Corporate Financial Distress Diagnosis in China

Edward I. Altman, Max L. Heine Professor of Finance
Salomon Center, New York University
44 West Fourth Street, Suite 9-160
New York, N.Y. 10012-1126, U.S.A.
E-mail: ealtman@stern.nyu.edu

Ling Zhang, College of Business Administration
Hunan University (South Campus)
Changsha Hunan, P.R.China, 410082
E-mail: jenyling@163.com or emba@hnu.cn

Jerome Yen, Professor,
Dept. of Finance, Hong Kong University of Science and Technology
Clearwater Bay, Kowloon, Hong Kong SAR
E-mail: jyen@ust.hk

New York University
Salomon Center Working Paper

November 2007

The authors would like to acknowledge the useful comments of Professor Jan Bilderbeek from Twent University and also the financial assistance of Natural Science Foundation of China (NSFC). Data assistance from Xiongwei Wu, Xin Zhang, Yanchun Cao and Shenzhen GuoTai'An Information Technology (GTA) is also acknowledged.

Corporate Financial Distress Diagnosis in China

Abstract. **With the enforcement of the removal system for "distress firms" and the Bankruptcy Law in China's securities market in June 2007, the development of the bankruptcy process for firms in China is expected to create a huge impact. Therefore, identification of potential corporate distress and offering early warnings to investors, analysts, and regulators has become important. There are very distinct differences in the accounting procedures and the quality of financial documents between the firms in China and those in the western world. Therefore, it may not be practical to directly apply those models or methodologies developed elsewhere to support identification of such potential distressed situations. And, local models are usually superior to ones imported from other environments.**

Based on the Z-Score family of models, we developed a particular model called Z_{China}Score to support identification of potential distress firms in China. Our model contains four factors, which include asset liability, working capital, return on total assets, and retained earnings ratios. Our four-variable model is very similar to the Z"-Score four-variable version -Emerging Market Scoring Model- developed in 1995. We found that the model was robust with very high accuracy. The model has forecasting power of up to three years with eighty percent accuracy for those firms categorized as Special Treatment (ST) – which indicated that they were problematic firms. Applications of our model to determine a Chinese firm's Bond Rating Equivalent are also demonstrated.

Keywords **financial distress, discriminant analysis, China stock market, credit risk, bond rating.**

1. Recent Developments in Chinese Security Markets and the Need for Improved Analytics

Over the past twenty years, China has achieved great success in its economic development that the annual GDP growth maintained above an average of over ten percent since 2000. China has also become the No. 1 country in attracting overseas investment and No. 1 in foreign currency reserves since 2006. Such wonderful achievements were not reflected in the performance of the main Chinese securities markets (Shanghai and Shenzhen) as their A-shares plunged over 40 percent from 2001-2005. The market changed direction in 2005 and the Shanghai Index went up from 998 in June 2005 to over 5800 in October 2007. What concerns analysts the most is that the market was perhaps irrational and fundamental analysis has become useless. Basically, too much liquidity chasing very few good stocks has pushed the market up beyond its fundamentals.

Many researchers and analysts worry that such a bull market will not run forever and the market has a possibility that it may change direction after the 2008 Beijing Olympics. And, after the market changes direction, then those firms that do not have good fundamentals will have a high possibility of distress. Many analysts believe that the sentiment of the market was overly optimistic and combined with inadequate market transparency, insufficient market regulation, and lack of sound and reliable models to assist investors will result in many distressed situations in the future. The enforcement of the removal system for “distress firms”, based on the Bankruptcy Law in China’s securities market, in June 2007, is expected to create a significant impact on the market.

The security markets in China are quite different from those in the western world due to the historical background of firms and the maturity of investors. For example, many listed firms are originally the state-owned enterprises (SOEs) and also a certain percentage of shares in such companies are not tradable. The tradable shares only occupy, on average, thirty percent of the total shares. Therefore, for stocks with high non-tradable shares, it is easier to manipulate the price and their volatility is potentially much higher.

