Early Warning Research on Financial Risk of Transportation Enterprises Based on Logistic Regression Analysis

Yueshan Han

Jiangsu University of Science and Technology, School of Economics and Management, 212100, Zhenjiang, China

2831718571@qq.com

Abstract. In the process of development, transport companies can be poorly operated thus resulting in sustained losses. To address such a situation, this paper adopts the data of listed companies in Luxembourg-Shenzhen transport from 2010 to 2022 as a sample, and applies factor analysis to screen out four principal component factors,then construct a financial risk early warning model for transport companies through binary logistic regression analysis. The results show that the overall correct rate of the model's early warning reaches 96.6%. Therefore, the model can better predict the financial crisis of listed transport companies

Keywords: transport companies; factor analysis; logistic regression

1 Introduction

China is a large transport country, and transport listed companies play an important role in our economy as the leading industrialisation of the transport sector. Since the outbreak of the New Crown epidemic, the operation of transport enterprises has been greatly affected by the reduction in travel demand and the increase in expenditure on epidemic prevention. National operational road passenger traffic, waterway passenger traffic and urban public transport passenger traffic fell sharply, and enterprises suffered serious losses and operational difficulties. Moreover, the special characteristics of transport enterprises in terms of industry operation and other aspects make them more prone to financial risks compared with other industries. Therefore, how to predict financial risk is a common problem faced by the transport industry.

Until now, scholars at home and abroad have conducted a large number of studies on the early warning of corporate financial risk. Early warning models include the following three: univariate models, multivariate models, neural network models. Univariate models are also known as univariate decision models. Foreign scholars Fitzpartrick (1932) [1] was the first to use a single financial indicator for financial risk prediction, divided the sample into crisis samples and healthy samples, and established a one-dimensional determination model to derive financial risk early

© The Author(s) 2024
V. Gaikar et al. (eds.), *Proceedings of the 2023 3rd International Conference on Financial Management and Economic Transition (FMET 2023)*, Advances in Economics, Business and Management Research 262,
https://doi.org/10.2991/978-94-6463-272-9_21

warning results. Merwin (1942) [2] and Beaver (1966) [3] similarly used a one-dimensional decision model for early warning of a firm's financial condition. Therefore, Ohlson (2015) [4] used Logistic regression, which is less demanding on samples, to construct an early warning model with an accuracy of 96.12 percent.

Domestic scholars for the study of financial risk started late, mostly drawing on foreign methods to establish a financial risk early warning model applicable to domestic enterprises. Zhou Shouhua (1996) [5] used data from 62 companies to build an F-score model. After that a large number of scholars studied Logistic regression model. Li Yan (2017) [6] used the financial data of urban commercial banks from 2008 to 2015 as a sample, established a Logistic early warning model, and concluded that the early warning effect is better. Xu K, Li DY, Jiang Y (2022) [7] A sample of A-share listed companies in Shanghai and Shenzhen from 2016 to 2020 is introduced with MD&A textual information, and a high warning accuracy is obtained.

2 Research design

2.1 Selection of the sample

Most of the early warning studies on financial risk in China use ST and *ST listed companies for one-to-one matching, while the actual situation is that among the transport listed companies, the number of ST companies is very low compared to the number of healthy companies. The use of one-to-one matching would make the sample size too small and produce unrepresentative early warning results. Therefore, this paper refers to Xinxin Chen and Hongtao Guo (2022) [8] who used an unpaired sample and extended the time horizon of the crisis sample to 2010-2022. As the number of healthy samples is larger than the number of crisis samples, the health sample in this paper is selected from 2022 only. To sum up, removing the listed companies in the transport sector with a lot of missing data, this paper selects a total of 87 sample companies from all A-shares in Shanghai and Shenzhen, including 81 healthy samples and 6 crisis samples.

