African Journal of Business Management Vol. 6(4), pp. 1375-1382,1 February, 2012
Available online at http://www.academicjournals.org/AJBM
DOI: 10.5897/AJBM11.1443
ISSN 1993-8233 ©2012 Academic Journals

Full Length Research Paper

Financial early warning of listed companies based on time serials data: Evidence from manufacturing listed companies in China

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Accepted 7 December, 2011

Considering the deficiencies in the field of researches on financial crisis prediction for the present, this paper build financial early warning model for manufacturing listed companies, using quarterly time serials data three years before special treatment (ST). We find out that the predictive validity of logistic financial early warning system based on time serials data is better than that based on cross-section data; logistic financial early warning is better than fisher multivariate discriminant analysis; corporate profitability, earnings per share (EPS) and general manager stake which significantly affect the financial distress.

Key words: Financial distress, Logistic model, Global principal component analysis.

INTRODUCTION

With the development of capital markets, more and more companies of China have chosen to raise money from capital market. However, companies getting into financial trouble that leads to business failure are also more than before. Therefore, establishing a rational and effective financial early warning model is of practical significance in other to identify and avoid financial risk for executives, investors and market regulators.

Chinese manufacturing listed companies play an important role not only for Chinese economy but also in a global context. By the end of 2009, 974 manufacturing companies have been listed in Shenzhen and Shanghai stock market, accounting for 59.1% of the total number. In the early 1990s, manufacturing industrial gross product accounted for 40% of the total. At the same time, the products of Chinese manufacturing enterprises are sent all over the world, affecting the global economy. Therefore, taking China's manufacturing listed companies as research object is meaningful.

Previous studies on financial early warning mainly focus on three aspects: early warning variables, early warning methods and early warning time point (Such as Blum, 1974; Cao and Wang, 2007; Deaken,1972; Dimitras, 1999; Hsin-I, 2010; Sun and Shenoy, 2007; Sun and Li, 2009; Laitinen, 1991, Frizpatrick, 1932). Previous studies mainly forecast financial crisis using static cross-section data based on relevant index of balance sheet and income statement. The most published contributions are from Beaver and Altman. Beaver (1966) utilized 30 financial ratios at first to establish univariate financial model. He found out that the ratios of cash flow/total debt (Total debt/Total assets) and Returns on assets achieved higher prediction one year prior to financial distress. Altman (1968) utilized the multiple discriminate analyses in this field. His model demonstrated the prediction of accuracy of 95% one year prior to company failure (please make the statement coloured green clearer and understandable). Since 1980s, cash flow statement has been given attention and studies based on it emerged. Olson (1980) constructed financial early warning system based on cash flow index, using logistic regression models. Aziz et al. (1988) compared the accuracy among the prediction models, and found that early warning model based on cash flow is the best.

Domestic dynamic financial early warning study started

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in the early part of this century. Wu and Chang (2005) established a financial early warning system based on cash flow statement, and suggested that this system's prediction accuracy ratio was 85% higher than traditional which was 65%. Jiang (2007) introduced cash flow index into early warning models, and made the dynamic financial early warning come true. Zhang (2009) established short-term and long-term financial early warning models, inducting companies' growth variables, and found that the former was timelier. Research literature shows previous studies focus on predicting financial risk using cross-section data. The generation of financial distress is a process of long-term accumulation and progressive development (Zhang et al., 2004). The main contribution of this paper is establishing a dynamic financial early warning model to give expression to cumulative effect of listed companies' financial situation, using quarterly time serials data.

METHODOLOGY

The database

This paper takes ST as the criteria of financial distress, while those which were never given special treatment are regarded as healthy ones. ST means company is specially treated by China Securities Supervision and Management Committee (CSSMC). China listed companies are specially treated usually because of two common reasons: they have had negative net profit in continuous two years or they publish financial statements with serious false and misstatement purposely. In this paper, ST samples chosen are all companies that have been specially treated because of negative net profit in continuous two years. This paper uses financial data three years before ST, which is often denoted as year (t-3) in literatures. In accordance with the principle that same industry (Category II), similar size (total assets less than 10% difference), 61 ST companies and 61 matched ones are selected by 1:1, of which the 100 take ST between 2006 and 2008 to conduct early warning model sample. The 22 companies in 2009 conduct predictive sample. Data in this paper mainly comes from financial reports of the companies published by Shanghai and Shenzhen stock exchange, China Center for Economic Research (CCER) and Tsinghua Financial Research Database.

