Business Bankruptcy Analysis with Explanations and Suggestions Based on Companies in Poland

Zuyi Li*

School of Management and Economics, Beijing Institute of Technology, Beijing, China

1120191008@bit.edu.cn

Abstract. This is a study on business bankruptcy analysis and prediction. Traditionally, business bankruptcy prediction study was to build models through different methods and then verify their validity and accuracy with the actual financial information of bankrupt companies. It was still developing over the years. The purpose of this study is to find out the obvious financial ratio that affects the company's bankruptcy, and to give a detailed explanation and analysis, rather than a mathematical equation or a conclusive model. The data was the change in the financial ratios of bankrupt and non-bankrupt companies over time instead of single financial information in the year of bankruptcy. Factor analysis, binary logistic regression, and non-parametric tests were used. By looking for commonalities and priorities in financial ratios, this study speculated on the causes of changes in financial ratios and provided suggestions to managers. The experimental results showed that "Total Assets Related", "Short-term Liabilities Related", "Total Liabilities Related", and "Fixed Assets Related" were significantly different between bankrupt and non-bankrupt companies. After further analysis, the study concluded that sources of financing, the liquidity of the company, and investment were likely to be significant factors that influenced business bankruptcy. The highlight of this study was the more detailed explanation of financial ratio analysis, and its value was the method of avoiding business bankruptcy rather than the judgment of the likelihood of business bankruptcy, as most previous studies have done.

Keywords: Business bankruptcy, Factor analysis, Binary logistic regression, Non-parametric test, Liability, Liquidity, Investment

1 Introduction

Business bankruptcy analysis and prediction have always been a hot and interdisciplinary subject in economics, finance, and management. The obvious value of business bankruptcy study can be seen from the theoretical and practical aspects. Theoretically, it establishes an interdisciplinary connection, that is, the statistical information of financial ratios reflects the management significance of the company's operation, in which the methodology of data processing and view of business finance are the determinants of the project. Practically, it is based on the current business environment and

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financial market to discuss the significance of some financial ratios, including profitability and risk management, to help enterprises timely adjust the direction of development and avoid bankruptcy. In essence, the analysis and prediction of business bankruptcy is the responsibility of traditional management accounting. However, with the change in business model and the process of economic globalization, companies as individuals need to face more fierce competition. It provides a constructive reference for the work of managers, accountants, financial analysts, and auditors in enterprises, as well as economists and industry analysts in modern society. Therefore, business bankruptcy analysis and prediction have a continuous and wide range of value.

This has been a traditional field due to the importance of bankruptcy prediction, but it has remained popular for decades and is still being refined by many scholars. In 1968, Altman emphasized the importance of financial ratios for bankruptcy analysis and prediction, using Multiple Discriminant Analysis (MDA) to establish a primary prediction model [1], which is considered to be the pioneer to use financial data models in business bankruptcy prediction. Since then, many methods and models have emerged. A classic one was the Logit model, which was proposed by Ohlson in 1980 [2]. Subsequently, many scholars have improved this model. For example, Barniv et al. proposed the ten-variable Logit model with five accounting indicators and five non-accounting indicators [3]. Hillegeist et al. developed Altman and Ohlson's model and proposed BSM-Prob [4]. Hensher and Jones applied Mixed Logit to have desirable econometric properties and overall predictive performance [5]. In addition, scholars tested and refined models in different regions and industries [6-9]. Although the model was relatively complete, the prediction accuracy of traditional models had an upper limit that was difficult to break through in different business environments.

With the development of science and technology, the neural network was used to predict business bankruptcy [10]. It was a milestone that greatly improved the accuracy of predictions compared to traditional models. Subsequently, the neural network framework of Zhang et al. also proved its advantages [11]. More scholars, including Atiya, Tsai & Wu, and Hosaka, applied neural networks flexibly to business bankruptcy prediction in various environments and recognized its obvious strengths [12-14]. Besides, Support Vector Machines (SVM) was another innovation in business bankruptcy prediction [15], and Li & Sun developed the SVM method later [16]. Newer methods such as AdaBoost also provided insights into business bankruptcy prediction [17-18]. Finally, Salehi & Shiri used a combination of several different bankruptcy prediction methods and compared them [19]. However, these methods were all results-oriented and placed exceeded emphasis on the application of models, while ignoring the financial information that could be obtained in the process of data exploration to avoid business bankruptcy, which was also the core value of business bankruptcy prediction and analysis. Obviously, more scholars will devote themselves to the research of business bankruptcy prediction in the future.

