Financial distress analysis of 'Special Treatment' companies in China

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Abstract: This paper aims to find out the financial ratios of the 'Special Treatment' (or financially distressed) companies in China that are significantly weaker than those of the regular companies and, consecutively, expose areas of poor financial performance that lead these companies to financial distress. The financial data of 'Special Treatment' companies during the period from 2002 to 2009 have been compared with that of financially non-distressed companies from the same period by applying discriminant analysis. The study finds that as many as five financial ratios, namely cash flow coverage ratio, net income to assets, cash ratio, quick ratio, current ratio and debt ratio, are significantly weaker in financially distressed companies.

Keywords: financial distress; 'Special Treatment' company; Shanghai Stock Exchange; discriminant analysis.

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1 Introduction

Financial distress refers to a situation of poor financial performance when firms suffer from cash shortage, high level of debt, inability to pay off debts and other liabilities and, quite often, bankruptcy litigations. In defining financial distress, different researchers emphasised different aspects of financial situations. Beaver (1966) viewed financial distress from creditors' perspective. To him, when firms suffer from cash flow shortage and become unable to meet corporate liabilities, they are in financial distress. Similarly, Zopounidis and Doumpos (2002), Baker and Thompson (2000) and Stiglitz (1999) emphasised on the inability of firms in meeting debt obligations in defining financial distress. Altman (1968) emphasised on legal perspective by defining corporate financial distress as a situation when a firm seeks legal protection from creditors or involves in legal actions by filing under the Bankruptcy Act.

A number of causes can be attributed to corporate financial distress. Baldwin and Glezen (1992) classified the causes of the failure into internal factors and external factors. Internal factors include poor managerial skills, poor financial management and record keeping, poor marketing and poor production strategies, while external factors refer to economic recession, market competition, unfavourable government regulation, difficult access to credit, higher interest rate and high service charges for the banks. Mallett (1998) also found the restricted access to credit financing an important factor for financial distress.

The characteristics of financially distressed firms are similar to that of 'Special Treatment' companies in China. 'Special Treatment' provision was first implemented in China in 1998 primarily to promote a healthy development of stock markets in China. The listed companies whose financial performances have been deteriorating and may face bankruptcy litigation are classified under the category of 'Special Treatment' with 'ST' before their stock symbols. The 'Fact Book of Shanghai Stock Exchange' characterises a 'Special Treatment' company as one that has suffered from negative 'net income' for two consecutive years or has been ordered by China Securities Regulatory Commission (CSRC) to correct serious errors or falsehoods in its financial report but fails to do so before the deadline or is likely to be dissolved, etc.

Financial distress is relevant for all stakeholders – shareholders, creditors, employees and government – because it may lead to shareholders' and creditors' loss of investment, employee's loss of job and government's loss of tax revenue. Clearly, such a condition is undesirable to the firm, society and economy as a whole. In China, such financial distress may disrupt the economic plan of the government, slow down the pace of development and adversely affect the capital market.

Therefore, academics and researchers have always been interested in studying financial distress and the related issues. However, not a wide range of work in this field has been done in China that may help the Chinese firms to know the probability of the distress in advance, to identify the causes of the distress and to take actions to combat such distress. Moreover, the limited amount of study that has been done in this field by Chinese scholars has mostly been published in Chinese-language journals, and therefore not very helpful for the rest of the world for sharing knowledge. The present study aims to fill these gaps.

The main purpose of this study is twofold: to identify those financial areas that are significantly weaker in 'Special Treatment' companies in comparison to the regular (financially non-distressed) companies and to observe how accurately 'discriminant analysis' predicts the imminent financial distress of 'Special Treatment' companies. The remainder of this paper is organised in the following order: literature review, methodology, empirical results and analyses, and conclusion.