Method

Based on the summary of previous studies, this paper first presents hypothesis corresponding to research purpose. Next, we conduct statistical test of chosen index variables, to examine whether there is significant differences between the normal corporate and financial difficulties. Then we analysed if the variables passed statistical test using global principal component analysis. And then we establish dynamic financial early warning model based on time serials data, test and evaluate the model with sample and correlation tests, and compare the results with that of conventional financial early warning model. Finally, a more reasonable and effective financial early warning model was chosen. In this paper, global financial early warning principal component analysis is used to extract variables. Classical principal component analysis is common in study of financial distress prediction, because it is a good solution to the Multicollinearity of financial indicators between the variables of the problem, but it can only handle cross-section data in a single point time. (Principal component analysis) PCA can retain the advantages of Classical principal component analysis as well as a good tool to deal with time serials data (Qiao F, Yao J ,2003).

By forming the data matrix with the previous observations in each observation vector, ARMAX model structures have been widely applied to the system identification of dynamic systems (Leontaritis & Billings, 1985). Integrating ARMAX with PCA is referred to as dynamic PCA (DPCA) It can extract the time-dependent relations in the measurements (Ku et al., 1995). When the data are stacked with the current observation vector and the previous observations, the resulting matrix is formed as

$$X_d = \begin{pmatrix} X^T(k) & X^T(k-1) & \cdots & X^T(k-d) \\ X^T(k-1) & X^T(k-2) & \cdots & X^T(k-d-1) \\ & \cdots & & \\ & \cdots & & \\ & \cdots & & \\ X^T(k+d-K) & X^T(k+d-K-1) & \cdots & X^T(k-K) \end{pmatrix}$$

Where x (k) = $[x_{1,k}\ x_{2,k} \cdots x_{J,k}]^T$ is the J -dimensional observation vector at time point k. Performing PCA on the data matrix can remove the input-output relationship of dynamic systems. The residuals of the DPCA model are much more uncorrelated than those of the traditional statistic PCA model. This means that DPCA is much better than the traditional static PCA in detecting the fault occurrence from serially correlated data (Junghui and Kun-Chih, 2002; Jie and Hui, 2011). In this paper, logistic regression and fisher linear discriminate logic are two methods to establish financial early warning models. Logistic regression is not strictly required to obey state variable analysis of assumptions. It have been confirmed as an effective modeling method by recent studies, and comparing with the neural network model, Logistic regression method have the advantage of easy to understand , and Can clearly show the factors and the relationship between corporate financial distress. Fisher linear discriminate model is also confirmed as a simple and effective method in predicting Chinese listing companies' financial failure (Wu and Lu, 2001; Jae and Young-Chan, 2005; Kourti and MacGregor, 1996; Lee et al., 2005; Odom and Sharda, 1990).

EMPIRICAL RESULTS

Hypothesis

Whether the company will fall into financial difficulties is affected by non-financial factors as well as financial factors. In the long run, listed companies with good profitability and progressive capacity can resist risks better even if they may get into financial problems because of debt-servicing difficulties in the short term. They can also have enough momentum to turn around.

Deteriorating financial position of listed companies is a gradual process. In China, whether a listed company gets special treatment or not is often based on the financial situation of the company in one (t-1) and two (t-2) years before ST. Although the company remains profitable in the year t-3, some financial indices have shown clues of deteriorating financial position. Therefore, this paper establishes financial early warning model based on time-serials data consisting of quarterly, semiannual and

Table 1. Summary of alternative indicators.