The data set selected for this study was about the forecast of business bankruptcy in Poland. In recent years, Brozyna's team has used classic regression models and other methods to predict the bankruptcy of enterprises in individual industries with relatively accurate results [20]. Ptak-Chmielewska compared the validity of LDA and SVM predictions using Polish SMEs as a case study [21]. Kitowsk's research team selected 50 companies in Poland to verify the international applicability of the traditional Logit model [22]. However, common flaws were that the sample size was too small, or that they concentrated on one industry in Poland, thus, the validity of the results was limited. Additionally, they focused on the testing of the bankruptcy prediction model, hoping to provide enterprises with the most intuitive results of bankruptcy, while managers may value the financial data itself to the contribution of the company bankruptcy and expect the suggestions that revive enterprises. The data I picked came from the Emerging Markets Information Service (EMIS), a database of information on emerging markets around the world. Companies in bankruptcy were analyzed between 2000 and 2012, while companies still in operation were evaluated between 2007 and 2013. In terms of data selection, different from previous studies that chose the financial data at the time of bankruptcy, this study selected the change value of financial data of bankrupt and non-bankrupt companies during a period.

The focus of this study was to explore the differences in the changes in the financial data of the two groups of companies, rather than the specific values of the changes in the financial data of some companies. For a sample of 10000 companies, 62 relevant financial ratios are available, and the ultimate bankruptcy is determined. For high-dimensional and huge financial data, such as many different but related financial ratios, factor analysis can effectively reduce dimension. Then, traditional binary logistic regression tended to find the relationship between the key factors and the result of bankruptcy, building a simple model and determining the logistic regression equation. After that, the non-parametric test in the comparative analysis was regarded as a back testing. The final stage was to trace the components of the key factors with significant variations, that was, the different financial ratios contained in the factors and the corresponding coefficients revealed specific influence. The main conclusions were that sources of financing, the liquidity of the company, and investment were likely to be significant factors that influenced business bankruptcy. Subsequently, some useful suggestions for managers were also given.

2 Methodology

Other than the traditional simple discriminant analysis model and logistic regression model, this study adopted factor analysis for data preprocessing, so that binary logistic regression built the model more accurately. Then, a non-parametric test was used as a post-hoc test. Ultimately, returning to the factor analysis of principal components analysis was meant to explain the influence factors and the possible reasons for bankruptcy. The whole method avoided the redundancy of financial ratios. Instead, the main differences were captured based on the characteristics of the data, and multiple tests were used to improve the accuracy of the analysis. Without the support of neural networks or SVM, this study maximized the advantages of the logical model in terms of principle understandability, logic clarity, and user convenience.

2.1 Factor Analysis

Faced with rich but fragmented ratios, researchers must focus on finding potential connections between the data. Factor analysis can reduce the dimension of this huge data set and cluster indicators with high correlation, which can reduce the number of indicators to be analyzed and thus reduce the complexity of problem analysis.

KMO Test is used to compare simple correlation coefficient and partial correlation coefficient between variables, and the result was 0.756, indicating that this data set was suitable for factor analysis. Meanwhile, the result of Bartlett's Test of Sphericity showed that the significance was less than 0.01, manifesting that the financial variances were correlated and the factor analysis was effective.

The communalities were good, and the explanatory value of 49 out of 62 variables was greater than 50%, which meant that the extracted common factors could better explain the overall financial ratios.

Table 1. Total Variance Explained

Component	Rotation Sums of Squared Loadings		
	Table column subhead	***% of Variance***	***Cumulative %***
1	10.914	17.603	17.603
2	9.02	14.548	32.151
3	3.936	6.348	38.499
4	3.535	5.702	44.201
5	2.673	4.311	48.512
6	2.322	3.745	52.258
7	2.282	3.681	55.938
8	2.062	3.325	59.264
9	1.869	3.014	62.278
10	1.083	1.746	64.024
11	1.043	1.682	65.707
12	1.002	1.617	67.323
13	1.002	1.616	68.94
14	1.002	1.615	70.555
15	1.001	1.615	72.17
16	1.001	1.615	73.785
Extraction Method: Principal Component Analysis.			

