ATLANTIS PRESS
Advances in Social Science, Education and Humanities Research, volume 205
The 2nd International Conference on Culture, Education and Economic Development of Modern Society (ICCESE 2018)

Financial Distress Prediction Model of Manufacturing Industry

Empirical Evidence from Shenzhen and Shanghai A-share Listed Firms

Lan Wu
Business School of Sichuan University
Chengdu, China

Pan Wan
Business School of Sichuan University
Chengdu, China

***Abstract*—Since financial distress prediction model have the features of information collection, financial monitoring, financial identification and financial prevention and so on, we selected financial data of 20 ST companies and non-ST companies from Shenzhen and Shanghai A-share listed companies on the basis of previous research in order to build a financial distress prediction model of manufacturing industry. Firstly, we carry out K-S normal distribution test of financial indexes. Those financial indexes which pass the test can enter into the second stage. Secondly, T test is in progress. This test's objects are what we mentioned above and non- financial indexes are also included in the T test. Thirdly, Mann-Whitney test is underway for all indicators. Lastly, Principal component analysis is prepared for which have passed the second test or the third test. We abstract 5 principal components and take advantage of coefficient of composition rotation component matrix to build financial distress prediction model.**

Keywords—manufacturing; industry; financial; distress prediction; empirical research

I. INTRODUCTION

There are a thousand definitions of financial distress in a thousand scholar's eyes. Most of them treat those companies with the sign ST as financial distress companies. But a few of scholars treat financial distress as a gradient process. They believe that there is not a clear line between into and not into financial crisis. We take the first one definition in this paper.

The reason why we select manufacturing industry of Shenzhen and Shanghai A-share listed companies as our research object is as follow: Firstly, different kinds of listed companies take different kinds of accounting standards. A-share listed companies follow China's accounting standards .While B-share and H-share listed companies take international accounting standards. To avoid the difference of different accounting standards, we select A-share listed companies. Secondly, manufacturing industry is of immense importance to the national economy. However, in recent ten years, the rise of the Internet has greatly impacted the traditional manufacturing industry. Therefore, it is necessary to build a financial distress prediction model for manufacturing industry. Thirdly, manufacturing enterprises form nearly one half of all listed companies. We can see from the CSMAR database that there are 1827 manufacturing enterprises of 3101 A-share listed companies, accounting for 58.92%, which provide a great of convenience for our study.

II. EMPIRICAL RESEARCH

A. Selection of the Data Sample

The financial data on the December 31, 2014 of 20 *ST and non-*ST companies from Shenzhen and Shanghai A-share listed companies are selected to build model. Another financial data of 9 *ST and non-*ST companies are selected for test. *ST companies mean that companies receive special treatment due to three-year continuous loss. In view of this, we choose the data on the December 31, 2014. The following data is from CSMAR.

B. Selection of the Indicators

On the basis of previous research, we choose not only financial indicators from 5 aspects to measure the company's financial position but also some non-financial indicators referring to their results. In all, there are 18 financial indicators (current ratio F1, cash ratio F2, interest coverage ratio F3, asset-liability ratio F4, ratio of asset inflation proof and incremental value F5 , operating income growth rate F6, net asset growth rate per share F7, rate of return on total assets F8, rate of return on fixed assets F9, earnings before interest and tax/total assets F10, asset impairment loss/revenue F11, the receivable turnover F12 and the inventory turnover F13, current assets turnover F14, total asset turnover F15, net cash content of profit F16, net cash content of operating income F17, cash flow from operating activities per share F18) and 5 non-financial indicators(fixed assets/ total assets NF1, audit opinions NF2, the number of meetings of the board of directors NF3, the number of meetings of the board of supervisors NF4 and the number of meetings of the shareholders' meeting NF5). We consider the above indicators as F1−F18 and NF1−NF5 to illustrate conveniently.