Solvency	Current RatioX1 QuickRatioX2 equity ratio X3 debt ratio X4	Operating capacity	Inventory TurnoverX5 Accounts receivable turnoverX6 asset turnover X7 fixed asset turnover X8 total asset turnover X9
Ability to grow	Growth rate of total assets X10 Net assets per share growth rateX11 revenue growth X12 Total profit growth rate X13	Profitability	Operating margin X14 ROE X15 Return on total assetsX16 EBIT ratio of total revenue X17
Shareholder Profitability	Earnings per shareX18 retained earnings per share X19 EBIT per Share X20	Cash Flow	net cash flow from operating activities per share X21 net cash flow per share X22 Sales Cash RatioX23
Board Structure	Board sizeK1 The proportion of independent directorsK2 Ownership of board K3 The proportion of state-owned shares K4	Ownership Structure	The proportion of corporate shares K5 The proportion of tradable sharesK6 Proportion of the largest shareholderK7 CT-5 K8 z K9 H5 K10
Manager Incentive	Amount of senior management of the three highest total compensationK11 Executives stakeK12 Chairman stakeK13 General Manager stake K14		

annual reports of t-3 in order to reflect the cumulative effect of financial dynamics.

This paper takes prediction three years prior to failure. Predicting financial failure with information of one or two years prior to special treatment will overestimate the predictive ability of the model. What's more, predicting in t-3 is timeliness stronger for both the investors and the manager of company compared with that in t-1 and t-2. So, we suppose:

H_1: dynamic financial early warning models based on time-serials data is superior to the conventional static financial early warning models.
H_2: conventional static financial early warning model is superior to dynamic financial early warning models based on the time-serials data set.

Indicator selection

25 financial indicators which cover solvency and operation capability, profitability, shareholder profitability, growth, cash flow and 14 non-financial indicators covering board structure, ownership structure and management incentives are selected as alternative indicators. These indicators can get from the database of CCER (a financial research database in china). The results are shown in table 1.

Significance test

This paper uses KS test to verify whether indicator variables are normally distributed. We conduct T test on variables that are normally distributed, and Wilcoxon rank sum test on those that are not normally distributed. Bendel and Afifi (1977) and Mickey and Gereenland (1989) pointed out in their studies that it may leave important variables out to take conventional level (for example, 5%) as touchstone. Afifi (1979) suggested it would be better if it take the significance level between 10 to 25% as touchstone. Therefore, this paper takes 25%

Table 2. Wilcoxon test results (financial indicator).

	1Q		2Q		3Q		4Q	
	Z value	Asymp. Sig. (2-tailed)	Z value	Asymp. Sig. (2-tailed)	Z value	Asymp. Sig. (2-tailed)	Z value	Asymp. Sig. (2-tailed)
X1	-1.430	0.153	-1.554	0.120	-0.837	0.402	-1.757	0.079
X2	-1.051	0.293	-1.408	0.159	-0.860	0.390	-1.448	0.148
X3	-1.348	0.178	-1.477	0.140	-0.699	0.485	-1.636	0.102
X4	-0.942	0.346	-1.274	0.203	-0.686	0.493	-1.844	0.065
X5	-1.326	0.185	-0.428	0.669	-0.344	0.731	-0.721	0.471
X6	-0.525	0.600	0.000	1.000	-0.206	0.837	-0.030	0.976
X7	-0.134	0.893	-0.425	0.671	-1.232	0.218	-0.531	0.595
X8	-0.133	0.894	-0.318	0.750	-0.063	0.850	-0.677	0.498
X9	-0.127	0.899	-0.290	0.772	-1.407	0.159	-0.744	0.457
X10	-0.152	0.879	-1.009	0.313	-1.626	0.104	-2.042	0.041
X11	-0.328	0.743	-1.030	0.303	-1.432	0.152	-0.676	0.499
X12	-0.519	0.604	-1.032	0.302	-0.619	0.536	-0.313	0.154
X13	-0.244	0.807	-0.872	0.383	-0.024	0.981	-0.420	0.175
X14	-0.152	0.179	-0.185	0.854	-0.806	0.420	-0.055	0.956
X15	-0.960	0.337	-1.079	0.280	-1.289	0.197	-0.522	0.602
X16	-1.084	0.279	-0.796	0.426	-1.123	0.261	-0.738	0.460
X17	-0.006	0.995	-0.749	0.454	-0.556	0.578	-0.472	0.137
X18	-1.106	0.269	-1.114	0.265	-0.732	0.464	-0.864	0.388
X19	-1.879	0.060	-1.627	0.104	-2.204	0.027	-1.173	0.241
X20	-0.323	0.747	-1.006	0.315	-0.038	0.970	-0.637	0.524
X21	-1.688	0.091	-1.279	0.201	-0.040	0.968	-0.352	0.725
X22	-0.344	0.731	-1.221	0.222	-1.982	0.047	-0.637	0.524
X23	-0.731	0.464	-1.005	0.315	-0.251	0.802	-0.264	0.792

as the significance level, and uses SPSS11.5 software for data processing. Test results are shown in Table 2. A total of 16 financial indicators pass the significant test, namely X1, X2, X3, X4, X7, X8, X9, X10, X12, X13, X14, X15, X17, X19, X21 and X22.