2 Literature review

Over the last 30 years, the issues of financial distress have received significant interests from academics and researchers alike to develop numerous distress prediction models due to its considerable corporate, societal and macroeconomic importance. Beaver (1966), the pioneer of financial distress research, introduced the use of financial ratios in predicting distress in his univariate analysis model. Altman (1968) pointed out that Beaver's (1966) model could be conflicting and confusing when multiple financial ratios are used simultaneously. Therefore, Altman (1968) applied the multivariate discriminant analysis that outperformed univariate analysis in measuring the probability of a firm's failure by analysing multiple ratios at a time. He devised a model of discriminant function that included all the predictor variables in a linear combination and formed a composite index *Z*-score which is still popular among investors to understand the future prospect of firm. Deakin (1972), in this model, combined the benefits of Beaver's (1966) higher classification accuracy and Altman's (1968) simultaneous use of multiple ratios in multivariate discriminant analysis. Edmister (1972) contributed to the literature by extending the research on small size firms which were never included in the financial distress study before. Besides, for the first time, he added time trend of financial ratios in financial distress study. He also contributed the bankruptcy literature by overcoming the problem of multicollinearity among the ratio variables. Blum (1974) recognised, similar to Beaver (1966), that financial distress was mainly a problem of cash flow generation. His use of measure of dispersion was also unique in the study of financial distress.

Ohlson (1980) was the first researcher who used logistic regression model that did not assume normal distribution of independent variables. Thus, he improved the flexibility of the statistical technique that was used to predict bankruptcy. Zavgren (1983) followed the path of Ohlson (1980) and modified the earlier study by improving the predictability of the model. The important contributions of his study were reduced sampling bias and improved selection criteria of independent variables by using a two-step factor analysis. Karels and Prakash (1987) conducted an interesting study by examining (1) the condition of normality assumption of discrimination analysis, (2) the impact of relaxing this assumption on the prediction accuracy and (3) the comparison of their results with previous studies using discriminant analysis. Platt and Platt (1990) contributed to the financial distress literature by introducing the concept of modifying data with industry characteristics and by improving the prediction accuracy. Finally, Gilbert et al. (1990) and Morris (1997) improved the explanatory power of the model and added more variables to observe their impact on financial distress.

At the advent of the 21st century, a new school of researchers started using various intelligent techniques in financial distress prediction. Some of the popular techniques are neural networks, case-based reasoning, decision trees, operational research, evolutionary approaches, rough set based techniques, fuzzy logic, support vector machine, isotonic separation and soft computing method. The researchers who belong to this new school of intelligent techniques are Lacher et al. (1995), Zhang et al. (1999), Atiya (2001), Jo et al. (1997), Park and Han (2002), Zimmermann (1996), Spanos et al. (1999), Andres et al. (2005), Min and Lee (2005), Jo and Han (1996) and Lin and McClean (2001).

The studies specifically directed to investigate the causes of financial distress were somewhat limited. Other than the studies of Baldwin and Glezen (1992) and Mallett (1998), few other notable works in this area were Desai and Montes (1982), Hudson (1986), McDonald (1995) and Rodway (1991). To observe whether growth rate of money supply and bank rate affect bankruptcy, Desai and Montes (1982) used a log-linear model and found growth rate of money supply and bank rate both affected the bankruptcy. In an attempt to find the effect of unemployment rates, various interest rates, unfilled vacancies and personal consumption expenditures on bankruptcies, Hudson (1986) used linear regression model by using quarterly data. His results showed that unemployment rate and changes in real interest rates were significant determinant of bankruptcies. Few years later, Hudson, with another researcher, Cuthbertson (Hudson and Cuthbertson, 1993), used autoregressive distributed lag model to observe how interest rates, the unemployment rate, new borrowing, profit margin and interest payment-to-net income ratio influenced bankruptcy. They found unemployment rate, changes in real interest rates and changes in the profit margin could affect bankruptcies. In separate studies, both McDonald (1995) and Rodway (1991) studied the effect of real interest rates, growth of domestic output and difference between expected and actual GDP on bankruptcies. Their findings showed changes in real interest rates and changes in output growth to be significant determinants of bankruptcies as these variables explained almost 96% variation in the number of bankruptcies. In China, the study of financial distress is somewhat limited. In recent years, some researchers have shown interests in studying the 'Special Treatment' companies. Jing (1999) used univariate and multivariate discriminant analyses to forecast financial distress of the 'Special Treatment' companies. Chang-e (2006) used logistic regression to predict financial distress of 'Special Treatment' companies, while Shu-e and Li (2005) used artificial neural network, an intelligent system approach. Therefore, there exists wide scope for conducting further studies in the field of financial distress in China.