2.2 Selection of indicators

This paper draws on previous empirical research results and combines the characteristics of the transport industry to select appropriate indicators. Therefore, this paper selects financial early warning indicators suitable for the transport industry based on previous studies, and screens the following indicators through the significance test:: Gearing Ratio (X1), Cash Ratio (X2), Interest Coverage Multiple (X3), Return on Assets (X4), Net Profit Margin on Total Assets (X5), Return on Net Assets (X6), Return on Invested Capital (X7), Operating Profit Margin (X8), Cost-Expense Profit Margin (X9), Shareholder's Equity Turnover (X10), Cash Suitability Ratio (X11), Growth Rate of Total Assets (X12), and Equity Ratio (X13). For the selection of crisis samples, the year in which the company is ST is regarded as T year, the previous year is regarded as T-1, the previous two years are regarded as T-2 years, and the previous three years are regarded as T-3 years. According to domestic and international research on financial risk, it can be concluded that T-3 year is not accurate for early warning. At the same time, the financial data of T-1 year, the enterprise has already appeared financial crisis at that time, which can not be recovered in time, and can not play the effect of early warning. Therefore, this paper selects the data of T-2 years as the crisis sample. the health sample data is selected for 2022. The data in this paper comes from CSMAR database, the published financial reports of Lushan Transportation listed companies in Oriental Fortune 2010-2022, and the empirical analysis uses the statistical software SPSS 18.0.

3 Financial early warning modelling

3.1 Factor analysis

In the course of the study, there is often a strong correlation between the indicators, and the data will partially duplicate information, making the results of the study often have a large gap with reality. In order to reduce the complexity and difficulty of analysing the data, factor analysis is often used to downscale the indicators and filter out the most critical ones, making it easier to move forward with the study. And before factor analysis, the selected variables need to be tested to determine whether the data are eligible for using factor analysis. The commonly used tests are KMO and Bartlett's test of sphericity. The formula is as follows:

$$\mathrm{KMO}=\frac{\sum_{i\neq j} r_{ij}^2}{\sum_{i\neq j} r_{ij}^2+\sum_{i\neq j} \beta_{ij}^2}$$

As seen in Table 1, the value of KMO is 0.657 and greater than 0.5, so the sample data can be analysed for factor analysis

Table 1. KMO and Bartlett's test

KMO Quantity of Sampling Suitability		.662
Bartlett's Sphericity Test	Approximate chi-square	1408.856
	Degrees of freedom	78
	Statistically significant	.000

3.2 Selection of principal component indicators

As can be seen from Table 2, there are five principal components with eigenvalues greater than 1. Meanwhile, the cumulative contribution rate of the variance of the first five principal components reaches 84.879%, and the sample can be better extracted raw financial information.

Table 2. Eigenvalues and contributions

Element	Initial eigenvalue			The sum of the squares of the loads			Rotational load sum of squares		
	Total	Percentage of variance	Accumulate %	Total	Percentage of variance	Accumulate %	Total	Percentage of variance	Accumulate %
1	4.805	36.961	36.961	4.805	36.961	36.961	3.662	28.171	28.171
2	2.042	15.711	52.672	2.042	15.711	52.672	2.294	17.644	45.815
3	1.915	14.729	67.401	1.915	14.729	67.401	2.160	16.616	62.431
4	1.215	9.343	76.745	1.215	9.343	76.745	1.785	13.731	76.162
5	1.057	8.135	84.879	1.057	8.135	84.879	1.133	8.717	84.879

Table 3. Component matrix after rotation

Number	Element					Element					
	1	2	3	4	5	Number	1	2	3	4	5
X1	.076	.048	.930	.110	.109	X11	.235	-.033	.188	-.008	.881
X2	.119	.160	.925	.058	.120	X12	.168	-.151	.541	-.102	-.470
X3	.621	.015	.275	-.022	-.185	X13	-.155	-.155	-.091	-.955	.005
X4	.944	.110	.065	.158	.119						
X5	.927	.126	.128	.231	.148						
X6	.563	.124	.021	.798	.055						
X7	.951	.087	-.008	.187	.157						
X8	.243	.933	.047	.084	-.023						
X9	.242	.939	.052	-.011	-.027						
X10	.246	-.643	-.051	-.297	-.102						

Table 3 shows that F1 is highly correlated with X3, X4, X5, X7, X10, so F1 can be explained by these five variables. F2 is highly correlated with X8, X9, so F2 can be explained by these two variables. F3 is highly correlated with X1, X2, X5, so F3 can be explained by these three variables. F3 is highly correlated with X1, X2, X5, so F3 can be explained by these three variables. F4 is highly correlated with X6, so F4 can be explained by this one variable. F5 is highly correlated with X11, X13, so F5 can be explained by these two variables.

