ISSN: 2688-9323

Research on Enterprise Financial Risk based on BP Neural Network

-- Taking Listed Manufacturing Companies in China as an Example

Han Gong

Guangzhou College of Commerce, Guangzhou 511363, China

Abstract

The listed companies selected in this article cover industries such as clothing, food processing, and textiles. Firstly, based on the combination of theories related to corporate finance and the selection principles of previous scholars, 22 financial data such as cash ratio were preliminarily selected as indicator variables. Then, the financial data of ST and non ST companies in 2022 were obtained for descriptive statistics to analyze the gap between the two companies in financial indicators. The data source was the Guotai An database. Then 220 listed companies were selected as model data samples, with a ratio of 1:3 between financially distressed companies and financially normal companies. Finally, 19 indicators were empirically tested as variables to construct a BP neural network model.

Keywords

Manufacturing Financial Crisis; BP Neural Network; Multivariate Discrimination.

1. Introduction

The steady improvement of the Chinese economy has driven the development and expansion of the securities market, and the role of listed companies in promoting market development has become increasingly prominent. Therefore, the manufacturing industry is gradually becoming an important cornerstone to ensure stable economic development. At the same time, however, listed manufacturing companies are vulnerable to the negative impact of external factors, such as international trade war competition and the outbreak of COVID-19, and thus financial risks arise. Therefore, in order to promote the sustainable development of China's economic market, China must pay attention to the economic development situation of the manufacturing industry and promote the stable development of listed manufacturing companies. In a market economy, whether a company has good development prospects depends on whether its financial situation is healthy. Enterprises need to ensure their financial health in order to have a solid financial foundation in the face of macroeconomic risks and fierce competition in the manufacturing industry, providing strong financial support for their daily operational activities and investment behavior, and promoting the development and innovation of the enterprise. If a company's finances are in trouble, it will bring economic turmoil to its managers and investors. In order to avoid bankruptcy, some companies may resort to illegal means such as financial fraud, which may cause market disorder and have a negative impact on the social economy. Therefore, conducting objective analysis and evaluation of the financial situation of listed manufacturing companies, strengthening control and early warning of potential financial risks, and avoiding the accumulation of financial risks that may lead to uncontrollable economic downturns or even bankruptcies, plays an important role in the healthy development of manufacturing enterprises. Establish an effective financial early warning system, detect

ISSN: 2688-9323

financial problems in advance, take corresponding measures in a timely manner to prevent serious risks and reduce losses for the enterprise. In summary, studying the financial situation of enterprises has a significant impact on their healthy and comprehensive development, and effective financial risk warning is of great significance for the stability of China's financial market and the interests of investors.

2. Literature Review

Huo Wenhui (2020) selected 304 financially distressed companies and 912 financially normal companies in a 1:3 ratio as research samples. To comprehensively reflect the effectiveness of the model, 253 indicators including relative value and company equity structure were selected from both financial and non-financial aspects to construct a convolutional neural network model. Empirical testing showed that the CNN model has very strong predictive ability, with a prediction accuracy of up to 96%[1]. Yan Jie (2021) selected financial data from 149 listed companies in the pharmaceutical manufacturing industry as the research sample, and selected 19 financial indicators from three aspects: production and operation, research and development investment, and fund use as variables to construct an MLP neural network model. The prediction accuracy of this model is as high as 98%, which can be well used for financial risk warning of pharmaceutical manufacturing companies[2]. Zeng Yuanyuan (2016) found through empirical analysis that the discrimination rate of the original Z-value scoring model was only 61%. Considering the development process and differences of China's agricultural and sideline product processing industry, modeling was conducted based on the existing research. After following the principles of sensitivity, practicality, and early perception of indicators, financial data of 36 agricultural and sideline product processing enterprises from 2011 to 2013 were selected as research samples. A discriminant function was established based on the financial data that underwent significance testing to determine 10 financial indicators and construct a new Z-value model. Combined with the research method of Fisher's criterion, the overall discriminant accuracy of the new Z-value model reached 86.1%[3]. Chen Hao (2018) conducted an empirical study on the financial risks of 19 independent colleges in Zhejiang Province using principal component analysis. When extracting factor variables, select 7 factors with eigenvalues greater than 1 as common factors to establish a factor score function. Based on correlation analysis and regression analysis, it is concluded that risk control for independent colleges should focus on three aspects: property rights factor, external benefits factor, and development strategy factor[4]. Wu Xiang, Duan Lihezi, and Li Hongrui (2022) selected 76 listed manufacturing companies in the Shanghai and Shenzhen A-share markets as research samples, and used principal component analysis to extract four common factors for data processing and construct a logistic model. After empirical testing of the test samples, it was found that the accuracy of the financial warning model reached 75%, which can effectively warn[5].

