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Identification of Financial Risks in Enterprises Based on Logistic Models

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Abstract

The diagnosis and identification of wealth risks and the construction of early warning models are crucial for operating enterprises, and have a profound impact on the management policies of the enterprise management and the work of the finance department. At present, there are many models used for financial risk identification and early warning in enterprises. However, in response to the low accuracy of existing models such as Z-score model, DE-SVM (Differential Evolution-Support Vector Machine) model in identifying and warning corporate risks, and the lack of significant impact on identifying corporate financial risks, this article referred to the logistic regression model to construct a corporate financial risk identification system. By studying 18 listed enterprises that have suffered losses for two consecutive years and 18 enterprises with normal financial conditions, financial indicators that can reflect significant differences between problem enterprises and normal enterprises were used as evaluation criteria to analyze the output results of the discriminant model. The results showed that the model had an accuracy of 94.68% in identifying financial risks in research enterprises, and had a good effect on identifying financial risks in enterprises. This study applied an efficient method for identifying corporate financial risks, enhancing detection accuracy to help enterprises more accurately assess financial risks and effectively prevent potential financial crises. The risk identification system based on the logistic regression model provides enterprises with effective risk management tools, aiding in the improvement of financial stability and maintaining competitiveness in complex market environments.

Keywords: Identification of financial risks in enterprises; financial index; z-score model; differential evolution-support vector machine model; logistic model.

1. Introduction

In the post pandemic era, the competition among existing enterprises in the gradually recovering market is also becoming increasingly fierce. However, the rapidly changing market conditions often lead to financial risks in business operations [1,2]. Among them, financial risk is usually considered as the risk that an enterprise may default on its debts. In literature related to corporate financial crisis, scholars often use bankruptcy or being ST (Special Treatment) as a signal of an enterprise falling into financial crisis, and based on this, conduct risk warnings and analyze the possible influencing factors of financial risk [3,4]. Identifying and predicting financial risks well, and clarifying the influencing factors of financial risks are the key to financial risk warning, but currently there is no unified standard in the academic community for such factors [5]. Therefore, research on corporate financial risk has gradually become a hot topic in the field of financial management.

The existing research on financial risk covers various disciplines, such as sociology, management, economics, politics, and social sciences. The research subject has also extended from macroeconomics to microeconomics, and among many studies, the most practical research direction for practical social related financial risk issues is the identification of financial risks [6].

Regarding the research direction of identifying financial risks, researchers such as Tung D T proposed using the Z-score model [7] to identify financial related financial risks [8]. The results of identifying financial risks through the Z-score model were simple and direct, and had comprehensive indicators [9]. However, because the Z-score model is a static model, it cannot reflect the fluctuations of market conditions in a timely manner, leading to results that easily overlook market factors [10]. Researchers such as Valaskova K used multiple regression models [11] to identify financial risks related to enterprises [12]. Multiple regression models have high flexibility and can select different independent variables based on specific problems, thus adapting to different business scenarios and financial characteristics. Moreover, multiple regression models can simultaneously consider multiple financial indicators, thereby more comprehensively evaluating the financial status of enterprises, which helps to capture the complex relationships between different indicators [13]. However, multiple regression models are based on some assumptions, such as linear relationships, normal distributions, etc. When these premises are not met, the reliability of the model may be affected [14]. Huang X and other researchers used Support Vector Machine (SVM) algorithm [15] to identify financial risks related to enterprises [16]. SVM performs well in high-dimensional spaces and is suitable for processing multi feature financial data, effectively handling a large number of financial indicators [17]. However, on large-scale datasets, SVM has high computational complexity, especially when using complex kernel functions, which may result in longer training time and is not suitable for large-scale data [18]. Researchers such as Qiao G combined Particle Swarm Optimization (PSO) with SVM to obtain PSO-SVM (Particle Swarm Optimization-Support Vector Machine) [19] algorithm for identifying financial risks related to enterprises [20]. PSO has adaptability and can adjust according to changes in the search space, which helps improve the adaptability of the model and reduces the tedious manual parameter tuning work, automatically finding the optimal SVM parameter configuration [21]. However, the PSO algorithm may require a significant amount of computational resources, especially on high-dimensional or large-scale datasets, which may result in significant computational overhead. Meanwhile, the PSO algorithm may perform well on certain problems, but it is not guaranteed to bring advantages on all problems, as its performance highly depends on the characteristics of the problem [22].

