Corporate Financial Distress Alarm Model based on Bayesian network

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Abstract

With the opening up of the financial market and the development of the securities market in China, listed companies in China are paying more attention to allocation of resources, raise of funds and promotion of company innovation etc. And their impacts on the whole economy is more profound and lasting. Therefore, the healthy operation of listed companies is extremely vital. If large-scale enterprises fall into financial distress, like subprime crisis, not only the enterprises themselves will suffer huge losses or even bankruptcy liquidation, but also the whole economy suffers a huge concussion. Thus, predicting the degree of the possible financial distress through the establishment of mathematical model is increasingly important to investors, stakeholders and even to the whole economic society. Bayesian network is a tool for reasoning and analyzing the uncertainty by the knowledge of mathematical statistics, by which the results can be expressed in graphics, meanwhile, the dependency relations among variables are visible. The prediction of enterprise financial risk via Bayesian networks is very valuable. The financial distress prediction model is constructed based on the Bayesian network and principal component analysis. And the results show that the accuracy in forecasting of the model is beyond 90%, so it can predict the financial distress of the listed companies.

Keywords

Financial distress, Bayesian network, Principal component analysis, Parameter learning, Conditional probability

1. Introduction

The influence of listed companies on the domestic economy is becoming more and more tremendous now. Meanwhile, they play an important role in the aspects of allocation of resources, fund procurement, enterprise innovation and business enterprise core competence. Thus, once the enterprise stuck in a dilemma, a wide range of financial difficulties would make a huge impact on the development of the whole economy, especially like the subprime crisis. Therefore, developed countries often regard the number of bankrupt companies as an index to measure national economic stability. It is essential to identify the signal of financial distress and take measures.

In general, it is a constant process for a company to run into financial distress. There will be omens in the aspects of financial situation, operating performance, stuck market performance, even worse in the aspects of governance structure imbalance, unreasonable share equity structure and management confusion. We can measure financial indicators by obtaining the data in the financial statements of listed companies to analyze its shareholding structure, governance structure and the performance of the stock market for early warning.

This paper aims to build a financial risk forecast model of listed companies based on Bayesian network. A model based on Bayesian network is widely used in the fields of aviation and military and operates well.

There are many researches studied in financial early-warning model in foreign countries. For instance, single-variable model select an important financial index to judge a company goes bankrupt or not.

American scholar Beaver selected 30 financial indexes such as asset-liability ratio, current ratio and net profit margin to judge. It showed that capital return was the most effective index to forecast. The next is multivariate linear discrimination method, American scholar Altman put forward Z-Score model. Compared with the model of the Beaver, it is more effective in forecasting a year before the bankruptcy, but when forecasting 5 years before the bankruptcy, its results is not persuasive, this method require that the sample data obeys normal distribution. The third one is logistic regression model, which uses the known financial indicators or characteristics to calculate the probability a company goes into financial distress in the future and sets a threshold, when the model results is greater than the critical value, the enterprise is judged to get into financial distress. Another model is survival analysis, which judges a company going into financial distress by predicting the time the enterprise bankrupts. The last model is connectionist model, which uses artificial neuron to imitate the operation and transmission mechanism of human or other biological. M.D.Odem and Sharda put this model into financial distress early-warning firstly. Besides these models, there are many other models which have not come into being a system.

In domestic, researches started late in financial distress early-warning, which mainly took example by foreign researches methods and results to study combined with china's reality. Zhou Shouhua and Yang Jihua put forward F score model based on Z-Score model. Song Li and Li Yao applied Bayesian network in financial distress prediction at the earliest in domestic. Zhu Huiming and Wu Hao put forward a financial distress early-warning model which only considered the company's financial indicators and didn't consider the interaction between the various financial indicators.

There are two defects in domestic researches. First, when building forecast index system, they didn't consider shareholding structure, governance structure and macroeconomic factors. Second, when building Bayesian network, they ignored the independence of the nodes.

To begin, I introduce the research background and summary overseas and domestic research status. Next I introduce the definition of financial distress and identification method; meanwhile I explore the causes of financial distress and apply the Bayesian network model to forecast financial distress. Next sample selection and matching method are introduced. Then select primal early-warning indexes and screen the indexes by principal component analysis, and calculate the comprehensive score of different affecting factors. Next I determine Bayesian network node and conduct structure learning, parameter learning and the inference of Bayesian network. I conclude by analyzing the research results and giving insufficient.