3. Research Hypothesis

3.1. The Relationship between Financial Risk and Financial Crisis

Firstly, financial risks and crises are both concrete manifestations of the financial activities of a company during its development process. Financial risk is the risk caused by uncertain factors in the production and operation process of an enterprise, resulting in the failure to repay debts. Financial crisis is an accumulation process and a highly deteriorating state of financial condition. When certain important related indicators are abnormal, it indicates that the enterprise is likely to experience financial crisis. Secondly, financial crisis is the most severe form of financial risk development. When enterprises can timely handle and formulate relevant

ISSN: 2688-9323

preventive measures, it can effectively avoid financial crises. Once a company fails to timely avoid the accumulation of financial risks, the potential financial crisis caused by the outbreak of risks will seriously affect the survival of the company. Finally, financial risk is a possible factor with uncertainty. If a company can exercise effective control in a timely manner, it is possible to achieve more than expected corporate profits. Financial crisis is more often manifested as an economic phenomenon of deteriorating financial management in enterprises. Once a financial crisis occurs, the company's profitability will inevitably suffer varying degrees of losses.

3.2. Financial Warning

The financial data in the process of enterprise operation is an important foundation for constructing a financial warning model, which is based on the concept of risk warning theory and analyzed using statistical and other application methods. When there is an abnormality in the data, it indicates the possibility of financial crisis for the listed company, and corresponding measures can be taken to avoid losses. Compared with other models, the neural network financial early warning model has better characteristics, which are not only time-saving and convenient, but also higher accuracy. Its strong generalization ability and non-linear fitting ability are also its advantages in being more widely used.

Based on this, the sresearch hypothesis of this article is proposed: the neural network financial early warning model has excellent prediction accuracy and better prediction performance than the multivariate discriminant analysis early warning model.

4. Empirical Design and Analysis

4.1. Financial Indicator Analysis

To effectively reflect the financial operation status of the enterprise, the selection of financial indicators should follow the principles of indicator sensitivity, systematicity, and effectiveness. Indicator information not only needs to reflect the company's situation in a timely manner, but also needs to have a certain degree of correlation between indicators to construct an early warning model. Therefore, this article constructs a financial research system by selecting 22 financial indicators, including the current asset ratio, from four aspects of the company's debt paying ability, development ability, operational ability, and profitability. The calculation formula and meaning are shown in Table 1.

Table 1. Preliminary Selection Table of Model Financial Indicators

category	Number	Indicator Name	Calculation formula	Explanation of indicator meanings
Debt paying ability	X1	Current asset ratio	Total current assets/total assets	Reflect the proportion of current assets that can be realized or utilized by the enterprise to owner's equity. The higher the current asset ratio, the stronger the debt repayment ability, but a high ratio indicates that inventory backlog seriously affects asset realization.
	X2	Cash asset ratio	Closing cash and cash equivalents balance/total assets	Reflect the proportion of cash assets and current liabilities in a company's operating activities. The higher the ratio, the better the liquidity of a

