	0.012	1.025	0.036	1.882
	X17	3.295	0.645	7.981	0.007	0.089	0.003	0.795
	Constants	0.671	1.425	5.935	0.112	26.931		

Then the model 3 regression equation is:

$$\ln\frac{p}{1-p} = 0.671 - 37.309x_8 + 1.166x_{12} + 0.015x_{13} - 1.725x_{15} + 3.295x_{16} \qquad (10)$$

Table 9 shows the regression equation predicting the probability of each company being ST p. Among them, 21 ST companies are correctly predicted with an accuracy of 87.8% and 26 non-ST companies are correctly predicted with an accuracy of 89.3%.

Taken together, the in-sample prediction accuracy of the logistic early warning model with the introduction of the management level indicator is 87.2%, which is higher than the accuracy of the early warning model with the introduction of the market price indicator, which is 81.3%.

Therefore, the introduction of management level indicators in the logistic early warning model helps to improve the accuracy of early warning.

Table 9 Model 3 Decision alert accuracy

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	Actual test		0	1	Percent correct
Step 5	ST	0	26	3	87.8%
	Non- ST	1	7	24	89.3%
Overall percentage			87.8%	89.3%	87.2%

Introducing a Decision Risk Warning Model for Corporate Reputation

Based on the introduction of management level indicators, one non-financial indicator corporate reputation (corporate qualification level X_{18}) is introduced into the logistic risk warning model (model 4) as:

$$p\left(s_t = 1\right) = \frac{e^{\beta_0 + \sum_{i=1}^{18} \beta_i x_i}}{1 + e^{\beta_0 + \sum_{i=1}^{18} \beta_i x_i}} \qquad (11)$$

Table 10 shows the regression results of model 4. Six of the variables are retained in model 4 as fixed asset turnover for fixed asset turnover X_3, total asset turnover X_4, return on net assets X_7, capital preservation and appreciation X_{12}, book-to-market ratio X_{15}, ability to provide timely and accurate statements X_{16} The Omnibus test for significance of the model coefficients is <0.05, indicating that at least one of the variables in model 4 has a statistically significant OR value. The R^2 of the model is 0.838, indicating that model 4 explains 83.8% of the causes. the significance level of the Hosmer-Lemeshaw test reaches 0.662, which shows that the goodness of fit of model 4 is relatively good.

Table 10 Omnibus test for model 4 coefficients

Step 6		B	Standard error	Wald	Significance	Exp(B)	95% confidence interval of Exp(B)	
							Lower limit	Upper limit
	X3	0.008	0.007	1.412	0.052	1.003	0.993	3.014
	X4	-6.235	3.256	3.381	0.223	0.002	0.000	1.339
	X7	-14.92	8.023	3.157	0.075	0.000	0.000	1.021
	X11	1.231	1.533	0.683	0.247	3.452	0.163	4.351
	X15	-1.166	0.774	4.515	0.019	1.781	1.025	3.471
	X16	2.221	0.988	5.117	0.124	9.154	0.425	10.256
	Constants	4.147	2.658	2.352	0.121	63.131		

Then the model 4 regression equation is:

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$$\ln\frac{p}{1-p} = 4.147 + 0.008x_3 - 6.235x_4 - 14.92x_7 + 1.231x_{11} - 1.166x_{15} + 2.221x_{16} \quad (12)$$

Table 11 shows the prediction probability p for the regression equation of model 4, in which 23 of the ST companies were correctly predicted with an accuracy of 92.1% and 27 of the non-ST companies were correctly predicted with an accuracy of 96.4%. Taken together, the in-sample prediction accuracy of the logistic early warning model with the introduction of corporate reputation indicators is 94.2%, which is higher than the accuracy of the early warning model with the introduction of management level indicators, which is 87.2%. Therefore, the introduction of corporate reputation indicators in the logistic early warning model helps to improve the accuracy of early warning.