2. Literature References

2.1 The definition of financial distress

So far, there is not a unified definition for financial distress in domestic and overseas. Beaver suggests that financial distress means enterprise bankruptcy, preferred stock dividends in arrears, bank overdraft. Deakin suggests that financial distress means the insolvency liquidation of the company. Ross suggests the definition of financial trouble should be divided into four aspects: business failure, bankruptcy in legal, technology bankruptcy and accounting bankruptcy. This paper gives a definition of financial distress that a company with special treatment for abnormal financial position.

2.2 The cause of financial difficulties

2.2.1 The macro factors

The macro factors are divided into three parts: national macro economy and policy, institutional factors and industry factors. The fluctuations of macro economy and the change of national monetary or fiscal policy have an effect on enterprise survival and development. A few years ago, the real estate industry overheated in domestic, and the government issued many policies, such as purchasing limited, the change of purchase loan interest and land circulation policy. All of which led to enterprise financial distress.

The next is institutional factors, The function of market in resource allocation is limited. Some enterprises in china went into financial distress for unsound economic system at the present stage in china.

The last is industry factors; every industry has its own lifecycle. For instance, in recent years, the internet enterprises have been developing in a rapid speed. In contrast, steel industry has been gradually declining; the enterprises go into financial distress easily.

2.2.2 The micro factors

The micro factors are divided into four parts: improper operation, the risk of business operation, financial risk management, governance structure. Some companies invest blindly and are not enough to investigate and analyze the market that is going to enter. Meanwhile, they have insufficient risk management ability, all of which led to financial distress.

The next is the risk of business operation; management risk refers to the problems due to production and operation, resulting in a decline in profitability. In the daily operation, the change of the mode of transportation or route may leads to the increase of purchase cost.

The financial management activities of an enterprise mainly include raise, use and recycling. Financial leverage has advantages and disadvantages, once improper handling, the enterprise may goes into financial distress.

The last is governance structure, in china, the independence of the board of directors is not high and the decision-making mechanism is not perfect, all of which increase the probability of financial distress.

2.3 Bayesian network learning

Bayesian network inference makes use of Bayesian network structure and conditional probability according to the sample data to the probability of nodes. According to the complexity of the Bayesian network, Bayesian network inference can be divided into two parts: precise reasoning and approximate reasoning. Arithmetic of precise reasoning mainly concludes multiple tree algorithm, junction tree algorithm and elimination algorithm. Arithmetic of approximate reasoning mainly concludes random sampling algorithm, search algorithm. The objective functions of the max posteriori distribution are as follows:

$$\hat{\theta} = \arg\max \frac{f(x|\theta)g(\theta)}{\int f(x|\theta')g(\theta')d\theta'} = \arg\max f(x|\theta)g(\theta) \tag{1}$$

3. Bayesian network node score model based on principal component analysis

3.1 The selection of sample data

In this paper, the sample data is from taian database, and I extract partial data of Shanghai stock exchange and Shenzhen stock exchange to check to ensure the authenticity and accuracy of the data.

3.1.1 The selection of the enterprise in financial distress

This paper sets the object of study as A-share manufacturing listed companies of Shanghai stock exchange and Shenzhen stock exchange, the reasons are as follows:

It is easier to obtain the relevant data of listed company than non-listed company. The internal data of non-listed company rarely release to the outside because of trade secret and enterprise competition.

The comparability of a-share company data is higher than of non-listed company.

I eliminate the industry difference. The management and financial problem of manufacturing listed companies is typical, in addition, the proportion of manufacturing industry listed companies in our country is the largest.

This paper selects 16 manufacturing listed companies in 2014 as sample enterprises.

3.1.2 Marching standard and quantity of financial normal company and financial distress company

In the aspects of matching criterion, control factors mainly include fiscal year and industry. I set relative asset size as a predictive variable, not a matching criterion index.

In the aspects of matching number, Zmijewksi found that the predictive ability of the model will be overrated with the pairing proportion 1 to 1. Thus, I select 48 manufacturing financial normal companies as paired sample.