C. Normal Distribution Test

There are lots of methods to conduct normal distribution test, such as histogram, box diagram, stem leaf graph, coefficient of skewness and coefficient of kurtosis in the calculation method, K-S test and Shapiro-Wilk test in non-parametric test. Here we take K-S test. Since K-S test is designed for continuous value variable, we test indicators numbered F1-F18 to see whether they are in a normal distribution. The result of the K-S test is in "Table I". As is shown in "Table I", there are 6 indicators (asset-liability ratio, operating income growth rate, current assets turnover, total asset turnover, net cash content of profit, cash flow from operating activities per share) whose P-value are more than 0.05. That means these 6 indicators passed the test and they are in normal distribution. Another 12 indicators should be culled because they do not pass the test and they are not in normal distribution.

TABLE I. KOLMOGOROV-SMIRNOV TEST

index	K-S	Asymptotic saliency	index	K-S	Asymptotic saliency
F1	2.754	0.000	F10	1.685	0.007
F2	2.458	0.000	F11	2.053	0.000
F3	2.619	0.000	F12	2.298	0.000
F4	1.166	0.132	F13	1.494	0.023
F5	1.377	0.045	F14	1.003	0.267
F6	1.030	0.239	F15	0.998	0.272
F7	1.557	0.016	F16	1.295	0.070
F8	1.432	0.033	F17	1.855	0.002
F9	2.884	0.000	F18	1.097	0.180

D. Independent T Test

The precondition of independent T test is that the indicator must be in normal distribution. Therefore, we choose the 6 indicators above and 5 non-financial indicators to conduct the T test. From "Table II", we can find that only 3 indicators (current assets turnover, total asset turnover, cash flow from operating activities per share) passed the T test by their P-value less than 0.05 at a significant level of 5%.

TABLE II. INDEPENDENT SAMPLE T-TEST

		T test of mean equation		
		t	df	Sig.
F4	the variance is equal	0.303	38	0.764
	the variance isn't equal	0.303	31.641	0.764
F6	the variance is equal	-1.428	38	0.161
	the variance isn't equal	-1.428	31.438	0.163
F14	the variance is equal	-2.678	38	0.011
	the variance isn't equal	-2.678	32.144	0.012
F15	the variance is equal	-4.021	38	0.000
	the variance isn't equal	-4.021	26.049	0.000
F17	the variance is equal	-1.532	38	0.134
	the variance isn't equal	-1.532	37.008	0.134
F18	the variance is equal	-2.202	38	0.034
	the variance isn't equal	-2.202	26.241	0.037
NF1	the variance is equal	0.751	38	0.458
	the variance isn't equal	0.751	36.289	0.458
NF2	the variance is equal	-0.872	38	0.389
	the variance isn't equal	-0.872	35.237	0.389
NF3	the variance is equal	-0.226	38	0.822
	the variance isn't equal	-0.226	37.675	0.822
NF4	the variance is equal	-1.114	38	0.272
	the variance isn't equal	-1.114	28.697	0.275
NF5	the variance is equal	0.623	38	0.537
	the variance isn't equal	0.623	36.088	0.537

TABLE III. MANN-WHITNEY TEST

Index	Sig	Whether to reject the original hypothesis	Index	Sig	Whether to reject the original hypothesis
F1	0.766	not	F11	0.000	yes
F2	0.160	not	F12	0.330	not
F3	0.130	not	F13	0.003	yes
F4	0.766	not	F14	0.040	yes
F5	0.003	yes	F15	0.030	yes
F6	0.006	yes	NF1	0.871	not
F7	0.004	yes	NF2	0.382	not
F8	0.000	yes	NF3	0.704	not
F9	0.000	yes	NF4	0.337	not
F10	0.000	yes	NF5	0.550	not

E. Mann-whitney U Test

There are only 3 indexes passed the T test, while it's not enough to build a model. Therefore, we conduct Mann-Whitney U test. The result in "Table III" shows that there are 10 indexes (ratio of asset inflation proof and incremental value, operating income growth rate, net asset growth rate per share, rate of return on total assets, rate of return on fixed assets, earnings before interest and tax/total assets, asset impairment loss/revenue, the inventory turnover, net cash content of profit, net cash content of operating income, cash flow from operating activities per share) passing the test.