The result of factor analysis was to reduce the dimension of 62 financial variances to 16 factors. The table contained the eigenvalues and variance contribution rates of 16 factors after rotation. According to the principal component analysis, the cumulative contribution rate of 73.785% could be obtained by 16 common factors, that was, 16 common factors could explain approximately 73.785% of the total variances, and the result was ideal.

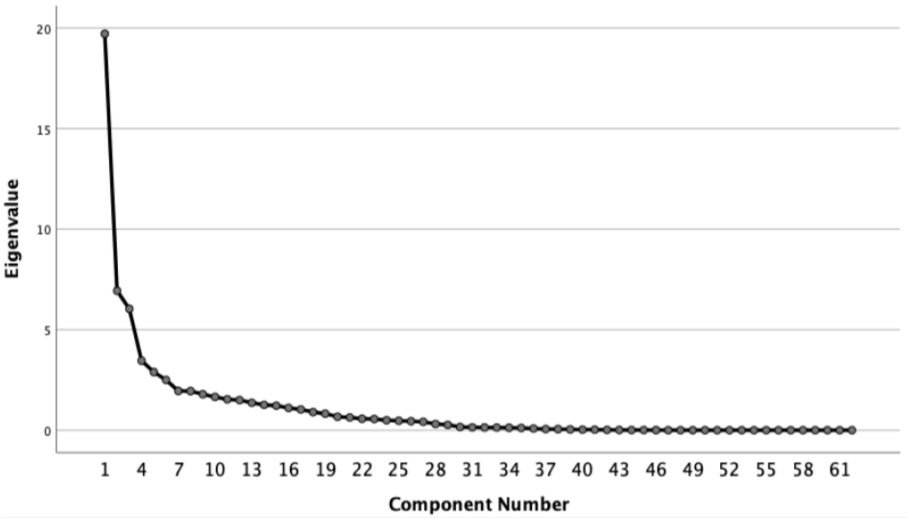

Fig. 1. Scree Plot

Obviously, it was found in the Scree Plot that the eigenvalue of the first four common factors changed the most, but combined with the total variance results, in order to balance the complexity of data processing and the accuracy of data analysis, when there was a certain gap between the sixth and seventh common factors, the first six factors were selected as the main influence factors. They could explain about 52.258% of the total variance and thus became new financial factors in this study for subsequent research.

In the rotated component analysis table, the component information of the first six factors could be mined. The denominator of all values in the first factor was "Total Assets", named "Total Assets Related"; The denominator of all values in the second factor was "Sales", named "Sales Related"; The denominator of all values in the third factor was "Short-term Liabilities", named "Short-term Liabilities Related"; The denominator of all values in the fourth factor was "Total Liabilities", named "Total Liabilities Related"; The component of the numerator of all values in the fifth factor contained "Profit", named "Profit Related"; The denominator of all values in the sixth factor was "Fixed Assets", named "Fixed Assets Related". In the follow-up study, these six factors were presented with new names.

2.2 Binary Logistic Regression

For the selected six factors, further research was needed to explore their variances' impact on bankruptcy. Six factors were continuous numerical variables, and bankruptcy was a binary categorical variable, so binary logistic regression was employed in this study. Under the assumptions of the constructed model, whether six factors had significant influences on bankruptcy were judged in the logistic regression equation.

Table 2. Classification Table

<table>
<tr><th colspan="2" rowspan="2"></th><th colspan="3">Predicted</th></tr>
<tr><th colspan="2">Bankruptcy</th><th rowspan="2">Percentage Correct</th></tr>
<tr><th colspan="2">Observed</th><th>0</th><th>1</th></tr>
<tr><td rowspan="2">Bankruptcy</td><td>0</td><td>5985</td><td>3812</td><td>61.1</td></tr>
<tr><td>1</td><td>36</td><td>167</td><td>82.3</td></tr>
<tr><td colspan="2">Overall Percentage</td><td></td><td></td><td>61.5</td></tr>
</table>

According to the classification table, the prediction accuracy of the model for bankrupt companies reached 61.5%. The model was used for bankruptcy analysis, so it needed to lose Precision to improve Recall (82.3%), which confirmed the effectiveness of the model.