3.2 Financial indicators comprehensive score evaluation model

It is known from the analysis of the above that macroeconomic factors, corporate governance structure and ownership structure, corporate financial indicators score are the main reason that the company goes into financial distress. Because of the synteny of indicators, this paper selects the main factor by principal component analysis to calculate the score.

3.2.1 The selection of financial indicators

Based on the reference and conclusion of previous scholar's analysis, this paper selects financial indicators in the aspects of debt paying ability, operation ability, profitability, growth ability. The detail classifications are as follows.

Table.1 financial indicators classifications

Indicators category	Indicators name	Indicators category	Indicators name
Debt paying ability	Quick ratio	operation ability	Accounts receivable turnover
	Current ratio		Inventory turnover
	Asset-liability ratio		Current assets turnover
	Cash flow ratio		Fixed asset turnover
	Times interest earned		Total asset turnover
growth ability	Total assets growth rate	profitability	Operating margin
	Growth rate of net assets per		Operating profit cash net
	Fixed assets growth rate		Net interest rate of the total
	Net assets yield rate		Return on equity
	Operating profit growth		Return on assets
	Net profit growth rate		Net cash net content

Test the sample of all the financial indicators by the mann-Whitney U test using SPSS 18.0 and take the indexes which have significant importance as financial characteristics indicators that judging the company's financial distress.

Through the test, I select 17 financial indicators except operation ability as predicting variables for analysis.

3.2.2 The PCA of financial indicators

I precede Principal component analysis aiming at 17 indicators; firstly, making the test of KMO&Bartlett to prove that if the sample is suitable for PCA.

Table .2 The KMO&Bartlett test of financial indicators

Kaiser-Meyer-Olkin measure the suitablility		.729
The Spherical verification of Bartlett	chi-square	9373.460
	df	171
	significance	.000

0.729 is greater than the baseline of 0.5, thus, the sample is suitable for PCA analysis.

Table.3 The total variance explained by the financial indicators

components	The initial Eigenvalue			Extraction of sum of squares loaded		
	Total	The percentage of variance	The accumulation	Total	The percentage of variance	The accumulation
1	5.333	31.369	31.369	5.333	31.369	31.369
2	2.526	14.862	46.230	2.526	14.862	46.230
3	2.016	11.858	58.089	2.016	11.858	58.089
4	1.340	7.880	65.969	1.340	7.880	65.969
5	1.082	6.367	72.336	1.082	6.367	72.336
6	1.002	5.895	78.231	1.002	5.895	78.231
7	.789	4.639	82.870			
8	.709	4.172	87.042			
9	.565	3.322	90.363			
10	.488	2.873	93.236			
11	.371	2.181	95.417			
12	.310	1.823	97.240			
13	.258	1.516	98.756			
14	.085	.502	99.258			
15	.072	.425	99.684			
16	.043	.250	99.934			
17	.011	.066	100.000			

Through the above information, I select the first 6 principal components to get into analysis according to the accumulation of variance

Table 4 Component Score Coefficient Matrix of financial indicators

	Component					
	1	2	3	4	5	6
Current ratio	-.110	.375	.051	-.005	.027	-.023
Quick ratio	-.120	.379	.076	-.021	.023	-.078
Times interest earned	.020	-.015	.013	.012	-.076	.903
Cash flow ratio	.017	.117	-.072	.210	-.221	.013
Asset-liability ratio	-.021	-.281	.095	-.038	-.035	-.054
Fixed assets growth rate	-.162	.017	.480	-.061	-.033	.027
Growth rate of total assets	-.089	.005	.453	.040	.135	-.005
Net assets yield rate	.337	-.090	-.189	-.053	.060	.121
Net profit growth rate	.286	-.032	-.154	-.018	.401	.221
Operating profit growth	.010	.038	.079	.036	.783	-.108
The growth rate of net assets per share	.081	-.070	.191	.043	.003	-.070
Net cash net content	-.034	-.006	.002	.463	.037	.008
Operating profit cash net content	-.040	.007	.014	.458	.064	.009
Return on assets	.180	-.037	.033	.017	-.152	-.088
Total assets net profit margin	.180	.012	.026	-.010	-.094	-.111
Return on equity	.256	-.044	-.049	-.034	-.024	-.062
Operating margin	.036	.096	.170	-.021	.134	.159

I get matrix of principal component values from that the results of the matrix of the standardized original variable values multiply the component score coefficient matrix. Each numerical represents the weight that each variable occupies the corresponding principal component scores.