				company's cash assets.
	X3	Current ratio	Current assets/current liabilities	Reflecting the ability of a company's current assets to be realized and repay its liabilities. The larger the current ratio, the stronger the short-term solvency of the enterprise. It is generally believed that the current ratio should be above 2.
	X4	Quick ratio	(Current assets inventory)/Current liabilities	The quick ratio is generally believed to be above 1, which reflects the liquidity of a company's assets and its ability to repay short-term debts.
	X5	Cash ratio	Cash assets/current liabilities	The ability of a company's cash and cash equivalents to guarantee its current assets is the most direct indicator of its repayment ability. The larger the cash ratio, the stronger the company's liquidity and ability to repay debts.
	X6	Asset liability ratio	Total liabilities/total assets	Reflect the proportion of corporate assets raised through debt. Generally speaking, a debt to asset ratio between 40% and 60% is more reasonable.
	X7	Equity multiplier	Total assets/total owner's equity	Reflect the ratio of total enterprise assets to total shareholder equity. The lower the value, the greater the proportion of capital invested by shareholders in assets, and the lower the degree of debt of the enterprise.
	X8	Property ownership ratio	Total liabilities/total owner's equity	Reflect the relative proportion of capital invested by corporate creditors and shareholders. As an important indicator of financial stability, it is used to measure a company's long-term solvency. The higher the equity ratio, the weaker the debt paying ability.
develop ability	X9	Fixed asset growth rate	(Net amount of fixed assets at the end of the current period - Net amount of fixed assets at the beginning of the current period)/Net amount of fixed assets at the beginning of the current period	Reflect the speed and level of fixed asset growth within a certain period of time for the enterprise. The larger the growth rate of fixed assets, the greater the expansion of enterprise production capacity, and the better the future performance growth

ISSN: 2688-9323

				trend.
	X10	Total asset growth rate	Total asset growth for the current period/total assets at the beginning of the period	Reflect the growth of the company's asset size in the current period. The higher the growth rate of total assets, the greater the expansion of the company's operating activities in the current period and the higher its development potential.
Operational capability	X11	Fixed asset ratio	Total fixed assets/assets	Reflect the utilization of enterprise funds. The lower the ratio, the less idle funds a company has and the better its operating conditions are.
	X12	Accounts receivable turnover rate	Net operating income/average accounts receivable	Reflect the speed of the company's collection period. The higher the ratio, the shorter the collection time and stronger the operational capacity of the enterprise.
	X13	Inventory turnover rate	Operating costs/average inventory	Reflecting the management ability of enterprises towards inventory, the faster the inventory turnover, the higher the production and operation liquidity of the enterprise.
	X14	Current asset turnover rate	Operating income/average amount of current assets	Reflecting the level of utilization of a company's current assets. The faster the turnover speed, the better the utilization effect of current assets.
	X15	Fixed asset turnover rate	Operating income/average fixed assets	Reflecting the level of utilization of fixed assets in enterprises. The higher the ratio, the higher the level of fixed asset management and the stronger the business vitality.
	X16	Total asset turnover rate	Operating income/average total assets	Reflect the ratio of enterprise asset investment scale and sales level. The higher the total asset turnover rate, the better the business performance and investment efficiency of the enterprise.
Profitability	X17	Asset return rate	(Total profit+financial expenses)/Total assets	Reflecting the ability of enterprises to use funds to earn profits. The higher the ratio, the higher the input-output level and profitability of the enterprise.
	X18	Net profit margin of total assets	Net profit/average balance of total assets	Reflect the profitability and input-output situation of the enterprise. The higher the ratio, the more effective the

				asset operation of the enterprise.
	X19	Net profit margin of current assets	Net profit/average balance of current assets	Reflect the effectiveness of using current assets and the economic development benefits of the enterprise. The higher the ratio, the stronger the profitability of the enterprise in utilizing current assets.
	X20	Net profit margin of fixed assets	Net profit/average balance of fixed assets	Reflecting the effectiveness of fixed asset utilization is an important indicator for measuring a company's profitability. The higher the ratio, the better the fixed asset management effect of the enterprise.
	X21	Return on equity	Net profit/average balance of owner's equity	Reflecting the growth rate of shareholder benefits in the enterprise. The higher the return on equity, the greater the investment return of the enterprise, and the greater the increase in benefits for shareholders.
	X22	Sales expense rate	Sales expenses/operating income	Reflect the unit sales expenses incurred by the enterprise to obtain unit income, including insurance premiums, handling fees, etc. The higher the sales expense ratio, the greater the sales expenditure and the lower the profit for the enterprise.