TABLE IV. KMO AND BARTLETT TEST

Take enough degrees of Kaiser - Meyer – Olkin measurements.		.560
Bartlett's test of sphericity	The approximate chi-square	307.755
	df	78
	Sig.	.000

F. KMO and Bartlett Test

KMO and Bartlett test is aimed to test whether the data is fit for principal component analysis. As is shown in "Table IV", KMO equals 0.560 more than 0.50 and the coefficient of significance is nearly 0.00 less than 0.05, which means the sample is fit for factor analysis and principal component analysis.

TABLE V. MANN-WHITNEY TEST

	initial	extract		initial	extract
F5	1.000	0.902	F13	1.000	0.836
F6	1.000	0.887	F14	1.000	0.732
F7	1.000	0.953	F15	1.000	0.863
F8	1.000	0.778	F16	1.000	0.542
F9	1.000	0.905	F17	1.000	0.665
F10	1.000	0.899	F18	1.000	0.816
F11	1.000	0.862			

G. Factor Analysis

Common factor variance is shown in "Table V". We can conclude that most of the information can be abstract since variable common degree is high in factor analysis. "Table VI" shows factor contribution rate. The eigenvalues of first 5 factors are more than 1, besides cumulative percentage of the eigenvalues of first 5 factors is 81.852%. So we abstract the First 5 factors as principal component.

TABLE VI. THE TOTAL VARIANCE OF THE INTERPRETATION

component	Initial eigenvalue			Rotation of squares and loads		
	Total	*The percentage of variance*	*Cumulative percentage*	*Total*	*The percentage of variance*	*Cumulative percentage*
1	3.906	30.049	30.049	2.927	22.513	22.513
2	2.305	17.73	47.779	2.513	19.334	41.846
3	1.934	14.874	62.653	2.083	16.026	57.872
4	1.46	11.233	73.886	1.565	12.035	69.908
5	1.036	7.966	81.852	1.553	11.944	81.852
6	0.84	6.46	88.312			
7	0.475	3.653	91.965			
8	0.337	2.589	94.554			
9	0.239	1.836	96.39			
10	0.193	1.481	97.871			

From "Table VII", we call the factors in "Table VII" E1–E5. From "Table VII", we know that the load of F5 and F7 on the factor E1 is the largest. They are 0.926 and 0.964. Therefore, E1 is named after growth ability. Similarly, the load of F11 on the factor E2 is 0.907. E2 is named after profitability. And so on, E3, E4, E5 are named after operating capacity, cash flow and manufacturing special profit indicators.

TABLE VII. ROTATION COMPONENT MATRIX

	component				
	1	*2*	*3*	*4*	*5*
F5	0.926	-0.088	0.153	0.110	-0.041
F6	0.292	-0.381	0.201	0.165	-0.767
F7	0.964	-0.026	0.147	0.025	0.016
F8	0.040	-0.746	0.303	0.318	0.166
F9	0.096	-0.126	0.153	0.011	0.925
F10	0.946	0.009	0.039	0.002	-0.046
F11	-0.093	0.907	-0.151	-0.080	0.021
F13	0.046	0.546	0.695	0.136	0.187
F14	0.083	-0.242	0.794	0.188	-0.040
F15	0.269	-0.281	0.841	0.074	-0.008
F16	-0.092	0.043	0.186	0.696	-0.110
F17	0.022	0.723	-0.002	0.339	0.164
F18	0.223	-0.058	0.066	0.871	0.025

TABLE VIII. COMPONENT COEFFICIENT MATRIX

indicator	component				
	1	*2*	*3*	*4*	*5*
F5	0.328	0.008	-0.045	0.012	0.012
F6	0.037	-0.070	0.076	0.042	-0.480
F7	0.351	0.031	-0.033	-0.050	0.044
F8	-0.048	-0.309	0.019	0.182	0.166
F9	0.055	-0.117	-0.008	0.007	0.625
F10	0.356	0.040	-0.084	-0.045	0.006
F11	0.014	0.375	0.030	-0.033	-0.060
F13	-0.046	0.294	0.440	-0.057	0.028
F14	-0.079	-0.017	0.421	-0.041	-0.060
F15	-0.009	-0.025	0.447	-0.142	-0.035
F16	-0.087	0.037	-0.016	0.474	-0.071
F17	0.025	0.296	-0.017	0.248	0.060
F18	0.044	-0.025	-0.190	0.625	0.059