The expressions of the principal component are as follows:

$$F_1 = -0.110A_1^* - 0.120A_2^* + 0.020A_3^* + 0.017A_4^* - 0.021A_5^* - 0.162A_6^* - 0.089A_7^* + 0.337A_8^* + 0.286A_9^* + 0.010A_{10}^* + 0.081A_{11}^* - 0.034A_{12}^* - 0.040A_{13}^* + 0.180A_{14}^* + 0.180A_{15}^* + 0.256A_{16}^* + 0.036A_{17}^* \quad (2)$$

$$F_2 = 0.375A_1^* + 0.379A_2^* - 0.015A_3^* + 0.117A_4^* - 0.281A_5^* + 0.017A_6^* + 0.005A_7^* - 0.090A_8^* - 0.032A_9^* + 0.038A_{10}^* - 0.070A_{11}^* - 0.006A_{12}^* + 0.007A_{13}^* - 0.037A_{14}^* + 0.012A_{15}^* - 0.044A_{16}^* - 0.096A_{17}^* \quad (3)$$

$$F_3 = 0.051A_1^* + 0.076A_2^* + 0.013A_3^* - 0.072A_4^* + 0.095A_5^* + 0.480A_6^* + 0.453A_7^* - 0.189A_8^* - 0.154A_9^* + 0.079A_{10}^* + 0.191A_{11}^* + 0.002A_{12}^* + 0.014A_{13}^* + 0.033A_{14}^* + 0.026A_{15}^* - 0.049A_{16}^* + 0.170A_{17}^* \quad (4)$$

$$F_4 = -0.005A_1^* - 0.021A_2^* + 0.012A_3^* + 0.210A_4^* - 0.038A_5^* - 0.061A_6^* + 0.040A_7^* - 0.053A_8^* - 0.018A_9^* + 0.036A_{10}^* + 0.043A_{11}^* + 0.463A_{12}^* + 0.458A_{13}^* + 0.017A_{14}^* - 0.010A_{15}^* - 0.034A_{16}^* - 0.021A_{17}^* \quad (5)$$

$$F_5 = -0.027A_1^* + 0.023A_2^* - 0.076A_3^* - 0.221A_4^* - 0.035A_5^* - 0.033A_6^* + 0.135A_7^* + 0.060A_8^* + 0.401A_9^* + 0.783A_{10}^* + 0.003A_{11}^* + 0.037A_{12}^* + 0.064A_{13}^* - 0.152A_{14}^* - 0.094A_{15}^* - 0.024A_{16}^* + 0.134A_{17}^* \quad (6)$$

$$F_6 = -0.023A_1^* - 0.078A_2^* + 0.903A_3^* + 0.013A_4^* - 0.054A_5^* + 0.027A_6^* - 0.005A_7^* + 0.121A_8^* + 0.221A_9^* - 0.108A_{10}^* + 0.070A_{11}^* + 0.008A_{12}^* + 0.009A_{13}^* - 0.088A_{14}^* + 0.111A_{15}^* - 0.062A_{16}^* + 0.159A_{17}^* \quad (7)$$

Table .5 The rotating component matrix table of financial indicators

	Component					
	1	2	3	4	5	6
Current ratio	.066	.948	.030	-.057	-.012	.004
Quick ratio	.079	.957	.072	-.089	-.021	-.053
Times interest earned	-.081	.006	.071	.011	-.067	.954
Cash flow ratio	.276	.379	-.017	.452	-.289	-.003
Asset-liability ratio	-.257	-.798	.128	-.058	.004	-.056
Fixed assets growth rate	.053	-.027	.845	-.112	-.099	.062
Growth rate of total assets	.242	-.026	.850	.108	.064	.015
Net assets yield rate	.864	.082	.006	-.029	-.008	.059
Net profit growth rate	.607	.122	-.072	-.003	.393	.188
Operating profit growth	-.150	-.036	-.026	.023	.874	-.090
The growth rate of net assets per share	.529	-.069	.529	.151	-.082	-.096
Net cash net content	.003	-.082	.013	.961	.020	.002
Operating profit cash net content	-.003	-.055	.025	.947	.049	.005
Return on assets	.800	.142	.366	.121	-.271	-.141
Total assets net profit margin	.815	.267	.339	.056	-.211	-.162
Return on equity	.887	.165	.242	.016	-.127	-.123
Operating margin	.380	.323	.404	-.027	.077	.167