Similarly, six non-financial indicators pass the significant test, namely K2, K3, K7, K11, K12 and K14 (as shown in Table 3).

Global principal component analysis

This section Global principal component analyzes how financial indicators passed the significance test to extract financial variables as principal components into financial early warning model.

Firstly, we conduct Kaiser-Meyer-Olkin (KMO) and Bartlett's test to verify the applicability of variables for global principal component analysis. Results show that KMO statistics is 0.637 and p value of Bartlett test is far less than 0.001, rejecting original assumption that units are interrelated.

Secondly, we conduct global principal component analysis on time serials data of the four time points. A total of 9 principal components are extracted and the contribution rate of cumulative variance is 87.614% which indicate that most of the original information is preserved.

Thirdly, in order to analyze how each major component work in company financial distress in-depth, we confer reasonable explanation upon principal component, and analyze the economic implications of each principal component qualitatively based on Rotation factor loading matrix.

As shown in Table 4. 1 solvency indices current ratio (X1), quick ratio (X2) and debt ratio (X4) contribute the most to principal component F1. 1) So F1 reflects the solvency of listed companies; 2) operations capacity indices asset turnover (X7), fixed asset turnover (X8) and total asset turnover (X9) contribute the most to principal F2. So F2 reflects the operating capacity of listed companies; 3) Profitability indices operating margin (X14) and return on equity (ROE) (X15) contribute the most to component F3, and F3 reflects the company's profitability; 4) Net cash flow per share (X22) contributes the most to principal component F4, and F4 reflects the company's ability to obtain; 5) net cash flow from operating activities per share (X21) contributes the most to component F5, and F5 reflects the cash obtaining ability of operating activities; 6) Revenue growth (X12) contributes the most to component F6, and F6 reflects the ability of revenue growth; 7) Equity ratio (X3) contributes the most to component F7 and F7 reflects the company's capital

Table 3. T test and Wilcoxon test results (non-financial indicator).

Variable	T test		Wilcoxon test	
	T value	Sig. (2-tailed)	Z value	Asymp. Sig. (2-tailed)
K1			-0.017	0.986
K2			-1.329	0.184
K3			-2.037	0.042
K4			-0.023	0.981
K5			-0.649	0.516
K6	-0.122	0.903		
K7	1.597	0.117		
K8	0.275	0.784		
K9			-0.111	0.912
K10			-0.767	0.443
K11			-1.491	0.136
K12			-1.260	0.208
K13			-1.088	0.277
K14			-2.777	0.005

Table 4. Rotation factor matrix.

Variable	Component								
	F1	F2	F3	F4	F5	F6	F7	F8	F9
X1: Current ratio	0.983	-0.014	0.045	-0.005	-0.066	-0.018	-0.069	-0.015	0.036
X2: Quick ratio	0.973	-0.025	0.061	-0.010	-0.055	-0.013	-0.066	-0.011	0.059
X3: Equity ratio	-0.147	0.019	-0.152	-0.007	-0.023	0.006	0.965	-0.004	-0.082
X4:Debt ratio	0.958	-0.035	0.040	-0.035	0.023	-0.006	-0.047	-0.003	0.049
X7:Asset turnover	-0.123	0.826	0.085	0.100	0.406	0.060	0.052	-0.036	-0.049
X8:Fixed asset turnover	0.046	0.795	-0.066	-0.085	-0.289	-0.032	-0.079	0.044	0.139
X9:Total asset turnover	-0.027	0.931	0.052	0.092	0.222	0.035	0.061	-0.031	-0.049
X10:Growth rate of total assets	-0.105	0.137	0.206	0.845	-0.132	0.002	0.110	0.027	0.095
X12:Revenue growth	-0.027	0.036	0.001	0.002	0.001	0.997	0.005	0.008	-0.002
X13:Total profit growth rate	-0.022	-0.011	0.137	0.009	0.032	0.008	-0.003	0.984	-0.036
X14: Operating margin	0.091	0.022	0.883	0.046	0.022	-0.004	-0.040	0.022	0.041
X15: ROE	0.061	0.179	0.835	0.013	-0.068	0.034	-0.068	0.029	0.049
X17: EBIT ratio of total revenue	-0.020	-0.176	0.668	0.107	0.179	-0.032	-0.068	0.131	0.156
X19: Retained earnings per share	0.132	0.035	0.217	0.118	0.160	-0.001	-0.090	-0.042	0.922
X21: Net cash flow from operating activities per share	-0.067	0.177	0.073	-0.009	0.892	-0.005	-0.031	0.039	0.158
X22:Net cash flow per share	0.047	-0.045	-0.035	0.895	0.121	0.002	-0.100	-0.012	0.028