Table 11. Model 4 Decision alert accuracy

	Actual test		0	1	Percent correct
Step 5	ST	0	27	3	92.1%
	Non- ST	1	1	29	96.4%
Overall percentage			92.1%	96.4%	94.2%

Early Warning Model for Decision Risk Introduced into the Governance Structure

Based on the introduction of corporate reputation indicators, three non-financial indicators governance structure (number of directors X_{19}, chairman and general manager concurrently X_{20}, percentage of independent directors X_{21}) were introduced into the logistic risk warning model (model 5) as:

$$p\left(s_t = 1\right) = \frac{e^{\beta_0 + \sum_{i=1}^{21}\beta_i x_i}}{1 + e^{\beta_0 + \sum_{i=1}^{21}\beta_i x_i}} \quad (13)$$

The regression results of model 5 are identical to model 4, with six variables included in the regression equation, namely fixed asset turnover X_3, total asset turnover X_4, return on net assets X_7, capital preservation and appreciation X_{12}, book-to-market ratio X_{15}, and the ability to provide timely and accurate statements X_{16}. Moreover, the in-sample prediction accuracy of model 5 is consistent with model 4 at 94.3%, and the out-of-sample prediction accuracy is also the same as model 4 the accuracy of out-of-sample prediction is also the same as model 4. Therefore, the introduction of governance structure indicators in the logistic early warning model does not improve the accuracy of early warning.

Decision risk early warning model with the introduction of audit indicators

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Based on the introduction of governance structure indicators, 2 non-financial indicators audit (non-standard opinion X_{22}, audit change X_{23}) were introduced into the logistic risk warning model (model 6) as:

$$p\left(s_t=1\right)=\frac{e^{\beta_0+\sum_{i=1}^{23}\beta_i x_i}}{1+e^{\beta_0+\sum_{i=1}^{23}\beta_i x_i}} \quad (14)$$

Table 12 shows the regression results for model 6, where seven variables are retained in model 6, for fixed asset turnover X_3, total asset turnover X_4, return on net assets X_7, capital preservation and appreciation X_{12}, book-to-market ratio X_{15}, ability to provide timely and accurate statements X_{16}, audit changes X_{23}. Omnibus test of significance < 0.05 for the model coefficients indicates that model 6 is significant overall. The model's R^2 is 0.887, indicating that the model 6 explanation is validated.

Table 12 Omnibus test for model 6 coefficients

Step 6	B	Standard error	Wald	Significance	Exp(B)	95% confidence interval of Exp(B)	
						Lower limit	Upper limit
X3	0.020	0.040	0.247	0.652	1.021	0.943	1.231
X4	-8.297	4.781	3.485	0.615	0.000	0.000	1.691
X7	-22.27	10.223	4.152	0.452	0.000	0.000	0.428
X12	1.226	0.588	4.443	0.035	3.174	0.109	11.481
X15	-2.124	0.105	5.809	0.041	0.192	0.014	0.874
X16	-2.926	1.025	1.415	0.015	19.135	1.781	103.965
X25	7.758	1.274	6.235	0.209	174.523	0.014	207.847
Constants	5.818	6.331	4.449	0.035	341.747		

Then the model 6 regression equation is:

$$\begin{aligned}\ln\frac{p}{1-p}&=5.838+0.020x_3-8.929x_4-22.271x_7+1.262x_{12}\\&-2.214x_{15}+2.951x_{16}+7.578x_{23}\end{aligned} \quad (15)$$

Predicting the probability of each company based on the regression equation p, 23 of the ST companies were correctly predicted with an accuracy of 92.0%, and 27 of the non-ST companies were correctly predicted with an accuracy of 96.4%.

Taken together, the in-sample prediction accuracy of the logistic early warning model with the introduction of audit indicators is 94.3%. Therefore, the early warning accuracy of model 6 is the same as that of model 5, and the introduction of audit indicators in the logistic early warning model cannot improve the early warning accuracy.

Experimental results and analysis of decision risk early warning model

As shown by the joint improved integrated logistic model, the financial data of all 60 sample companies for 180 different time periods over three years were next aggregated as required according to the requirements of the model for the financial index parameters. As the test data set of the integrated model, the ZP(y)1 values and ZP(y)2 values of the integrated logistic financial risk warning model and the logistic integrated financial risk warning model based on factor analysis are validated, respectively. The results are represented here in a more visual way with graphs.