This article refers to the logistic regression model [23] for identifying corporate financial risks [24]. This model may perform worse in some nonlinear situations compared to linear situations [25], but it has advantages such as strong interpretability, high computational efficiency, wide applicability, and less overfitting. Compared to other models, it performs better in identifying corporate financial risks.

2. Methods

2.1 Selection of financial risk indicators

People have different opinions on selecting financial risk identification indicators for enterprises. According to past research findings, previous studies have mostly used traditional financial indicator classification methods, dividing them into four categories: solvency, profitability, operating condition, and growth ability. However, with the gradual implementation of the accrual system, cash flow indicators have become crucial in building a financial risk identification system for enterprises. Looking back at previous research, both scholars who use traditional financial indicators as financial risk identification indicators and those who integrate cash flow information into indicator systems [26] have similar principles for indicator selection. The selected financial risk identification indicators should have high discriminability, strong applicability, and a relatively simple way of obtaining them.

In summary, this article selects 28 indicators from 5 categories, including solvency, profitability, operating conditions, growth ability, and cash flow, as financial risk indicators:

Solvency: Solvency indicators help evaluate an enterprise’s ability to pay off its debts. Investors, creditors, and other stakeholders are concerned about whether the enterprise can repay its debts on time, including debt ratio and interest coverage ratio. These indicators provide key information on an enterprise’s debt level and its ability to pay interest.

Profitability: Profitability indicators provide information on how an enterprise can achieve profitability in its normal business activities. Indicators such as net profit margin and operating profit margin help evaluate the profitability of an enterprise when selling goods or providing services, which is crucial for investors and management, as profitability is the foundation of an enterprise's long-term survival and growth.

Operating conditions: Operating condition indicators include accounts receivable turnover rate and inventory turnover rate, which are used to measure the operational efficiency of the enterprise. These indicators help evaluate how an enterprise manages its assets and liabilities, as well as its competitiveness in the market.

Growth ability: Growth ability indicators are crucial for investors and management as they provide the potential for an enterprise's future growth. Indicators such as sales growth rate and net profit growth rate help predict the long-term business prospects of an enterprise.

Cash flow: Cash flow is the lifeblood of an enterprise's survival, so cash flow indicators (such as operating cash flow) are crucial for evaluating whether an enterprise can pay short-term debts, invest in future projects, and distribute dividends to shareholders. These indicators provide information on the robustness and flexibility of enterprises in cash, as shown in Table 1.

Table 1 Financial risk identification indicator system.

Type	Variable	Financial indicators
Solvency	x_1	Current ratio
	x_2	Quick ratio
	x_3	Cash ratio
	x_4	Interest coverage ratio
	x_5	Liabilities ratio
	x_6	Net cash flow generated from operating activities to current
	x_7	Cash flow interest coverage ratio
	x_8	Cash flow maturity debt coverage ratio
	x_9	Asset liability ratio
Growth ability	x_{10}	Growth rate of total operating revenue
	x_{11}	Growth rate of total operating costs
	x_{12}	Sustainable growth rate
Operating condition	x_{13}	Accounts receivable turnover rate
	x_{14}	Inventory to revenue ratio
	x_{15}	Accounts payable turnover rate
	x_{16}	Fixed asset turnover rate
	x_{17}	Capital intensity
Profitability	x_{18}	Operating profit margin
	x_{19}	Net profit margin from sales
	x_{20}	Net profit margin on total assets
	x_{21}	Return on equity
Cash flow	x_{22}	Cash flow ratio
	x_{23}	Debt coverage ratio
	x_{24}	Operating income cash ratio
	x_{25}	Cash recovery rate of all assets
	x_{26}	Net cash flow from operating activities per share
	x_{27}	Net cash flow from financing activities per share
	x_{28}	Net cash flow from investment activities per share

2.2 Logistic algorithm

2.2.1 Introduction to logistic model

The core idea of the logistic model is to map the linearly combined features to a probability value between 0 and 1 through the logistic function. The mathematical form of the logistic model is shown in Equation 1.

$$P(Y = 1) = \frac{1}{1+e^{-(b_0+b_1x_1+b_2x_2+\ldots+b_nx_n)}} \tag{1}$$

Among them, $P(Y = 1)$ refers to the probability of observing category 1; b_0, b_1, ..., b_n are the model parameters; x_1, x_2, ..., x_n are characteristic variables.