Rotating component matrix can be used to further test the results of principal component extraction. The financial indicators can be simplified as follows:

$$F_1 = 0.337A_8^* + 0.180A_{14}^* + 0.180A_{15}^* + 0.256A_{16}^* \quad (8)$$

$$F_2 = 0.375A_1^* + 0.379A_2^* - 0.281A_5^* \quad (9)$$

$$F_3 = 0.480A_6^* + 0.453A_7^* + 0.191A_{11}^* \tag{10}$$

$$F_4 = 0.210A_4^* + 0.463A_{12}^* + 0.458A_{13}^* \tag{11}$$

$$F_5 = 0.401A_9^* + 0.783A_{10}^* \tag{12}$$

$$F_6 = 0.903A_3^* \tag{13}$$

I get the financial index score model by the weighted results of 6 principal components.

$$ZF = 0.314F_1 + 0.149F_2 + 0.119F_3 + 0.079F_4 + 0.064F_5 + 0.059F_6 \tag{14}$$

3.2.3 The PCA of non financial indicators

The scholars study the performance evaluation of enterprises by the indicators of the company's ownership structure and the governance structure.

The above-mentioned data proves that, there is no visible difference in the indicators of executives and supervisor between two samples. So I select the part-time situation of Chairman and general manager as the preventatives of the governance structure to predict the financial distress.

Table 6 The mann Whitney U test of the governance indicators

	Shareholders correlation	The part-time situation of Chairman and general manager	Directors	Supervisor	Executives	The consistency of working place	The proportion of the independent directors	The number of Directors Supervisor Executives who don't receive compensation
Mann-Whitney U	301.500	319.500	366.500	341.500	359.500	372.500	335.500	338.000
Wilcoxon W	437.500	1447.500	1494.500	1469.500	1487.500	1500.500	1463.500	1466.000
Z	-1.328	-1.357	-.182	-.607	-.265	-.064	-.724	-.606
Asymptotic significance(bilateral)	.184	.046	.856	.544	.791	.949	.469	.545

a. Grouping variable: ST or not

Table .7 The total variance explained by ownership concentration

components	The initial eigenvalue			Extraction of sum of squares loaded			Rotation of sum of squares loaded		
	Total	The percentage of variance	The accumulation	Total	The percentage of variance	The accumulation	Total	The percentage of variance	The accumulation
1	6.705	74.499	74.499	6.705	74.499	74.499	6.691	74.343	74.343
2	1.626	18.067	92.566	1.626	18.067	92.566	1.640	18.223	92.566
3	.551	6.126	98.691						
4	.111	1.237	99.928						
5	.006	.062	99.990						
6	.001	.010	100.000						
7	4.730E-6	5.256E-5	100.000						
8	5.078E-8	5.642E-7	100.000						
9	-9.425E-17	-1.047E-15	100.000						

I simplify the expression of two principal components as follows:

$$N_1 = 0.144C_1 + 0.150C_2 + 0.149C_3 + 0.139C_6 + 0.144C_7 + 0.144C_8 + 0.144C_9 \tag{15}$$

$$N_2 = 0.454C_4 - 0.565C_5 \tag{16}$$

$$ZN = 0.745N_1 + 0.181N_2 \tag{17}$$

3.2.4 The PCA of Macroeconomic indicators

Considering the time lag of effects that macro economy makes on single enterprise, I select the data of macro economy which a year earlier than the financial data.