3 Methodology

Discriminant analysis, a statistical technique that is frequently used in classifying an observation into one of several a priori groupings, is applied in this study. It is a suitable statistical technique when the dependent variable is categorical and the independent variables follow interval scale (Klecka, 1980). In this research, discriminant analysis is used to identify the most highly contributing financial ratios that differentiate a financially distressed company from a non-distressed one. Simultaneously, the technique will also test how accurately the cases are classified as predicted. The dependent variable in this study is the financial status of the company during the period of observation. This dependent variable is dichotomous with the following two dimensions: (a) companies that are financially distressed and (b) companies that are not financially distressed. The companies that are classified under 'Special Treatment' suffer from financial distresses. In the discriminant model of this study, the dependent variable has been quantified as follows: (a) a company classified as 'Special Treatment' in Shanghai Stock Exchange is indicated as 1 and (b) a company that is not classified as 'Special Treatment' and, therefore, financially not distressed is indicated as 2.

As many as 36 different financial ratios are used as independent variables in this study. Financial ratios were used in many studies in the past to analyse the causes of corporate bankruptcy and financial distress due to their ability to reveal financial situation and performance (Beaver, 1966; Tamari, 1978; Gibson, 1982; Altman, 1968; White et al., 1994; Malonis, 2000; Hossari and Rahman, 2005). In those studies, financial ratios acted as discriminating factors between financially distressed and financially non-distressed companies. Six categories of financial ratios, namely liquidity ratio, cost ratio, profitability ratio, efficiency ratio, leverage ratio, and cash flow, ratio are used in this study. Table 1 lays out constituent ratios of financial situation under each of these categories.

During the period from 2002 to 2009, 50 pairs of companies from the manufacturing sector have been selected for this study. The companies in the first group are classified as 'Special Treatment' companies and, therefore, considered financially distressed companies. The companies in the second group are regular companies with no sign of financial distress. These two groups are carefully paired based on their asset size, production capacity and product line. The purpose of this paring is to keep the homogeneity between two groups as much as possible so that test results can be free from bias.

While the 50 'Special Treatment' companies in the first group have been selected by simple random sampling method, the members in the second group are mostly selected by their pair matching criteria. When several regular companies meet the eligibility for having desirable criteria, random sampling method has been adopted to choose one from them. All these 100 companies are enlisted in Shanghai Stock Exchange.

Table 1 List of independent variables

Categories	*Financial ratios*
Liquidity ratio	Current ratio, quick ratio, cash ratio, accounts payable turnover ratio, cash debt coverage, debt income ratio and long-term debt ratio
Cost ratio	Fixed charge coverage ratio, fixed costs-to-total assets, variable costs-to-total assets, overhead-to-variable costs, overhead-to-variable costs and labour cost-to-total costs
Profitability ratio	Cash return on assets, contribution margin ratio, operating margin, net income to assets (ROTA), profits per employee (net income per employee), fixed asset turnover ratio and total asset turnover
Efficiency ratio	Defensive interval period, accounts receivable turnover ratio, collection period, inventory conversion period, average obligation period or payment period, collection period to payment period, operating cycle, payment period to operating cycle and revenue per employee
Leverage ratio	Debt ratio and debt-to-equity ratio
Cash flow ratio	Cash flow from operations to net income, cash flow coverage ratio, operating cash flow to current liabilities and operations cash flow plus fixed charges to fixed charges

The values of independent variables for this study are collected directly from Wind Financial Database (WindDB), a comprehensive financial database in China. The sources of these financial data are the financial statements and annual reports of the firms chosen for this study. Financial statements (such as balance sheet, income statement, cash flow statement, etc.), financial ratios, financial notes and audit opinions of financial statement are reported in this database on a quarterly, half-yearly and yearly basis. The data for independent variables (financial ratios of the sampled companies) have been taken 1 year prior to the official announcement of 'Special Treatment' classification.