In financial risk identification, whether an enterprise has financial risk as the dependent variable is a qualitative variable, so a binary selection model should be selected as the financial risk identification model. Otherwise, using a linear model as a financial risk identification model would not be able to adapt to the values of explanatory variables.

Therefore, in this article, 1 indicates that the enterprise has financial risk, and 0 indicates that the enterprise has no financial risk. In order to ensure that the predicted value p of y is within the range of [0, 1], the logistic model feature variables x_1, x_2, ..., x_n are set as variables in Table 1, and the probability p is used to determine whether the enterprise is at risk. If p>0.5, it is determined that the enterprise has financial risk; otherwise, it is determined that the enterprise does not have financial risk, as shown in Equation 2.

$$y = \begin{cases} 1, p > 0.5 \\ 0, p \leq 0.5 \end{cases} \tag{2}$$

If an enterprise cannot meet its solvency and enters bankruptcy proceedings, it is in a state of financial crisis. In China, the situation is relatively unique, as listed enterprises may become “shell resources” and rarely truly face bankruptcy. Therefore, most scholars choose to collect specially processed data from listed enterprises for financial crisis research, and whether they have been specially processed is used as the standard for determining an enterprise’s financial crisis.

2.2.2 Logistic feature variable processing

Before constructing a logistic model, it is necessary to perform the K-S (KoImogorov-Smirnov) test on the feature variables in Table 1 [27,28]. The test results are divided into two groups: one is the group that follows a normal distribution, and the other is the group that does not follow a normal distribution. Characteristic variables that follow a normal distribution group would undergo significance testing [29], while characteristic variables that do not follow a normal distribution group would undergo non parametric testing [30]. The main indicators are extracted based on the first two sets of data, and finally, a logistic model is constructed based on the principal component factors. The specific process is shown in Figure 1.

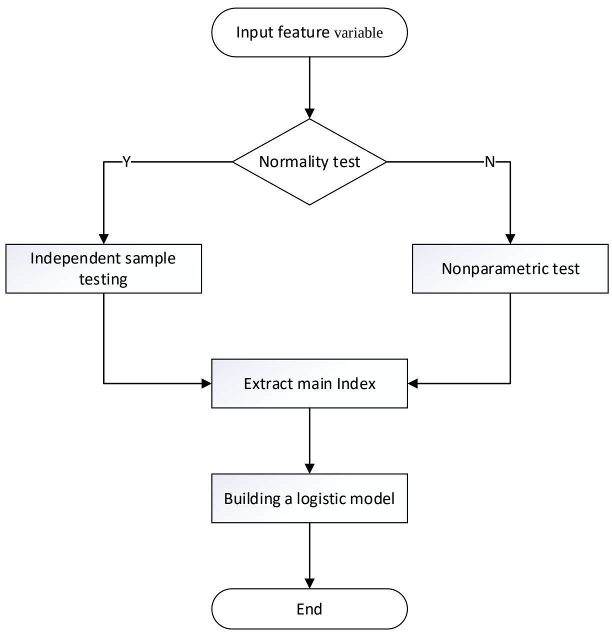

Figure 1 Logistic model construction process diagram

3. Experiments

3.1 Selected samples

The occurrence of a financial crisis in an enterprise is usually caused by a continuous process of change. Therefore, this study focuses on the financial status of listed enterprises, and conducts in-depth analysis of the process from normal to difficult. 36 listed Internet enterprises (including 18 ST enterprises and 18 non ST enterprises) with complete financial data in the past 10 years are selected as the research samples. In the model, the implementation of ST by the China Securities Regulatory Commission on enterprises is considered as an event of financial crisis, which is the sample group in the research object.

3.2 Logistic model

3.2.1 Normality test

In order to verify the significance of each indicator and screen out the indicators that have a significant impact on the model, the distribution of each indicator is first tested. In this study, a single sample K-S normality test is used as the evaluation criterion, and the indicators are divided into two categories: those that follow a normal distribution and those that do not follow a normal distribution.

Establishing the null hypothesis H_0: Indicator Xi follows a normal distribution. If the corresponding P-value is greater than 0.05, it is considered that the indicator follows a normal distribution; otherwise, it is considered non compliant. Table 2 presents the results of the univariate K-S test.