4.2. Sample Selection

Table 2. Statistics of Financial Crisis Companies and Financial Normal Companies from 2018 to 2022

year	2018	2019	2020	2021	2022
Financial Crisis Company	65	66	63	58	55
Financial normal company	2072	2139	2289	2636	2952
total	2317	2205	2352	2694	3007
Proportion	3.04%	2.99%	2.68%	2.15%	1.83%

Since the reform and opening up, the manufacturing industry, as the main driving force of the real economy, has been the focus of China's supply side structural reform and technological innovation, and also the main driving force for driving China's GDP growth. At the same time, abundant labor force is a necessary support for the development of manufacturing industry, and the number of employed people in our country has also increased. In summary, financial research in the manufacturing industry has its research significance. This article takes A-share manufacturing listed companies in the Shanghai and Shenzhen stock markets as the research objects. After screening and removing samples with missing indicators, 55 financially abnormal

ISSN: 2688-9323

companies from manufacturing listed companies in 2022 were selected, and 165 financially normal companies were randomly selected as data samples in a 1:3 ratio for the study.

To gain a better understanding of the financial situation of manufacturing listed companies in recent years, Table 2 shows whether manufacturing A-share listed companies on the Shanghai and Shenzhen Stock Exchanges experienced financial crises from 2018 to 2022.

4.3. Empirical Testing and Result Analysis

4.3.1. Significance Test

To avoid the occurrence of variable related randomness and eliminate variables with insignificant differences between ST companies and non ST companies, this article uses significance tests to screen and determine the final variable indicators. Based on the results of the normality test in the previous text, independent sample t-test is used for X1 based on its normal distribution, and non parametric test is used for the remaining 21 variables. The test results are shown in Tables 3 and 4.

Table 3. Independent Sample T-Test

X1	Levin's test for homogeneity of variance		Mean isotropy t-test						
	F	Sig.	t	degree of freedom	Sig.	Mean value difference	Standard error value	95% confidence interval for difference	
								lower limit	upper limit
Assuming equal variance	0.954	0.330	-2.231	218	0.027	-0.054664	0.024504	-0.102959	-0.006369
Assuming unequal variances			-2.166	88.229	0.033	-0.054664	0.025232	-0.104806	-0.004521

Table 4. Non parametric tests

	Mann-Whitney U	Wilcoxon W	Z	Progressive significance
X2	7211.500	20906.500	6.541	0.000
X3	6816.0	20511.000	5.573	0.000
X4	6497.000	20192.000	4.793	0.000
X5	7121.000	20816.000	6.319	0.000
X6	2287.000	15982.000	-5.505	0.000
X7	2287.000	15982.000	-5.505	0.000
X8	2287.000	15982.000	-5.505	0.000
X9	6746.000	20441.000	5.402	0.000
X10	7234.000	20929.000	6.596	0.000
X11	4361.500	18056.500	-0.431	0.667
X12	5700.500	19395.500	2.845	0.004
X13	4340.000	18035.000	-0.483	0.629
X14	6056.000	19751.000	3.714	0.000
X15	5637.000	19332.000	2.689	0.007
X16	6193.000	19888.000	4.049	0.000
X17	7367.000	21062.000	6.921	0.000
X18	7451.000	21146.000	7.127	0.000
X19	7443.000	21138.000	7.107	0.000
X20	7357.000	21052.000	6.897	0.000
X21	7401.000	21096.000	7.004	0.000
X22	3940.000	17635.000	-1.462	0.144

ISSN: 2688-9323

From the analysis of the results of the above two variable tests, it can be seen that at a confidence level of 5%, the Sig value of X1 is 0.027<0.05. Based on this, it can be concluded that there is a significant difference in the current asset ratio indicator data between ST companies and non ST companies. In the non parametric test of X2-X22, if the P-values of the variables X11, X13, and X22 are greater than 0.05 and fail the significance test, they need to be excluded. In summary, the following text will use a total of 19 variables, including X1-X10, X12, and X14-21, to construct a financial warning model for prediction.