Table 3. Variables in the Equation

	B	S.E.	Wald	df	Sig.	Exp(B)
Total Asset Related	1.179	0.582	4.105	1	0.043	3.251
Sales Related	0.002	0.055	0.002	1	0.969	1.002
Short-term Liabilities Related	-1.750	0.320	29.821	1	0.000	0.174
Totals Liability Related	-0.412	0.091	20.669	1	0.000	0.662
Profit Related	-0.660	0.070	89.447	1	0.000	0.517
Fixed Assets Related	-0.075	0.062	1.465	1	0.226	0.928
Constant	-4.357	0.104	1742.860	1	0.000	0.013

All six factors passed the model test. According to the result, the significance of the Sales Related factor and Fixed Assets Related factor was greater than 0.05, indicating that they had no significant influence on business bankruptcy. On the contrary, the significance of the Total Assets Related factor, Short-term Liabilities Related factor, Total Liabilities Related factor, and Profit Related factor was less than 0.05, indicating that they had a significant impact on the business bankruptcy. Specifically, the Total Assets Related factor was positively correlated with the bankruptcy risk, which could be explained as the business bankruptcy risk increased by 225% when the Total Assets Related factor increased by one unit. However, the Short-term Liabilities Related factor was negatively correlated with the bankruptcy risk, which could be explained as the business bankruptcy risk decreased by 83% when the Short-term Liabilities Related factor increased by one unit. Similarly, the Total Liabilities Related factor was negatively correlated with the bankruptcy risk, which could be explained as the business bankruptcy risk decreased by 34% when the Total Liabilities Related factor increased by one unit. Profit Related factor was also negatively correlated with the bankruptcy risk, which could be explained as the business bankruptcy risk decreased by 48% when Profit Related factor increased by one unit.

Finally, the binary logistic regression model can output the equation for business bankruptcy prediction and analysis:

$$\ln(P/1-P) = -4.357 + 1.179x_1 - 1.75x_3 - 0.412x_4 - 0.66x_5 \tag{1}$$

x_1=Total Assets Related
x_3=Short-term Liabilities Related
x_4=Total Liabilities Related
x_5=Profit Related

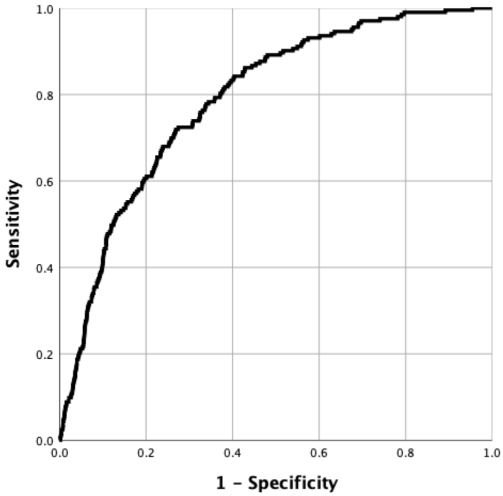

Fig. 2. ROC Curve

Additionally, the ROC curve was drawn based on the predicted probability and bankruptcy under the model. The results showed that the area under the curve was 0.789, which was relatively high. The curve meant that the regression equation under this model was appropriate to business bankruptcy prediction with high reliability.

From the logistic regression equation, a preliminary explanation could be given. Bankrupt companies had a higher level of Total Asset Related factor. Combined with the "Total Assets" in the denominator, it indicated that the increase of the ratio of other financial data of bankrupt companies divided by total assets was higher than that of non-bankrupt companies. However, the nature of these other financial data added uncertainty to the results. If they were more profit and loss accounts such as revenues and costs, the Total Asset Related factor reflected the performance of the assets in the operation of the company in this period; If they were more liabilities or equity accounts such as trade payable, retained earnings, shares, Total Asset Related factor reflected the source of financing of the asset in this period. Obviously, it was a result influenced by a variety of causes, and it could not be arbitrarily concluded that a relatively low value of total assets was more likely to lead to bankruptcy, which required further analysis based on factor components.