Analysis of test results for the value of ZP(y)1

The value of ZP(y)1 is a weighted average of the logistic regression results obtained by discriminating the financial data of the respective year based on the corresponding logistic financial risk warning model for three years. In this paper, the logistic regression value is set at a threshold of 0.5, and the size of ZP(y)1 is used to determine whether a sample's financial condition is a warning for delisting. When the value of ZP(y)1 is greater than or equal to 0.5 it can be judged, based on the available data, that the financial condition of the sample company is warning delisted, setting its sample attribute to 1. Conversely, when the value of ZP(y)1 is less than 0.5, the model judges that the sample company is a financially normal company, and the sample attribute is set to 0.

Generally speaking, the value of ZP(y)1 of the comprehensive judgment of the listed companies whose financial risk status is warning delisting should be greater than 0.5, that is, the point should fall within the interval of 0.5 to 1. The value of ZP(y)1 for the composite judgment of the sample companies with normal financial status should be less than 0.5, which means that the corresponding point should fall in the interval from 0 to 0.5.

Figure 3 shows the prediction results of the logistic financial decision risk warning model. The ZP(y)1 values of most of the sample companies with misjudgment are close to the cut-off line of 0.5. 7 listed companies with financial problems are misjudged to be in the financial normal category, and their ZP(y)1 values appear in the interval of 0~0.5, with a misjudgment rate of 9.3%. 4 companies with financial normal are misjudged to be in the abnormal category, and their ZP(y)1 values appear in the interval of 0.5~1, with a misjudgment rate of 7.2%. Within the range of 0.5 to 1, with a misclassification rate of 7.2%.

Therefore, the combined prediction accuracy of the integrated logistic financial risk early warning model for the full sample is 86.7%. The prediction differentiation ability of the integrated logistic model is generally inclined to the small and medium-sized listed companies with normal financial status, and the prediction accuracy of the sample companies with warning delisting financial status is improved compared with the prediction situation of the companies with normal financial status. It indicates that the logistic financial decision risk warning model synthetically improves the prediction ability.

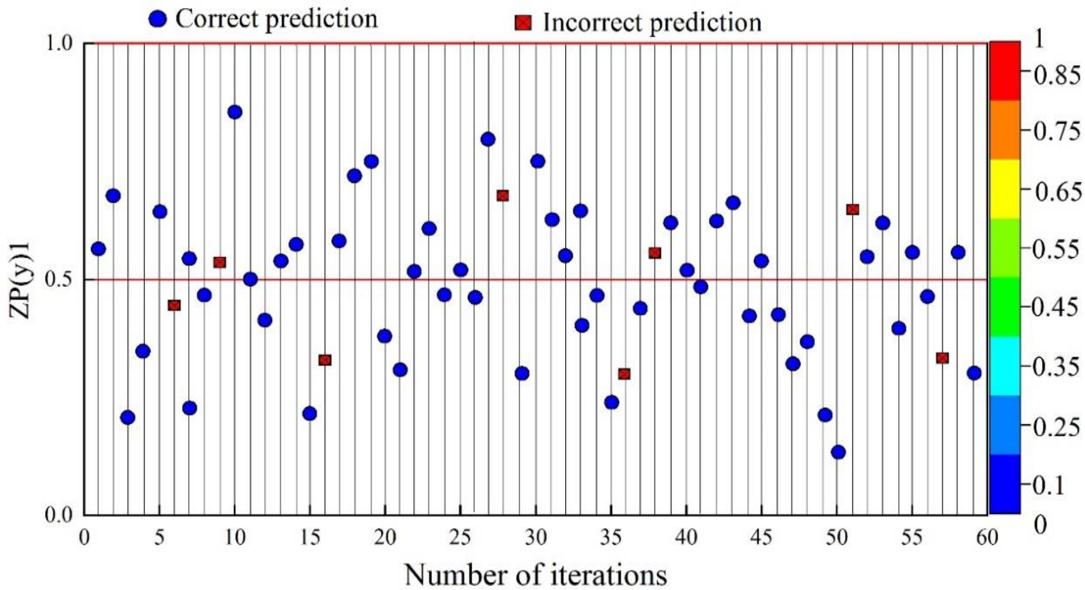

Figure 3 Comprehensive prediction results of logistic model

Analysis of test results for the value of ZP(y)2

The value of ZP(y)2 is the weighted average of the corresponding logistic regression P(y) values of the three factor analysis-based logistic financial risk warning models, i.e., the combined prediction results of the factor analysis-based logistic financial risk warning models. The magnitude of the ZP(y)2 value is compared with the threshold value of 0.5, and based on the results, the sample attributes of the sample companies Judgment is made.