We feel that the fundamentals of firms might not be totally reflected in their stock prices. For example, the stock prices of some troubled firms that were marked as Special Treatment (ST), which indicated that they had experienced losses in the past two years, increased significantly in certain periods. Models to identify potential distress firms is very important. Also, investment strategies of the majority of institutional investors in China favor long-term holding, which might cover several years. Therefore, to have a sound and reliable model to predict the survivability of firms over longer horizons is extremely important.

With respect to banking regulation and innovation, with the Basel II new Capital Accord, agreed upon in 2004 and scheduled for implementation in many countries in 2008, many active western banks will use the models developed internally to estimate their Capital

Adequacy Requirements (CAR). If they opt for such an approach, they have to show that the models they developed are sound and robust. Based on the historical data captured, such models should estimate the probability of default (PD) and for the "Advanced Approach," the probability of loss given default (LGD).

The Chinese government has indicated that Pillar One (Capital Adequacy), will not be adopted before 2009, but Pillars Two and Three will be adopted in 2007 so that the internal management and public disclosure of banks will be improved. In order to stimulate banks to improve their capability in the measurement and management of credit risk, the Chinese government has encouraged banks to develop their own default (distress) prediction models.

Over the past ten years, some researchers from western countries and China have attempted to develop distress prediction models for Chinese firms. Most of such studies are summarized in Section 2 – Literature Review. However, we found many weaknesses in these studies.

The first weakness is the lack of a solid theoretical basis or a deep understanding of Chinese accounting procedures. Some researchers selected variables based on their prior studies that were conducted in the western countries. However, the situations in both places were quite different, especially in the accounting rules, quality of data, due diligence, equity structure, and the factors that affect the performance of firms. Such models might not be accurate in that they could not reflect the true nature of Chinese firms, unless the data was carefully constructed.

The second weakness is the lack of cash flow variables in the model development. Many studies in western countries[1] indicated that cash flow information were very important, such as, liquidity, financial flexibility, profitability. Such information is very important in the classification of failed and non-failed firms. Before 1998, the listed firms in China were not required to disclose cash flow information, which restricted the use of such western models in prior studies and researchers were forced to develop models that lacked such data.

The third weakness of most of the prior studies is the insufficiency of distressed firms to support independent holdout tests or follow-up predictive studies. This has been a major challenge to researchers who wanted to study distress or bankruptcy prediction of Chinese firms. Unlike Moody's or Standard & Poor's databases, which have tens of thousands of healthy and unhealthy firms over the past 30 years. However, data about Chinese firms is limited, especially the distressed firms.

In order to overcome the above weaknesses, we set the objectives of our study to be:

[1] Largay and Stickney,1980; Gambola and Ketz,1983; Casey and Bartczak,1985; Gentry, Newbold, and Whitford,1984,1985a&b,1987; Banson,1987,Lau and Lau,1989; Gilbert, Menon, and Schwartz,1990,etc.

(1) To use the variables that truly reflect the special condition of China's accounting procedure, corporate governance, and the unique structure of equity components of Chinese share-holding companies[2]. In our study, we considered a broader coverage of financial ratios (see Table 1 in Section 3) and five cash flow variables were first introduced in our model.
(2) Consider the unique structure of equity components[3] of Chinese share-holding companies, which include both tradable and non-tradable shares. We calculated two ratios for market capitalization: market value of total shares (including tradable and non-tradable shares) to total liabilities (X_{30}) and market value of tradable shares to total liabilities (X_{31}).
(3) Answer the question such as "Can financial distress cases in China be predicted by the published financial information under current accounting procedure and quality of data?"
(4) To test the accuracy and robustness of our model on Chinese firms.
(5) To provide some insightful views about the financial risks in China's stock market. We would like to see if our research could provide stakeholders a useful analytical tool to classify and predict financial distress and to assess performance of firms.
(6) To see if such model could be used by government regulators, such as China's Securities Regulatory Commission (CSRC), as a thermometer in measuring the financial health condition of each sector and of individual firms.