4.3.2. BP Neural Network Model

Based on the above tests, we used the 19 final indicators as variables and used STATA software to group and test the 220 manufacturing enterprises selected in 2021 according to the set proportion. All 220 samples were valid, so there was no need to exclude them. The test results are shown in Table5. Secondly, process the data by assigning values of "0" and "1" to financially distressed companies and financially normal companies respectively, and finally input the data into the model. The output results are shown in Table 6.

Table 5. Sample Processing

		N	percentage
sample	train	153	69.5%
	test	67	30.5%
Effective		220	100.0%
Excluded		0	
total		220	

Table 6. BP neural network model output results

sample	Actual measurement	forecast		
		0	1	Correct percentage
train	0	23	10	69.7%
	1	6	114	95.0%
	Total percentage	19.0%	81.0%	89.5%
test	0	13	9	59.1%
	1	3	42	93.3%
	Total percentage	23.9%	76.1%	82.1%

Based on the analysis of the above output results, the overall accuracy of the training samples reaches 89.5%. The accuracy rate of ST company's prediction is 69.7%, while the accuracy rate of non ST company's prediction is as high as 95.0%; The overall accuracy rate of the test samples reached 82.1%, with prediction accuracy rates of 59.1% for ST companies and 93.3% for non ST companies, respectively. Based on the above, it can be concluded that the prediction level of this model is high. Due to the difference in sample size between the two companies, there is also a certain gap in prediction accuracy.

In financial warning models, it is impossible to avoid the first and second types of errors. The former, also known as erroneous rejection, refers to misjudging a financially distressed company as a financially normal company; The latter is the opposite, also known as erroneous reception. Based on the above results, the probability of errors in predicting two sets of samples using the BP neural network model is shown in Table7.

Table 7. Prediction Error Probability of BP Neural Network Model

	First type error	Second type error
training sample	$P_{1(A)}$=10/33×100%=30.3%	$P_{2(A)}$=6/120×100%=5%
Test samples	$P_{1(B)}$=9/22×100%=40.9%	$P_{2(B)}$=3/45×100%=6.7%
	P_1=(30.3%+40.9%)/2=35.6%	P_2=(5%+6.7%)/2=5.85%

The above empirical results indicate that the BP neural network model has high prediction accuracy, and the neural network financial early warning model proposed in hypothesis two has excellent discrimination prediction rate. Meanwhile, the probability of the first type of error occurring in this model is much higher than that of the second type.

4.3.3. Robustness Testing

Discriminant analysis is widely used in traditional statistical methods in different fields, with the aim of discovering linear combinations of predictive variables. In order to further enhance the reliability and consistency of the empirical test results mentioned above, this article will use discriminant analysis as the robustness test, and input the data into the discriminant analysis model to obtain the test results as shown in Table 8.

Table 8. Discriminant analysis classification results

ST is 0 No ST is 1			Prediction group members		Total
			0	1	
initial	count	0	41	14	55
		1	19	146	165
	%	0	74.5	25.5	100.0
		1	11.5	88.5	100.0

Based on the above results, the overall prediction accuracy of the discriminant model and the probability of errors in predicting two groups of samples are shown in Table9.

Table 9. Discriminant analysis model prediction results

Overall prediction accuracy	P=(220-14-19)/220×100%=85.0%
First type error probability	P_1=14/55×100%=25.5%
Second type error probability	P_2=19/165×100%=11.5%

Based on the above results and the prediction results of the BP neural network model, the probability of false rejection errors occurring in financial early warning is significantly higher than that of false acceptance errors.