4 Empirical results and analyses

Discriminant function of this study estimates discriminant score of each company by using the values of independent variables (financial ratio) according to the following formulation:

$$Z = b_1 x_1 + b_2 x_2 + \ldots + b_n x_n$$

where b_1, b_2, …, b_n are discriminant coefficients and x_1, x_2, …, x_n are independent variables.

At first, the author would like to test the null hypothesis that the mean values of the discriminant scores of both groups (financially distressed group and financially non-distressed group) are equal. The test statistic that is commonly used for this purpose is Wilks' lambda. The value of Wilks' lambda ranges from 0 to 1 such that the lower the value (near 0) of the test statistic, the higher the difference between mean values of the discriminant scores of two groups. In this study, the value of Wilks' lambda is 0.203, which transforms to a χ^2 of 128.199 with 35 degrees of freedom (Table 2). This indicates that the null hypothesis is rejected with a statistical significance beyond the 0.05 level. Another utility of Wilks' lambda is to explain the total variance in the discriminant scores. Although, both squared canonical correlation and Wilks' lambda can be used to explain the variance in the dependent variable, Wilks' lambda measures the variation in dependent variable not explained by the independent variables, whereas squared canonical correlation measures the variation in dependent variable (discriminant score) explained by the independent variables. The value of squared canonical correlation in Table 2 suggests that this model explains 79.7% of the variance for the dependent variable discriminated by the independent variables. The remaining unexplained part of the variation, as is evident by the value of Wilks' lambda, is 20.3%.

Table 2 Canonical discriminant functions

Function	*Eigenvalue*	*Percentage of variance*	*Cumulative percentage*	*Canonical correlation*	*Square of canonical correlation*
1	3.916	100	100	0.893	0.797
	Wilks' lambda	χ^2	*df*	*Sig.*	
	0.203	128.199	35	0.000	

Table 3 Tests of equality of group means

Predictor variable	*Wilks' lambda*	*F*	*df1*	*df2*	*Sig.*
Cash flow coverage ratio	0.567	74.793	1	98	0.00
Cash ratio	0.637	55.902	1	98	0.00
Current ratio	0.693	43.312	1	98	0.00
Debt ratio	0.732	35.895	1	98	0.00
Net income to assets (ROTA)	0.734	35.492	1	98	0.00

Wilks' lambda (in Table 3) also tells us which predictor variables are more contributive to discriminant function in discriminating group difference. Here, Wilks' lambda is the ratio between within-group sum of squares and the total sum of squares for each predictor variable. The value of lambda varies between 0 and 1, where the smaller the value of lambda for an independent variable, the more that variable contributes to discriminant function. Table 3 shows only those predictor variables whose Wilks' lambda values are the lowest among all. Only five predictors out of 36 are contributing the most to group discrimination. These are cash flow coverage ratio, cash ratio, current ratio, debt ratio and net income to assets. Wilks' lambda for each of these variables is significant by *F*-test beyond the 0.05 level.

To estimate the discriminatory power of the discriminant function, eigenvalue is measured (Table 2). Eigenvalue is the ratio of between-group sum of squares to within-groups sum of squares. Eigenvalue in this study is 3.916, which accounts for 100% of the explained variance, and is significant beyond the 0.05 level. This is a large eigenvalue that indicates the superiority of the discriminant function of this model and its high discriminatory power. Besides eigenvalue, canonical correlation also measures the efficiency of the discriminant function in defining group membership. The value of canonical correlation ranges from 0 to 1, where higher the value, more efficient the discriminant function in defining group membership. The value of canonical correlation for the discriminant function is 0.893 (Table 2), which is indicative of high efficiency of this model in determining group differences.