The remainder of the paper will be organized as following. Section two provides a literature review about distress prediction research. Section three provides a discussion about the development of the MDA model. Section four discusses a two-stage validation test. In this section, we will provide a discussion about a follow-up study on the prediction on a large population. Section five summarizes the conclusions and provides some discussion for future research.

2. Literature Review

In this section, we will first discuss the previous research in the western countries and then the similar research in China.

[2] Four categories on the basis of investing entities and ownership: state shares (non-tradable), legal person shares (non-tradable), internal/employee holdings and public/individual shares. About more than half percent shares are not tradable in Chinese Stock Exchanges.
[3] Four categories on the basis of investing entities and ownership: state shares (non-tradable), legal person shares (non-tradable), internal/employee holdings and public/individual shares. About more than half percent shares are not tradable in Chinese Stock Exchanges.

2.1 Prior Research in Developed Countries

The development of empirical models that discriminate failing firms from the surviving entities started in the mid 1960s. The pioneering research included Beaver (1966) and Altman's (1968) works in business failure classification by the use of the univariate and multivariate discriminant analysis (MDA). The essence of the latter technique is an issue of classification under several assumptions. It assigns a score (the Z score) to each of the observed firms. The Z score is a linear combination of several independent variables and a cutoff score is estimated to divide the firms into healthy and unhealthy ones. The general MDA form is expressed as:

$$Z = \alpha + \sum_{j=1}^{k} \beta_j X_{jt} \qquad (2.1)$$

Where, Z is the score used to classify the objects, α is the constant term, β_j are the discriminant coefficients or weights, and X_{jt} are discriminant variables.

Since then, extensive research has been conducted to evaluate the usefulness of different financial ratios for constructing the discriminant and related models. Over the past four decades, more sophisticated methodologies have been developed to support corporate failure assessment, which included gambler's ruin, option pricing, hazard, neural networks, as well as the application of other statistical techniques, such as logit analysis, to the failure prediction problem. Such approaches were developed with a strong theoretical foundation about "How a firm goes bankrupt when the market (liquidation) value of its assets falls below its debt obligations or liabilities". Such structural models were developed and modified by Wilcox (1972), Merton (1974), and others. The commercial usage of such an approach include the famous KMV model (1995), now part of Moody's.

A second group of models include those that seek to impute implied probabilities of default (PD) from the term structure of yield spreads between default free and risky corporate securities. These are known as reduced-form models, e.g., Jarrow, Lando and Turnbull (1997).

A third class of models are the capital market based models, which include the mortality rate model of Altman (1988, 1989) and the aging approach of Asquith, Mullins and Wolff (1989). The latest approaches include the application of neural network to support the risk classification.

Despite the variety of approaches used in failure prediction, statistical methods, like discriminant analysis, still dominate due to their simplicity (Matthias Kerling) and accuracy, and remain as the mainstream of the descriptive school of thoughts[4]. In

[4] For example, Altman (1968); Altman, Haldeman and Narayanan (1977); Deakin (1972); Edmister (1972); Elam (1975); Casey and Bartczak (1985); Gentry, Newbold, and Whitford(1985), and Altman, Hartzell and Peck (1995). Many of these models are reviewed in Altman and Hotchkiss (2005).

general, these models have been featured with high classification accuracy, low cost, time saving, as well as convenience in application in solving real world problems. The methodologies mentioned above have been replicated and improved to support failure prediction around the globe (see Altman & Narayanan (1997).

Financial distress has been examined by many researchers. Guthmann and Dougall (1952) defined three stages of financial difficulty: temporary or technical insolvency, debt burden unsupportable and reorganization. Dewing (1952) identified four causes of business failures: excessive competition, unprofitable expansion, cessation of public demand for the firm’s products or services, and excessive payment of capital charges. Beaver (1966) defined failure as bankruptcy, bond default, an overdrawn of bank account, or nonpayment of a dividend on preferred stock. Altman (1968) defined failure as a company that had filed a bankruptcy petition under Chapter X of the Bankruptcy Act of 1938. Donaldson (1969) treated failure as low “financial flexibility”. Newton (1975) perceived that firms in financial distress passed through four stages of deterioration before declaring bankruptcy: incubation, cash shortage, financial insolvency and total insolvency.