H. Build a Financial Distress Prediction Model

We can see score coefficient of every factor from table VIII, We can draw a conclusion: We assume the indicators in table VIII as

$X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8, X_9, X_{10}, X_{11}, X_{12}, X_{13}$

Then ,

$E1=0.328X_1+0.037X_2+0.351X_3-0.048X_4+0.055X_5+0.356X_6+0.014X_7-0.046X_8-0.079X_9-0.009X_{10}-0.087X_{11}+0.025X_{12}+0.044X_{13}$,

$E2=0.008X_1-0.070X_2+0.031X_3-0.309X_4-0.117X_5+0.040X_6+0.375X_7+0.294X_8-0.017X_9-0.025X_{10}+0.037X_{11}+0.296X_{12}-0.025X_{13}$

And so on, we can know E3, E4and E5 in the same way.

According to "Table VI", we can set a model as following:

$Z=0.22513*E1+0.19334*E2+0.16026*E3+0.12035*E4+0.11944*E5$

TABLE IX. Z-SCORE DISTRIBUTION

Type	interval	frequency	frequency	Cumulative percentage
Normal company	Z＞1	11	0.55	55%
	0.7＜Z≤1	4	0.20	75%
	Z≤0.7	5	0.25	100%
ST company	Z＜0.1	6	0.30	30%
	0.1≤Z≤0.7	11	0.40	85%
	Z＞0.7	3	0.15	15%

I. Define the Cut-off Point

According to the model Z, we calculate Z-score of above sample companies. Then we draw "Table IX". According to "Table IX", we can draw a frequency distribution table, as is shown in "Table IX", for companies with financial health, when Z-score are more than 0.7, cumulative percentage is 75%. For *ST companies with financial crisis, when Z-score are less than 0.7, cumulative percentage is 85%. Therefore, we can set Z-score equals 0.7 as the cut-off point.

III. CONCLUSION

We set up a model for manufacturing industry through a series of test. This model can predict financial crisis in our study. The innovation point of this article is as follows: first, we distinguish ST companies with *ST companies. ST companies mean that they have been in lossfor 2 year while *ST companies mean they have been in loss for 3 years. Second, we add the specific index of manufacturing enterprise to build the model. The disadvantages of this paper are as follow: First, the definition of financial crsis does not have a specific and uniformed view, this paper chooses *ST as a sign of financial crisis for it is continent to collect data. Second, we only choose the data of 2014 as our study object. We should choose more data to predict accurately.

REFERENCES

[1] Philippe du Jardin. Predicting bankruptcy using networks and other classification methods: The influence of variable selection techniques on model accuracy[J]. Neurocomputing, 2010: 2047-2060.

[2] SUN JIE, JIA MINGYUE, LI HUI. Adaboost Ensemble for Financial Distress Prediction: an Empirical Comparison with Data from Chinese Listed Companies[J]. Expert Systems with Applications, 2011(38): 5-12.

[3] Maryam Sheikhi．Financial Distress Prediction Using Distress Score as a Predictor. International Journal of Business and Management, 2012: 169-187.

[4] Kyung-Shik Shin, Taik Soo Lee，Hyun-jung Kim. An application of support vector machines in bankruptcy prediction.Expert Systems with Applications, 2005 : 127-135.

[5] Jingtao Y, Joseph P, Herbert. Financial Time-series Analysis with Rough Sets[J]. Applied Soft Computing, 2009(9) : 1000-1007.

[6] Hyunchui A, Kyoung-jae K. Bankruptay Prediction Modeling with Hybrid Case-reasoning and Genetic Algorithm Approach[J]. Applied Soft computing，2009(3): 599-607.