Figure 4 shows the results of ZP(y)2 value detection. It can be seen that 6 of the listed companies with warning delisting financial status were misclassified as companies with normal financial status, and the value of ZP(y)2 fell in the interval of 0~0.5, resulting in a misclassification rate of 11.2% for the sample companies with warning delisting financial status by the integrated equation.

Two financially normal listed companies were misclassified as companies with warning delisting financial status, and the misclassification rate for the sample companies with normal financial status was 6.7%. Overall, the composite judgment equation obtained from the logistic risk decision warning model based on factor analysis has a combined correct prediction rate of 91.3%

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for the full sample.

The judgment result of the integrated model has a stronger prediction judgment ability for the SMB listed companies with normal finances than for the SMB listed companies with financial problems.

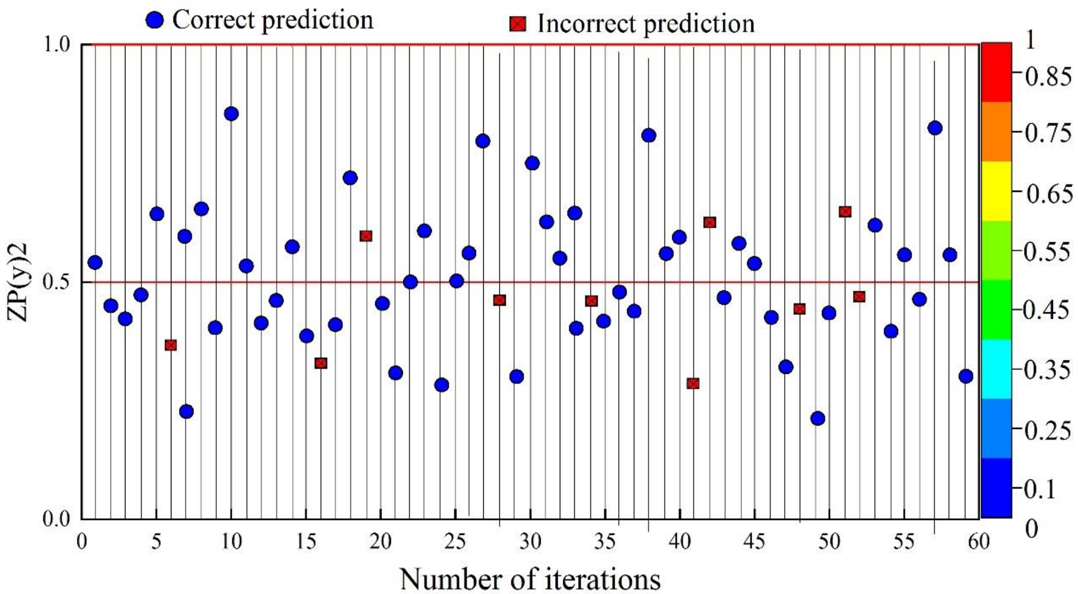

Figure 4 Prediction results of logistic model based on factor analysis

Conclusion

In this paper, ST companies and paired non-ST companies in 2021 are selected as samples, and a logistic financial risk early warning (FEW) model is established with 2017 data to predict the probability of a company being ST after 3 years. In the construction of the indicator system, traditional financial indicators were used as the basis, and five types of non-financial indicators were added, which were market price, management level, corporate reputation, governance structure and audit indicators.

Therefore, the correctness of the predictions of the six logistic financial risk early warning models (FEW) was verified by comparing their early warning accuracy, and the robustness of the selected logistic financial decision risk early warning model (FEW) was further tested.

The results show that adding three indicators of market price, management level, and corporate reputation to the logistic financial risk early warning (FEW) model all help to improve the early warning accuracy of the model, however, introducing governance structure and audit indicators to the logistic model does not improve the early warning accuracy of the model.

In addition, by comparing the logistic model selected in this paper with the three Z-score models, we found that the logistic model has the highest early warning accuracy of 94.3%, which has a high robustness.

In conclusion, the introduction of non-financial indicators in the logistic financial decision risk early warning model (FEW) can help improve the early warning accuracy of the model and provide some reference for the further development of risk early warning models.

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