Table 2 Normality test.

Variable	Kolmogorov-smirnov Z	Progressive significance (Bilateral)	Whether to comply normal distribution
x_1	0.878	0.432	Y
x_2	0.869	0.002	N
x_3	1.691	0.004	N
x_4	0.865	0.403	Y
x_5	1.631	0.001	N
x_6	2.182	0.016	N
x_7	2.071	0.024	N
x_8	2.355	0.002	N
x_9	1.032	0.217	Y
x_{10}	0.928	0.326	Y
x_{11}	0.985	0.023	N
x_{12}	0.907	0.032	N
x_{13}	1.45	0.221	Y
x_{14}	0.721	0.024	N
x_{15}	1491	0.0046	N
x_{16}	1.391	0.035	N
x_{17}	1.691	0.012	N
x_{18}	1.265	0.023	N
x_{19}	1.116	0.134	Y
x_{20}	0.737	0.043	N
x_{21}	0.564	0.001	N
x_{22}	0.805	0.535	Y
x_{23}	0.811	0.539	Y
x_{24}	0.897	0.4	Y
x_{25}	0.781	0.721	Y
x_{26}	0.466	0.967	Y
x_{27}	0.386	0.014	N
x_{28}	0.793	0.015	N

Progressive significance (Bilateral) >0.05 indicates a normal distribution.

According to Table 2, the 11 financial risk identification indicators, x_1, x_4, x_9, x_{10}, x_{13}, x_{19}, x_{22}, x_{23}, x_{24}, x_{25}, and x_{26}, follow a normal distribution. Next, significance tests are conducted on these 11 indicators, and non parametric tests are conducted on the remaining 17 indicators that do not follow a normal distribution.

3.2.2 Significance test

Significance test is a statistical method used to determine whether an effect has statistical significance. Through significance testing, statistical inference can be made on whether the research results have practical significance. Therefore, this article conducts the independent sample t-test in the significance test for the 11 indicators that follow a normal distribution in Table 2. The test results are shown in Table 3.

Table 3 Independent sample t-test.

	Mean	Standard deviation	Standard error of mean	t	Df (degrees of freedom)	Sig (Bilateral)
Pair1(x_1)	1.376	10.731	2.190	0.615	17	0.521
Pair2(x_4)	2.484	9.24	1.89	1.335	17	0.2
Pair3(x_9)	-0.66	1.635	0.385	-0.776	16	0.043
Pair4(x_{10})	-0.053	0.123	0.025	-2.106	16	0.32
Pair5(x_{13})	-40.501	197.33	41.146	-0.986	16	0.333
Pair6(x_{19})	-1.072	3.342	0.682	-1.536	17	0.12
Pair7(x_{22})	-0.038	1.125	0.23	-0.166	17	0.86
Pair8(x_{23})	0.012	0.197	0.04	0.235	17	0.821
Pair9(x_{24})	0.045	2.47263	0.505	0.082	17	0.9
Pair10(x_{25})	0.312	0.803	0.16	1.886	17	0.07
Pair11(x_{26})	-0.29	2.128	0.434	-0.655	17	0.511

Sig (Bilateral) <0.1 is considered as passing the t-test.

According to Table 3, it can be seen that the Sig(Bilateral) of x_9: Asset reliability ratio; x_{25}: Sig(Bilateral)<0.1 of cash recovery rate of all assets, which means it has passed the t-test with a significance level below 10% and can be considered as the main indicator.

3.2.3 Non parametric tests

The remaining 17 non normally distributed indicators identified by K-S tests are subjected to non parametric tests. Considering that the selected sample is an independent sample, the Mann-Whitney U test is chosen.

Table 4 Mann-Whitney U test.

	U	Asymptotic significance (bilateral)
Pair2(x_2)	2765	0.031
Pair1(x_3)	2459	0
Pair3(x_5)	2500	0.1
Pair4(x_6)	2206	0.03
Pair5(x_7)	2158	0.026
Pair6(x_8)	2193	0.046
Pair7(x_{11})	2306	0.25
Pair8(x_{12})	2108	0.08
Pair9(x_{14})	2232	0.15
Pair10(x_{15})	2259	0.005
Pair11(x_{16})	2463	0.006
Pair12(x_{17})	2236	0.008
Pair13(x_{18})	3200	0.91
Pair14(x_{20})	2865	0.75
Pair15(x_{21})	2665	0.048
Pair16(x_{27})	2334	0.026
Pair17(x_{28})	2315	0.016

Asymptotic significance (bilateral)>0.05 is considered as passing the test.