Table .8 The total variance explained by macro economy

components	The initial eigenvalue			Extraction of sum of squares loaded			Rotation of sum of squares loaded		
	Total	The percentage of variance	The accumulation	Total	The percentage of varianc	The accumulation	Total	The percentage of varianc	The accumulation
1	9.439	42.904	42.904	9.439	42.904	42.904	6.443	29.286	29.286
2	5.861	26.641	69.545	5.861	26.641	69.545	6.273	28.513	57.798
3	2.656	12.073	81.618	2.656	12.073	81.618	3.355	15.249	73.048
4	1.249	5.678	87.295	1.249	5.678	87.295	2.602	11.827	84.875
5	1.102	5.009	92.305	1.102	5.009	92.305	1.634	7.429	92.305
6	.573	2.604	94.908						
7	.418	1.900	96.809						
8	.342	1.553	98.361						
9	.183	.833	99.194						
d 10	.079	.358	99.552						
11	.035	.160	99.711						
12	.024	.111	99.823						
13	.020	.092	99.915						
14	.012	.053	99.968						
15	.003	.012	99.980						
16	.002	.008	99.988						
17	.001	.005	99.993						
18	.001	.003	99.996						
19	.001	.003	99.999						
20	.000	.001	100.000						
21	1.548E-5	7.038E-5	100.000						
22	4.092E-16	1.860E-15	100.000						

I simplify the expression of five principal components as follows:

$$W_1 = 0.072B_3 + 0.212B_9 + 0.215B_{10} + 0.188B_{11} + 0.159B_{12} + 0.108B_{16} + 0.114B_{17} + 0.159B_{19} \tag{18}$$

$$W_2 = 0.179B_6 + 0.182B_7 + 0.179B_8 + 0.175B_{13} + 0.173B_{14} + 0.176B_{15} \tag{19}$$

$$W_3 = 0.136B_{16} + 0.148B_{17} + 0.357B_{18} + 0.258B_{20} + 0.328B_{21} \tag{20}$$

$$W_4 = 0.3039B_1 + 0.592B_4 + 0.354B_5 \tag{21}$$

$$W_5 = 0.508B_2 + 0.550B_{22} \tag{22}$$

$$ZW = 0.429W_1 + 0.266W_2 + 0.121W_3 + 0.057W_4 + 0.05W_5$$

4. Results

4.1 The determination of Bayesian network nodes

According to the above analysis, I select the macro economy, equity concentration, governance structure and financial score as Bayesian network nodes.

While a company gets into financial distress, called S1, a company which is in a normal financial situation, called S2.

4.2 The parameter learning of Bayesian network nodes

I extract 10 companies which are in financial distress, 30 companies which are in normal financial situation as samples from 16 companies which are in financial distress, 47 companies which are in normal financial situation. The remaining 6 ST companies and 17 companies which are in normal financial situation are selected as test samples to examine the accuracy of the model.

The joint probability of macro economy, ownership concentration, governance structure, and financial score is as follows.

Table 9 The joint probability of financial score and its father node

	W_3					
	N_g		N_m		N_b	
	E_1	E_2	E_1	E_2	E_1	E_2
A_b	0	0	0	0.44	0	0.38
A_m	0.75	0.41	0.58	0.25	0.5	0.31
A_g	0.25	0.59	0.42	0.31	0.5	0.31

Ab, Am, Ag respectively represents the financial score is high, middle, low.

Table 10 The conditional probability of company which is ST or not

	A_b	A_m	A_g
S_0	0.29	0.83	0.97
S_1	0.71	0.17	0.03

S_0 represents that a company is in a normal situation,S_1 represents that a company is in financial distress.

4.3 The accuracy test of predicting model

Table .11 The test of predicting model

	normal	ST	total
normal	16	2	18
ST	0	6	6
accuracy(%)	88.89	100	91.67

According to the above information, the total accuracy of the model is 91.67%.

5. Conclusion

Financial risk management plays an important role in the listed companies; this paper further studies the early warning model of financial distress. I find that macro economy, ownership concentration, The part-time situation of Chairman and general manager, financial indicators score are four factors affect the company gets into financial distress or not. Meanwhile, the accuracy of the model is 91.67%, which is very high.

The conclusion of this paper has very significant meanings. Firstly, this paper finds the four factors affect the company's financial distress or not. Secondly, The stakeholder can use this model to predict the financial situation of listed company, which provides a function of guidance.

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