More modern concepts about distress include the following: Lau (1987) defined financial distress as a three stage process: incubation, deficit funds-flow, and financial distress or recovery. Gilbert, Menon, and Schwartz (1990) defined distress firms as firms that declared bankruptcy and firms that had negative cumulative earnings over three consecutive years. Westerfield and Jaffe (2006), stated that “Financial distress is a situation where a firm’s operating cash flows are not sufficient to satisfy current obligations and the firm is forced to take corrective action”. It is difficult to define precisely what distress or bankruptcy is due to the variety of accounting procedures or rules in different countries at different times, as well as various events that sent the firms into financial distress. However, for most studies conducted in US, they used the criterion that firms filed for protection under either Chapter X of the Bankruptcy Act of 1898 or Chapter 11 of the 1978 Bankruptcy code. Also, most researchers used the contents of the financial statements and based on the prediction model to discriminate the failed firms from those financially healthy firms.

- -

2.2 Research in China

Research on financial distress and bankruptcy prediction is still at the beginning stage in China. However, for special reasons, such as, the volatile performance of the China equity market over the past few years, such research has attracted great attention from practitioners and the government. Before going into the details concerning China’s special situation, a discussion about the criterion that defines firms as being in a state of financial distress is perhaps desirable.

In China, the first Bankruptcy Law came into effect on Nov.11, 1988. Many firms, especially those non-listed firms, declared bankruptcy or liquidated under such Law. But due to the fact that the process might go to different levels of courts, for example, at the county, at the municipal, or at the provincial level, it is virtually impossible to retrieve those companies' financial records. Therefore, researchers in China found it difficult to obtain sufficient bankrupt cases to support model development. Also, the quality of data is still a major concern relating to non-listed firms and due diligence has always been a major issue that challenged the accountants and analysts. Therefore, academicians were unable to obtain enough bankrupt firms to support rigorous analyses.

The new Bankruptcy Law came into effect just recently on June 1, 2007, which is applicable to all types of enterprises. However, no listed firm so far has filed for bankruptcy. Delisted distressed firms are moved to the "third board" in Chenzhen and trade once a week. The major reason is to strike a balance between the level that the society can afford to let companies go bankrupt and the degree in which it can develop a social security system to avoid huge social problems. The reason behind the continuation of these distressed enterprises was that many of such firms are the backbone in their particular industry. The top priority of such firms may not be profit making, but just to keep workers employed. Yet, in some industries the situation just got worse and worse. For example, many trading firms exhibit a deteriorating financial trend that is difficult to recover from.

To protect the interests of investors and as a message from the government that investors should be aware of the default risk, China's Securities Regulatory Commission (CSRC) decided in March, 1998 to differentiate those firms in financial difficulties by launching a new policy to offer "special treatment"[5] (hereinafter called "ST" firms) to such firms. These "ST" firms include:

(1) Companies that had negative cumulative earnings over two consecutive years or net asset value (NAV) per share below par value (book value).

(2) Companies that had negative earnings for one year, but the current year shareholders' equities are below its registered capital.[6]

(3) Companies that received the auditors' "going concern opinion".

The "ST" firms are pressed to improve their financial situation by efforts such as reorganization, mergers, etc. Those that exhibit no sign of financial improvement in the following year will receive "particular transfer" warning (hereinafter called "PT" firms) given by the CSRC. If the "PT" firms are still unable to revitalize in the following year, their shares will be deleted from the stock exchange – the action of delisting. In this regard, we define these "ST" and "PT" companies as financial distress firms. The symptoms of Chinese "ST" and "PT" firms are very close as to what was perceived earlier by Newton (1975), by Lau (1982) and by Gilbert, Menon and Schwartz (1990).