structure; 8) Total profit growth rate(X13) contributes the most to F8, which reflects the growth of profits; 9) Retained earnings per share (X19) contributes the most to F9, which reflects the profitability per share. Fourthly, we establish linear expression of principal components on the original financial ratios, according to the factor score coefficient matrix. Specific results are shown in Table 5. We express all the principal components as a linear combination of all scalars. Thus, value of each principal component in the sample can be calculated to establish early warning model.

Modeling and analysis

This paper sets up logistic financial early warning models based on time serials data and cross-sectional data, to compare their effectiveness. We also establish Fisher multiple discriminant analysis (MDA) financial early warning model based on time serials data to compare

Table 5. Principal component matrix.

Variable	Component								
	F1	F2	F3	F4	F5	F6	F7	F8	F9
X1	0.52	-0.06	0.21	0.07	0.06	0.03	0.08	0.06	-0.05
X2	0.52	-0.06	0.20	0.06	0.05	0.03	0.08	0.07	-0.03
X3	-0.22	-0.09	0.10	0.10	0.26	0.02	0.29	0.81	0.28
X4	0.50	-0.06	0.20	0.05	0.00	0.06	0.13	0.10	-0.05
X7	-0.14	0.45	0.33	-0.03	-0.05	0.02	0.08	0.05	-0.17
X8	-0.02	0.24	0.40	-0.07	0.26	-0.17	-0.18	-0.25	0.34
X9	-0.10	0.44	0.42	-0.01	0.09	-0.04	0.02	0.01	-0.08
X10	-0.02	0.27	-0.19	0.58	0.25	-0.04	-0.01	0.01	0.05
X12	-0.04	0.05	0.03	-0.02	0.15	0.96	-0.21	-0.03	0.05
X13	0.02	0.09	-0.18	-0.20	0.30	0.10	0.77	-0.39	0.25
X14	0.20	0.31	-0.32	-0.23	0.19	-0.06	-0.13	0.20	-0.15
X15	0.17	0.34	-0.23	-0.24	0.26	-0.05	-0.20	0.12	-0.08
X17	0.14	0.23	-0.39	-0.14	-0.03	-0.01	0.04	0.11	-0.05
X19	0.20	0.25	-0.13	0.08	-0.44	0.02	-0.15	0.03	0.77
X21	-0.05	0.29	0.04	-0.10	-0.61	0.14	0.36	0.14	-0.21
X22	0.04	0.17	-0.15	0.68	-0.03	0.05	0.10	-0.14	-0.19

Table 6. Dynamic Logistic model empirical results.

	B	S.E.	Wald	df	Sig.	Exp(B)
F3	-0.571	0.282	4.093	1.000	0.043	0.565
F9	0.618	0.281	4.831	1.000	0.028	1.855
K14	-32.303	17.173	3.538	1.000	0.060	0.000
Constant	-4.965	2.520	3.881	1.000	0.049	0.007
H-L	8.737 (0.365)					

Table 7. Dynamic Logistic model prediction results.

	NST	ST	Total prediction rate	Re-distinguish rate
NST	72.0%	28.0%	76.0%	80.0%
ST	20.0%	80.0%		

quality of logistic and fisher MDA model.

(1) Logistic financial early warning model based on time serials data.