In contrast, the decrease of the ratio of other financial data of bankrupt companies divided by short-term liabilities and total liabilities was lower than that of non-bankrupt companies. Traditionally, one public opinion is that too much debt is disadvantageous and dangerous, and the statistics bore it out. Whether other financial data as the numerator was assets, equity, or profit and loss, the excessive debt might reveal the company's high cost of financing, lack of cash flow, and operation problems such as instability, especially the unreliability of short-term debt financing source, which could eventually lead going concern problem and increase the risk of bankruptcy. It was also understandable that the decrease of the ratio of profit of bankrupt companies divided by other financial data was lower than that of non-bankrupt companies. Profitability was the basics of a company's going concern, and the lack of profitability obviously constituted an important reason for the company's bankruptcy.

However, the insignificance of the difference in Sales Related factor and Fixed Assets Related factor between bankrupt companies and non-bankrupt companies could be regarded as that the variance of the ratio of other financial data divided by sales and fixed assets was not the key to determining bankruptcy under this model. This might break the stereotype in the public consciousness that companies with higher sales did better because they have stable revenues, or it might be a compromise forced by the pursuit of the accuracy of the regression equation. The above was only a brief interpretation of logistic regression results based on factor analysis.

2.3 Non-parametric Test

After testing, the data did not fit the normal distribution. All companies were divided into two groups, independent of each other, depending on whether they went bankrupt or not. Therefore, the mann-Whitney U test, a non-parametric test of two independent samples, was used as a post-hoc test of binary logistic regression in this study.

Table 4. Non-parametric Test Result

	Group	PLT	Z	p
Total Assets Related	0	0.0059322 (-0.0433662~0.0573354)	-8.812	0.000
	1	0.0480166 (0.0183143~0.0815281)		
Sales Related	0	0.0198745 (0.0028067~0.0426677)	-0.585	0.559
	1	0.0228212 (-0.0127909~0.0440533)		
Short-term Liabilities Related	0	-0.1184787 (-0.2296517~0.0562227)	-8.091	0.000
	1	-0.2065788 (-0.3063365~-0.1184208)		
Total Liabilities Related	0	-0.2288975 (-0.4492635~0.1410803)	-4.587	0.000
	1	-0.3356913 (-0.5098223~-0.1252551)		
Profit Related	0	-0.084651 (-0.4108933~0.3782263)	-10.419	0.000
	1	-0.443609 (-1.0093171~-0.1665084)		

Fixed Assets Related	0	-0.0284154 (-0.1132601~0.0705049)	-5.197	0.000
	1	-0.0842216 (-0.1738421~0.0214817)		

The results of the Mann-Whitney non-parametric test showed that only the Sales related factor had a significant level greater than 0.05. The original hypothesis was retained, that is, there was no significant difference in the changes of the Sales Related factor between bankrupt companies and non-bankrupt companies, which indicated that the company probably did not go bankrupt due to the significant decline in sales. The changes in the Total Asset Related factor showed significant differences between the two groups ($p<0.01$). The median comparison meant that the increase of the Total Asset Related factor of bankrupt companies is much higher than that of non-bankrupt companies, so it was necessary to further analyze the principal component of this factor. There were also significant differences between the two groups in the changes of the Short-term Liability Related factor and Total Liability Related factor ($p<0.01$). At the median, the decrease in these two factors for bankrupt companies was 2 and 1.5 times that of non-bankrupt companies respectively, indicating that bankrupt companies did have a more significant growth in liability. Significant differences could also be seen in the changes of Profit Related factor and Fixed Assets Related factor between the two groups ($p<0.01$). The dramatic fall of Profit Related factors of bankrupt companies might indicate the lack of corporate profitability, but it still needed to pay attention to the data of the denominator in the principal component. Fixed Assets factor was not included in the equation under the assumption of the binary logistic regression model, but it was still found that the decrease of this factor for bankrupt companies was approximately 4 times that of non-bankrupt companies after post-hoc test.

3 Analysis

The highlight of this study was to provide a more detailed analysis and possible reasons for the results of data exploration, and finally, put forward useful suggestions for readers. This was also not the case in traditional business bankruptcy studies, which provided only predictive models.

All the interpretation of the experimental results above was based on factor analysis, with 6 representative factors. In order to further explore the specific reasons for business bankruptcy, the study analyzed the components of the 6 factors, so as to determine which aspect of the company would have a greater impact on bankruptcy. Therefore, components in factor analysis appeared in Table 5 except the Sales Related factor, where the number represented the explanatory ability of the factor to these financial ratios. The higher the value, the stronger the explanatory power, and the higher the similarity between factors and these financial ratios.