[5] Special treatment is a daily price limitation of 5% applied to those firms in financial difficulties.
[6] Registered capital equals the share capital initially committed in accordance with the Articles of Association.

These “ST” or “PT” firms in general will go through “one or more of “four stages”: omit or reduce the annual dividend payments due to cash shortage, default on loan payments leading to a law suit, reorganization or taken over, or deleted from the stock exchange and transfer to Asset Management Companies[7] for disposal.

Several Chinese researchers studied the corporate financial distress classification problem. Qing Chen (1999) was the first to use the financial data of 27 “ST” and non-ST firms to construct a MDA model with an overall predictive accuracy of 92.6 percent. But this study did not include a holdout sample for test purposes and was not relevant to the current environment in China. Xiao Chen and Zhihong Chen (2000) established a logit model with an overall predictive accuracy of 86.5 percent. Ling Zhang (2000) developed a 4-variable discriminant model out of 11 ratios and found it had a predictive ability of up to four years prior to “ST”. Shilong Wu and Xianyi Lu (2001) conducted a study by using a linear probability model (LPM), Logistic and MDA, the results indicated a predictive accuracy of 72 percent four years prior to “ST”. The works above formed a base to support further studies of Chinese firms. They were all published in Chinese language journals and suffered from the types of shortcoming, discussed earlier.

3. Theoretical Foundation of Z-Score

Credit risk evaluation originated from the analysis of financial status change of firms, since credit crisis is usually caused by financial issues, such as, cash flow reduction. So through the discovery of characteristic financial indicators, it is possible to identify the potential distress. Such financial indicators can be used to develop credit scoring or credit rating models to predict or determine the credit ratings of firms, which is the foundation for pricing credit loans and decision making for investments. Based on such motivation, researchers usually turned the measurement of credit risk into the evaluation of corporate financial health.

Altman (1968) used a linear discriminant analysis method to study credit risk measurement and developed a famous five-variable Z-score model. This model was generated from analysis of 22 financial ratios through a statistical filter that was based on a sample that consisted of 33 distressed companies during 1946 to 1965 and 33 non-distressed companies. In 1977, he and others (Altman, et al) improved this model and developed the Zeta discriminant model which is still frequently used currently. Since its inception, and especially in the last decade, the Z-Score models have been extensively applied to corporate credit risk measurement and ratings equivalent, including for firms in the emerging market. Under Altman’s influential work, many financial institutions in the developed countries, such as, Japan, Germany, France, England, Australia and Canada, have developed their own discriminant models. Altman Z-score model is now available at *Bloomberg* terminals throughout the world.

[7] In 1999, the Chinese government set up four asset management companies to purchase and deal with those non-performing loans or bad debts transferred by state banks. The four corporations include: China Greatwall Asset Management Corp., China Orient Asset Management Corp., China Huarong Asset Management Corp. and China Cinda Asset Management Corp.

Multivariate Discriminant Analysis（MDA）attempts to classify objects into categories they belong to. The technique identified a set of factors which offered enhanced information about the subjects from a set of variables (such as financial ratios) which indicated a number of characteristics of the observed objects, such as the possibility of distress. This set of variables can be used to establish the discriminant function which minimizes the probability of false judgment in sample classification. A general form of discriminant function is expressed in Equation (2.1), above.

Fisher (1936) believed that in order to allow the Z-score to classify two different populations most effectively, the discriminant coefficient (β) must estimate deviation sum of squares (B) of $E(Z_i)$ between two populations relative to the variance of Z-score as large as possible, i.e.,

$$\max_{(\beta_j)} \frac{B}{W} \tag{3.2}$$

Where $B = [E(Z_1) - E(Z_2)]^2$;

$$W = Var(Z_{ia}) = \beta_i' Cov(X)\beta_i = \beta_i' \sigma_{jj'} \beta_i; \quad a = 1, 2, \cdots, n_i;$$

Cov (X) is the variance-covariance matrix among variables.