Taking the nine financial and six non-financial indicators as been extracted as warning variables, we establish logistic financial early warning model based on time serials data, with the end of t-3 as early warning time point. Empirical results are shown in Table 6.

From the empirical results, we can infer: 1) The probability of HL statistic is 0.365, statistically insignificant, which means that the model fits well. 2) Variables F3 (profitability factor), F9 (earnings per share of capacity factor) and K14 (General Manager of ownership) are significant to getting into the model, which indicates whether a company will fall into financial difficulties and it is closely related to the ability of growth and profitability, more even affected by the general manager stake.

We regard mistaking ST Company as normal as error type I, and the opposite as error type II. The test sample is put into the model to test the prediction accuracy (results shown in Table 7). The accuracy of the model is 80%, with the total prediction accuracy as 76% and error type I rate as 20%.

(2) Comparison between dynamic financial distress prediction model and the static. The static Logistic financial distress prediction model based on Cross-section data is established using the data of t-3 to

Table 8. Static Logistic model empirical results.

	B	S.E.	Wald	Sig.	Exp(B)
X10	0.03	0.01	5.74	0.02	1.03
K14	-13525.13	7228.69	3.50	0.06	0.00
Constant	-0.06	0.24	0.07	0.79	0.94
H-L	15.052 (0.058)				

Table 9. Static Logistic model prediction results.

	NST	ST	Total prediction rate
NST	58%	42%	64%
ST	30%	70%	

Table10. Dynamic Fisher linear discriminant model result.

	Lambda	F Statistic	df1	df2	Sig.
F3	0.958	4.323	1	98	0.040

Table 11. Dynamic Fisher linear discriminant model prediction result.

	NST	ST	Total prediction rate
NST	48.0	52.0	56.0
ST	36.0	64.0	

Table 12. The out-of-the-sample prediction results of the three financial distress prediction models.

Model	I error (%)	II error (%)	Comprehensive prediction accuracy (%)
Logistic financial early warning model based on time serials data	20	28	76
logistic financial early warning model based on cross-section data	30	42	64
Fisher discriminated model based on time serials data	36	48	56

compare with the dynamic model above. The result is shown in Table 8.

As is shown in Table 9, both established in three years prior to ST, the accuracy of static model is lower than dynamic model.

(3) Comparison between Logistic model and Fisher linear discriminate model based on time serials data. We also establish dynamic Fisher linear discriminate model based on time serial data to compare with the dynamic Logistic model. The dynamic Fisher linear discriminant mode result is shown in Tables 10 and 11.

According to the result of dynamic Logistic model, variables F3 (profitability factor) also pass the significant test in Dynamic Fisher linear discriminate model, having significant effect with the financial performance of company. Results in Table 12 shows that financial early warning model based on the time serial data is superior to that based on sectional data and Fisher discriminated financial early warning of models. Both types of false positives of the former are lower than the latter two, and the comprehensive prediction accuracy rate is higher than the latter two. Therefore, we can infer that the logistic financial early warning model based on time serials data is better in prediction, and the hypothesis two is accepted.

DISCUSSION

This paper tries to establish a scientific and effective financial early warning model based on time-serials data and integrated financial and non-financial factors, which is consistent with accumulating features of financial cycles. According to the research, we find out that: (1) financial early warning model based on time serials data in t-3 year is good in fitting and prediction, superior to the mode based on the cross-sectional data. (2) In three years prior to financial failure, the dynamic Logistic early warning model is better than dynamic Fisher discriminate model with our data. The accuracy of Logistic model is higher. (3) Whether a company will fall into financial difficulties is closely related to the ability of growth and profitability, more ever affected by the general manager stake. Therefore, listed companies should improve financial position by increasing their profitability and growth ability, and at the same time, develop reasonable policy on general managers' incentives. Our conclusions cannot only help market players to identify financial risks in advance, but also can help managers prevent risks fundamentally.

However, there are also some limitations in this paper. Firstly, the period of time serials data is quite short which only cover four time points. Secondly, the financial condition is also affected by external factors such as market, Macroeconomic environment and policy etc. these factors should be taken into account when establishing the financial distress prediction model. Further research may improve the financial distress prediction model by extending the time serials and adding external factors to the company.

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