Table 5. Rotated Component of Factor Analysis

Total Assets Related	**total liabilities / total assets**	0.996
	constant capital / total assets	-0.995

	EBIT / total assets	0.995
	equity / total assets	-0.995
	gross profit / total assets	0.991
	net profit / total assets	-0.980
	(equity - share capital) / total assets	-0.971
	retained earnings / total assets	-0.952
	~~profit on operating activities / total assets~~	~~0.822~~
	~~(gross profit + extraordinary items + financial expenses) / total assets~~	~~0.803~~
	EBITDA (profit on operating activities - depreciation) / total assets	0.772
	~~profit on sales / total assets~~	~~0.709~~
Short-term Liabilities Related	**current assets / short-term liabilities**	0.891
	(current assets - inventory) / short-term liabilities	0.890
	operating expenses / short-term liabilities	0.838
	sales / short-term liabilities	0.826
	(current assets - inventory - receivables) / short-term liabilities	0.790
Total Liabilities Related	**total assets / total liabilities**	0.934
	book value of equity / total liabilities	0.933
	current assets / total liabilities	0.793
	~~(gross profit + depreciation) / total liabilities~~	~~0.552~~
	~~(net profit + depreciation) / total liabilities~~	~~0.540~~
Profit Related	~~profit on operating activities / total assets~~	~~0.511~~
	~~(gross profit + extraordinary items + financial expenses) / total assets~~	~~0.524~~
	~~profit on sales / total assets~~	~~0.597~~
	~~(gross profit + depreciation) / total liabilities~~	~~0.700~~
	~~(net profit + depreciation) / total liabilities~~	~~0.696~~
	gross profit / short-term liabilities	0.504
Fixed Assets Related	**sales / fixed assets**	0.852
	working capital / fixed assets	0.831
	constant capital / fixed assets	0.822

First of all, the explanatory factor greater than 0.5 was valuable for the original ratio, as retained in Table 5. Then, according to the basic principle of factor analysis, different factors contain the same original ratio, for example, "profit on sales / total assets" appeared simultaneously in the Total Assets Related factor and Profit Related factor, which was the phenomenon of cross-loading, so it was considered to delete such ratios.

Each factor was interpreted in detail. Among Total Asset Related factors, "total liabilities / total assets", "EBIT / total assets", and "gross profit / total assets" were positively correlated with the factor, that was, these three ratios of bankrupt companies increased more. The rise in "total liabilities / total assets" undoubtedly indicated that the proportion of the company's debt financing would increase, which might lead to higher financial expenses or a debt crisis. The ascent in "EBIT / total assets" and "gross profit / total assets" suggested that bankrupt companies might have healthy profitability. However, some ratios were negatively correlated with the factor. ratios that "constant capital / total assets", "equity / total assets", "net profit / total assets", "retained earnings / total assets" of bankrupt companies had fallen more sharply. Three of them were equity accounts, which represented equity financing. The decrease in the share of equity financing of bankrupt companies also reflected the increase in the share of debt financing. This variance in gearing showed a shift in funding sources. Unhealthy gearing would naturally lead to debt crisis and bankruptcy. Moreover, the decline in "net profit / total assets" contrasted with the rise in "gross profit / total assets" presumably revealed high expenses of bankrupt companies, especially financial expenses such as interest.

"Total assets / total liabilities", "book value of equity / total liabilities", and "current assets / total liabilities" represented by the Total Liabilities factor, also supported the above view. They were positively correlated with the factor. The rapid decline in "Total assets / total liabilities" and "book value of equity / total liabilities" of bankrupt companies illustrated the variance in gearing. "Current assets / total liabilities" could be analyzed in combination with the Short-term Liability Related factor. The ratios represented by the Short-term Liability Related factor were all positively correlated with the factor. "Current assets / short-term liabilities", "(current assets - inventory) / short-term liabilities", "(current assets - inventory - receivables) / short-term liabilities", and "Current assets / total liabilities" reflected the liquidity of the company. The liquidity of bankrupt companies was significantly worse than that of non-bankrupt companies. The company, without enough cash flow to adjust strategy and investment in response to market changes, had to resort to short-term liabilities. Short-term liabilities were risky, and high-interest rates exacerbated poor liquidity. Although it was concluded that the profitability of bankrupt companies remained stable, the imbalance between profitability and liquidity was likely to lead to bankruptcy.