The above empirical process shows that the BP neural network model and discriminant analysis method have good predictive performance, with prediction accuracy of 89.5% and 85.0% respectively, both reaching 85% or above. The high prediction accuracy of discriminant analysis further confirms the reliability of the empirical results of the BP neural network model. Meanwhile, the difference in prediction rates between the two financial warning models also indicates the superiority of the BP neural network model.

Therefore, the hypothesis two proposed in the above content of the article is valid. The neural network financial early warning model has excellent prediction accuracy and better prediction performance than the multivariate discriminant analysis early warning model.

ISSN: 2688-9323

5. Conclusion

In recent years, with the development of economic globalization, the constantly changing macro environment has to some extent intensified the possibility of financial crises for enterprises, and the development of the manufacturing industry is also facing challenges. This article is based on relevant theories such as financial risk, and carefully studies and summarizes the literature of domestic and foreign scholars on financial warning models. Based on a deep understanding of concepts such as financial risk, financial crisis, and financial warning, the financial data of 220 listed companies in the manufacturing industry in 2022 were randomly selected as research samples. The final variable indicators were determined using STATA software for model construction. The conclusions of theoretical research and empirical testing are as follows:

Firstly, by analyzing the data of manufacturing A-share listed companies in Shanghai and Shenzhen from 2018 to 2022, it can be concluded that the number of financially normal companies continues to increase, while the proportion of financially distressed companies among all companies has decreased. However, the development of enterprises is currently affected by many factors, so financial crisis companies still need to seek profit points to promote their own development, and the economic market also needs to provide certain support policies.

Secondly, through the analysis of relevant financial indicators of listed companies, it is found that companies facing financial crises have common problems such as insufficient debt repayment ability, weak profitability, and inefficient operational management capabilities. Profit is the biggest goal of enterprise development, but the invested funds do not create corresponding benefits. Without benefits, debt cannot be repaid. Persistent income deficit is like a broken balloon, which will inevitably lead to bankruptcy. Meanwhile, the difference in financial indicator data between financially distressed companies and financially normal companies also confirms the first hypothesis proposed in the article, which is that financially normal companies perform better in financial indicator data than financially distressed companies.

Finally, the financial indicator system was determined through methods such as normality test and significance test to construct the model. Empirical analysis showed that the prediction accuracy of the BP neural network model and the multivariate discriminant model were both above 85%, which can reasonably predict financial risks and promote enterprises to timely grasp financial information to avoid financial crises. Using discriminant analysis as a robustness test, the comparison between the empirical results and the results of the BP neural network model confirms hypothesis two proposed in the article, which is that the neural network financial early warning model has excellent discrimination accuracy, and the prediction results of the neural network model are better than those of the discriminant analysis early warning model.

Acknowledgments

This work was supported by the Fund project: Guangzhou Business School's 2022 Excellent Course Construction Project "Financial Big Data Mining and Analysis" (Project Number: XJYXKC202204)

References

[1] Huo Wenhui. Research on Financial Crisis Warning Model for Listed Companies Based on Convolutional Neural Networks. China Academy of Financial Sciences, 2020.

[2] Yan Jie Research on Financial Risk Warning in the Pharmaceutical Manufacturing Industry: An Empirical Study Based on Neural Networks Financial Management Research, 2021 (03): p. 45-48.

ISSN: 2688-9323

[3] Zeng Yuanyuan. Research on Financial Warning of Agricultural and Sideline Food Processing Industry Based on Z-Score Model. China University of Petroleum (Beijing), 2016.

[4] Chen Hao. Research on Financial Risk Control in Independent Colleges: A Case Study of Independent Colleges in Zhejiang Province . Friends of Accounting, 2019 (17): p. 119-125.

[5] Wu Xiang, Duan Li Hezi, Li Hongrui. Research on Financial Warning of Manufacturing Enterprises in China, Small and Medium sized Enterprise Management and Technology, 2022 (13): p. 187-189.