The obtained test results are compared with the pre-set significance level. If the P-value is less than 0.05, the original hypothesis can be rejected. This means that there are significant differences between variables at different levels of dependent variables, so it is necessary to retain this indicator; on the contrary, if the P-value is greater than or equal to 0.05, the null hypothesis cannot be rejected, indicating that the differences between variables are not significant at different levels of the dependent variable. Therefore, it may be considered to exclude this indicator. The specific inspection results are detailed in Table 4.

According to Table 4, x_5, x_{11}, x_{12}, x_{14}, x_{18}, and x_{20} pass the Mann-Whitney U test and can be considered as the main indicators.

3.2.4 Construction of logistic model

According to the results of t-test and Mann-Whitney U test, the main indicators can be obtained as shown in Table 5.

Table 5 Main indicators.

Test type	Variable	Index
T test	x_9	Asset liability ratio
	x_{25}	Cash recovery rate of all assets
Mann-Whitney U test	x_5	Liabilities ratio
	x_{11}	Growth rate of total operating costs
	x_{12}	Sustainable growth rate
	x_{14}	Inventory to revenue ratio
	x_{18}	Operating profit margin
	x_{20}	Net profit margin on total assets

For the 8 main indicators in Table 5 that passed the k-s test, t-test, and Mann-Whitney U test, three methods from logistic regression analysis are used to construct the model, including full variable method, forward stepwise method, and backward stepwise method. In these two stepwise selection methods, the removal of variables is mainly based on the following three criteria: the first is the likelihood ratio probability value of maximum likelihood estimation; the second is the likelihood ratio probability value of conditional parameter estimation; the final is the probability values that are based on the Wald statistic. Subsequently, the constructed model is subjected to backtesting to ultimately evaluate the fitting accuracy of the model. The accuracy of the constructed model is shown in Table 6.

Table 6 Accuracy of logistic model.

Function	Model	Accuracy
All variable	$P = \frac{1}{1 + e^{-(0.35+2x_{25}+2.6x_5+2.9x_{18}-1.5x_9-3.3x_{11}-0.052x_{12}-0.05x_{14})}}$	93.52%
Forward step	$P = \frac{1}{1 + e^{-(-1.192+1.568x_9+3.311x_{14}-3.79x_{18}-3.752x_{25})}}$	94.68%
Backward step	$P = \frac{1}{1 + e^{-(0.8+1.836x_{18}+3.025x_{25}+2.696x_{20}-3.5x_9-0.05x_{11}-2.95x_{12})}}$	92.1%

According to Table 6, it can be seen that the accuracy of the forward step method in identifying corporate financial risks can reach up to 94.68%. Obviously, the forward step method using logistic models has a significant impact on identifying financial risks in enterprises.

4. Conclusions

This article used a Logistic regression model to identify corporate financial risks, aiming to develop a more precise risk warning tool. The study comprehensively considered traditional financial indicators such as solvency, profitability, operational status, and developmental stage, while innovatively incorporating the indicator of cash flow capability to enhance the model's sensitivity and accuracy in identifying financial risks within the Chinese market environment. Through empirical analysis of financial data from 36 listed companies, including 18 ST companies and 18 companies with normal financial conditions, a Logistic regression-based financial risk identification model was constructed. The results demonstrated that the model achieved a high accuracy rate of 94.68% in identifying corporate financial risks, indicating its superiority in promptly recognizing potential financial crises. The primary contribution of this study lies in proposing an efficient method for identifying corporate financial risks, which allows businesses to assess their financial risks more accurately and take effective measures to prevent potential financial crises. The enterprise financial risk identification system based on Logistic regression provides robust risk management tools, contributing to enhancing financial stability and maintaining competitiveness in complex market environments. This research offers a new perspective and tool for managing financial risks in enterprises, laying a solid foundation for future studies. Future research can further explore diverse financial indicators and their combinations, as well as the model's performance in different industries and market conditions, aiming to provide more targeted risk management strategies for a wider range of enterprises.

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