Both "working capital / fixed assets" and "constant capital / fixed assets" referred to capital invested in operating activities. For the Fixed Assets related factor, it represented the profitability of fixed assets. Bankrupt companies performed much worse than non-bankrupt ones, probably because they invested too many fixed assets and did not use them to create enough value, with sales barely changing. There was only one ratio left in the Profit Related factor, which was not highly explanatory and could be ignored.

4 Conclusion

4.1 Causation

Overall, through the above analysis, this study has identified some important causes leading to business bankruptcy:

- Sources of financing. Too much debt financing can lead to a heavy debt burden in the future.

- Liquidity. Excessive short-term liabilities and lack of liquidity increase the debt crisis of enterprises.
- Investment. Inefficiency in fixed asset investment also affects profitability.

Finally, the traditional five dimensions were used to rate their impact on bankruptcy risk, and the results were shown in the chart.

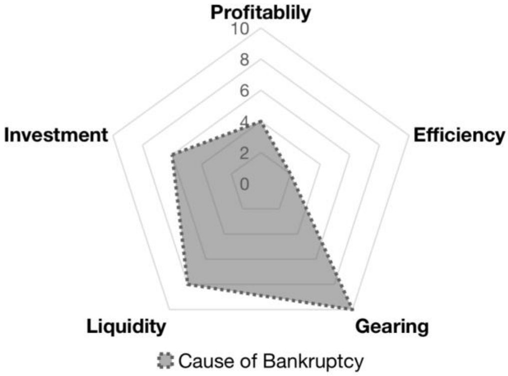

Fig. 3. Causes of Bankruptcy

It was worth mentioning that the regression equation and non-parametric test results obtained in the research process were only the initial conclusions of this study and were used for the final analysis of factor components. Their research objects were all factors after data dimensionality reduction, so they could not be used as a real bankruptcy prediction model in the business environment.

4.2 Suggestions

According to the conclusion, some practical suggestions are put forward. Just like the classic IPO model, the operation of a company can be divided into three stages:

- Input stage. A good financial gearing can ensure the stability of financing sources. Controlling debt financing and short-term liabilities can reduce the debt crisis and interest burden.
- Process stage. Sufficient cash flow can improve capital liquidity, so the enterprise can deal with all kinds of threats and opportunities calmly, while the balance of profitability and liquidity is able to support the continuous operation of the enterprise.
- Output stage. Efficient use of capital and investment in valuable projects will promote the development of the business, so managers need to avoid excessive unprofitable investments.

4.3 Limitations

One limitation of the raw data was that it was different from the financial information in the year of bankruptcy. It provided the change in financial ratio in the period prior to bankruptcy. Although it could more intuitively see the trend of the variation of financial data to determine the bankruptcy of the company, it might not be extremely accurate because it needed to collect more years of financial information and calculate the percentage change.

Another limitation of statistical methods was the screening of financial ratios by factor analysis. The results of factor analysis could successfully identify the more influential financial ratios and represent them with factors that would facilitate subsequent research. However, at the same time, it threw away much financial information that was deemed superfluous. Although it improved the efficiency of research, the discarded financial information might still have some value in understanding why companies bankrupt.

Finally, like many other studies of business bankruptcy prediction, this study failed to consider the impact of non-financial data. It was mainly because non-financial data were not available easily and the extent of the impact was difficult to calculate.

4.4 Prospects

Looking forward, it is necessary to place emphasis on both the financial information in the year of bankruptcy and the changing trend in the years before bankruptcy in data collection. The combination of static and dynamic research results can effectively improve the accuracy of the conclusions, which is progressive in the field of business bankruptcy analysis and prediction.

Multiple modelling approaches should be utilized when dealing with large financial datasets, which can compensate for the precision lost in factor analysis. There is clearly value in spending time analyzing comprehensive financial data.

As non-financial factors such as corporate culture were playing an increasingly important role in corporate performance, future research on business bankruptcy analysis and prediction should consider their differences to improve the accuracy of the study. Other research methods such as observation, questionnaire, and interview can be used in the study of non-financial information, which will contribute significantly to the development of corporate bankruptcy analysis and prediction.

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