Table 4 Standardised canonical discriminant function coefficients

Predictor variables	*Function*
	1
Cash flow coverage ratio	–1.351
Debt ratio	1.272
Net income to assets (ROTA)	1.203
Quick ratio	0.956
Cash return on assets (including interest)	–0.934

The partial results of standardised canonical discriminant function coefficients in Table 4 show the predictor variables that contribute the most to the discrimination between financially distressed and financially non-distressed companies. Standardised coefficients eliminate the effects of different mean scores and standard deviations in independent variables and facilitate a meaningful comparison among predictor variables. The higher the absolute value of the coefficient, the stronger the discriminating power of the associated predictor.

In Table 5, structure coefficients or discriminant loadings show the correlations between observed variables and discriminant score of a discriminant function. The higher the value of the structure correlation, the more the contribution of corresponding variable in the discriminant function.

Table 5 Structure matrix

Predictor variables	*Function*
	1
Cash flow coverage ratio	–0.441
Cash ratio	–0.382
Quick ratio	–0.337
Current ratio	–0.336
Debt ratio	0.306
Net income to assets (ROTA)	–0.304

Based on the results in Tables 3–5, the most poorly performing financial ratios in distressed companies are cash flow coverage ratio, net income to assets, cash ratio, quick ratio, current ratio and debt ratio. A number of possibilities are there as the underlying causes for their weaknesses. Poor level of cash, higher level of accounts payables, poor level of sales and higher level of operating expenses can all be attributable to the poor financial performance that lead them to be classified as 'Special Treatment' companies. Further research work can possibly probe into the actual causes of financial distress and the factors that influenced the financial performance.

'Functions at group centroids' (Table 6) shows the mean values of discriminant scores for both groups. The mean value of discriminant scores for financially distressed firms is 1.959, which is quite far from the mean discriminant score (–1.959) for financially non-distressed firms. The wide gap between two group centroids also reflects the high accuracy of correctness in classifying a firm. This discriminant model classifies a firm between distressed and non-distressed groups, as well as predicts the imminent financial distress, with an average of 97% accuracy (Table 7). Type I error is 4% and Type II error is 2%. Type I error occurs when a distressed firm is misclassified as non-distressed firm. On the other hand, Type II error occurs when a non-distressed firm is misclassified as a distressed firm.

Table 6 Functions at group centroids

Financial distress	*Function*
	1
1	1.959
2	–1.959

Table 7 Classification results

	Financial distress	*Predicted group membership*		*Total*
		1	*2*	
Original count	1	48	2	50
	2	1	49	50
%	1	96	4	100
	2	2	98	100

5 Conclusion

This paper identifies those areas of financial performance of 'Special Treatment' companies in China that are accountable for financial distress. This investigation applies discriminant analysis to compare the financial performance between two groups of companies, one of which consists of 'Special Treatment' or financially distressed companies and the other contains regular or financially non-distressed companies. All these samples are randomly chosen from Shanghai Stock Exchange during the period from 2002 to 2009. To analyse the financial performance, six categories of financial ratios, namely liquidity ratio, cost ratio, profitability ratio, efficiency ratio, leverage ratio and cash flow ratio, are chosen. After running discriminant analysis, it has been found that cash flow coverage ratio, net income to assets, cash ratio, quick ratio, current ratio and debt ratio are significantly weaker in financially distressed companies. The underlying reasons for such weaknesses may be due to poor level of cash, high level of short-term liabilities, a declining sales trend and mismanaged overhead expenses. The discriminant analysis model also distinguishes 'Special Treatment' companies from non-'Special Treatment' companies with 97% accuracy.

The increasing number of companies facing financial distress and falling into 'Special Treatment' category each year is worrisome for Chinese economy at the time when the government has pledged to strengthen the country's economic base. Though this study is not aimed at divulging the firm-specific problems, it certainly can shed light on general problems faced by the majority of the 'Special Treatment' companies in the manufacturing sector. Further researches can be initiated to find out if the causes of these common industry-specific problems are due to policy mistakes at the macro level. As for the firm managers, this study can assist them in narrowing down their focus on certain areas that are poorly managed which have led the firm into financial distress.

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