The "best discriminant point" of Fisher's two-category linear discriminant analysis adopted in this research is determined by a "full symmetry classification principle". That is, by calculating the means of two category samples ($\overline{Z_1}$ *and* $\overline{Z_2}$) according to the linear discriminant model. Then the "best discriminant point" is given by

$$M = \frac{n_1 \overline{Z_1} + n_2 \overline{Z_2}}{n_1 + n_2} \tag{3.3}$$

if $n_1 = n_2$, then $M = \frac{\overline{Z_1} + \overline{Z_2}}{2}$. If Z score derived from substituting variables for observed values in the discriminant function is larger or equal to M, the sample is classified into group two, otherwise into group one.

4. Development of the Four-Variable Model

In this section, we will discuss the process of how we developed the four-factor Z-Score (China) model. The dataset will be discussed first.

4.1 Data and Sample collection

As discussed before, starting with loan and bond markets, foreign researchers often selected bankrupt companies and non-bankrupt companies or defaulted loan/bond and non-default loan/bonds as their samples to analyze and discover those characteristic indicators which can be used to predict financial distress. Due to historical reasons, loan and corporate bond markets in China started late and are under rapid development now. Therefore, it is very difficult to obtain data from the loan market and financial information of bankrupt firms. Moveover, a countrywide historical default database has not yet been built. As a result, we could not follow foreign researchers' routes to conduct our research. Instead, the authors turned to the stock market and chose ST and non-ST companies as our sample. We will discuss the technical meaning of a ST firm later. A similar methodology of only using stock market listed firms was adopted in many models in newer economies

As noted earlier, according to "listing rules", companies that have had negative cumulative earnings over two consecutive years or net asset value (NAV) per share below its par value would be given "special treatment" (hereinafter "ST"). If these companies are still unable to revitalize in the following year, they will be suspended and may be finally delisted from stock exchanges. So, comparatively, "ST" companies are more risky than normal listed companies. To support our research, the sample set consists of 120 listed companies in both Shenzhen and Shanghai Stock Exchanges.

All the financial data were extracted from the financial database of Chinese listed companies provided by Shenzhen GuoTaiAn Information Technology (GTA) and the single stock profile database provided by China Finance Net. The sample covered 16 industries, i.e., home appliances/electronic information, medicine, chemistry, metallurgy, mechanics, mobile manufacturing, travel, comprehensive, traffic and energy, light manufacturing, textile, agriculture, building material & construction, vintage, as well as posts and telecommunications.

These companies were divided into two groups. The first group (training group) consisted of 60 companies, which included 30 "ST" companies announced in 1998 or 1999 and 30 healthy companies. The second group (test group) also consisted of 60 companies with 21 "ST" companies and 39 random chosen non-ST companies. Then the balance sheet and income statement one year before the "ST" announcement and of those non-ST companies in the same year were collected. Furthermore, 15 financial ratios were selected and calculated to cover the aspects of profitability, solvency, liquidity, asset management efficiency, sustainable growth and capital structure, see Table 4.1.

As for the selection of variables, based on the comprehensive reflection of company's financial status, we considered those ratios that are widely accepted in China as well as those deemed contributive in previous studies, such as the predictive variables in Altman's Z-score model and financial rating indicators adopted by Standard & Poor's. Also, we consider those that appeared in the performance evaluation system for competitive companies of industrial and commercial category jointly promulgated by four ministries of China, as well as those indicators used by Industrial & Commercial Bank of China (ICBC) for customer ratings. Therefore, our selection of variables covered the widest among all of the studies done on Chinese firms.

Profitability

ROI (X_1) directly reflects corporate competitive strength and sustainable growth. It is an important indicator in the attractiveness of the equity in the eyes of investors.

Returns on total assets (X_7) effectively reflects corporate profitability, which can be used to evaluate the performance of management in the utilization of assets.