4 Logistic regression analysis and model establishment based on principal component factors

4.1 Overview of Logistic Regression Analysis

Logistic regression model is a probabilistic model, which takes the probability P of whether an event occurs or not as the dependent variable, and suggests a regression model between the dependent and independent variables affecting the value of P, and analyses the relationship between the probability of the event occurring and the independent variables. The formula is as follows:

$$p = \frac{1}{1 + \exp\left(-\left(\beta_0 + \sum_{i=1}^{k} \beta_i x_i\right)\right)}$$

4.2 Logistic regression analysis and final establishment of the model

According to the five principal components obtained through factor analysis above as the explanatory variables of the binary Logistic regression, through the SPSS software, the final establishment of the model is as Table 4

Bringing the above equation into equation 1, the final financial early warning model for transport companies is obtained as:

$$P(Y=1)=\frac{1}{1+\exp\left(-(-7.248-2.848F1-3.297F2-3.557F3-1.475F4-2.021F5)\right)}$$

4.3 Model early warning results

Table 4 shows that the accuracy of this early warning model for the early warning of China's transport listed companies falling into financial crisis reaches 66.7%. For normal companies, the accuracy of early warning reaches 98.8 per cent. The overall accuracy rate reaches 96.6%, and the accuracy rate of early warning for financial crisis is good.

Table 4. Early warning effectiveness test table

Real measurement		Projections		
		Serial number		% Correct
		Non-ST	ST	
Serial number	Non-ST	80	1	98.8

	ST	2	4	66.7
Overall percentage				96.6

5 Conclusions

This paper selects the financial data of listed companies in the transport industry, and extracts five common factors from many financial indicators by factor analysis method. Logistic regression analysis was then used to construct a financial risk early warning model suitable for transport enterprises, and the overall prediction of the model reached 96.6%. The early warning accuracy of this model is high, which can provide reference for China's transport listed companies. The results of the study show that the financial loading status of transport listed companies can be studied from the aspects of solvency, profitability, operating ability, development ability and cash flow. Among them, profitability has a greater impact on the finances of listed transport companies, and the probability of financial crisis will be small if the company continues to make profits. Therefore, strengthening the operational capacity of enterprises can also effectively reduce the probability of financial crisis.

References

1. FITZPATRICK P J. A comparison of ratios of successful industrial enterprises with those of failed firms[J]. Certified public accountant,1932(12):598-729.
2. Merwin C L. Financial small corporations in five manufacturing industries, 1926-36[R]. National Bureau of Economic Research, 1942(11):121-124.
3. Beaver W. Financial rations as predictors of failure[J]. Supplement to Journal of Accounting Research,1966(4):71-111.
4. Ohlson J. Financial ratios and the probabilistic prediction of bankruptcy[J]. Journal of Accounting Research,1980(18):109-131.
5. Zhou Shouhua, Yang Jihua, Wang Ping. On Early Warning Analysis of Financial Crisis I F-score Model [J]. Accounting Research, 1996,(8):8-11.
6. Li Yan. Research on financial risk early warning system of urban commercial banks based on factor analysis [J]. Financial theory and practice, 2017, (4): 31-34.
7. XU Kai, LI Dongyang,JIANG Yu. Early warning research on financial crisis of listed companies based on MD&A text analysis[J]. Friends of Accounting,2022(17):88-95.
8. CHEN Xinxin, GUO Hongtao. Joint use of factor analysis and logistic regression in financial early warning of agricultural listed companies[J]. Mathematical Statistics and Management,2022,41(01):11-24.

Open Access This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (http://creativecommons.org/licenses/by-nc/4.0/), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.