Returns on net assets. (RONA, X_{12}) not only can be used to measure the ability of making profit for any given amount of capital, but also can be used in decision analysis of trading on equity. **X_{12}** is one of the most comprehensive and representative indicators in firm valuation. It is not confined by the variance in industry and therefore has strong robustness. Generally speaking, a higher RONA means that a given investment in capital earns more profit, and the profitability of the company is stronger, and therefore the interest of investors is better protected.

Liquidity and Solvency

Liquidity ratio, current assets/current liabilities (X_3) is an important indicator which measures short term financial status of a company and directly reflects its ability of offering cash, covering short term liabilities and sustaining normal operation. A high liquidity ratio indicates that a company can quickly liquidate assets and cover short term liabilities. But too high of a liquidity ratio may not be good in that too much assets may be placed on high liquid assets, which may not generate good profitability. Also, when a firm has financial difficulties, its short-term assets may grow involuntarily.

Interest coverage ratio (X_2) measures a company's ability to meet its interest payments on long term debt. This ratio calculates how many times are corporate operating earnings relative to interest payments on liabilities. The higher the interest coverage ratio, the less the debt burden is on the company. The size of interest coverage ratio not only reflects corporate solvency, but also reflects its ability in paying debt capital. In fact, if a company has a high credit history in paying debt interest, i.e. it pays debt interest with the full amount all the time, it may never need to use liquid assets to pay debt capital. Instead, it can pay old debt by borrowing new loans. If the interest coverage ratio is low, it means that corporate's profits cannot provide sufficient guarantee on paying debt interest and thus creditors may possibly lose interest in the company.

Table 4.1 Financial ratio set

Ratios	Ratio calculating formula	Expected Sign
X_1（ROI）	EBIT/total assets EBIT=net profit+taxes+financial expenditure	+
X_2 (Interest Coverage Ratio)	EBIT/ interest expenses EBIT=net profit+ taxes + financial expenditure	+
X_3 (Liquidity Ratio)	Current asset/current liabilities	
X_4 (liabilities to share capital book value)	Total liabilities（short term loans + long term loans）/Total share capital book value (Total share capital book value means the total number of closing ordinary shares)	-
X_5 (trading shares liability ratio)	Market value of trading shares/total liabilities	+
X_6 (asset-liability ratio)	Total liabilities/total assets	-
X_7 （ROA）	net profit/average total assets average total assets=（current year's total assets + last year's total assets）/2	+
X_8 (working capital to total assets)	working capital/total assets working capital=current asset-current liabilities	+
X_9 (retained earnings to total assets)	Retained earnings/ total assets Retained earnings= earned surplus + Retained profits	+
X_{10} (Book value of total shares to market value of total shares)	Book value of total shares / market value of total shares (total shares include all trading and non-trading ordinary A share, and does not include B share and H share)	-
X_{11} (total asset turnover)	Main business revenue/average total assets	+
X_{12}（ROE）	net profit/average shareholders' equity average shareholders' equity =（shareholders' equity current year+ shareholders' equity last year）/2	+
X_{13} (account receivable turnover)	Main business revenue/average accounts receivable	+
X_{14} (Inventory turnover ratio)	Main business cost/average inventory	+
X_{15}(Earnings growth ratio)	(current year's net profit-last year's net profit)/ absolute value of last year's net profit	+

Asset Management Efficiency.

Total asset turnover(X_{11}) reflects a company's sales generated in a year on every dollar it invests. Therefore it indicates the efficiency of the company in utilizing assets. The higher the total asset turnover, the stronger the selling ability is. A higher ratio means that the efficiency of corporate investment is higher and as a result profit margin also increases. On the contrary, a lower ratio means that a company takes less advantage of assets and the benefit of corporate investment is smaller. But this ratio varies significantly in different capital intensive industries.

Inventory turnover(X_{14}) measures the inventory asset turnover rate in a certain period, which indicates the efficiency of a company in producing, buying and selling. Generally speaking, the higher the inventory turnover, the faster the inventory turnover rate and the better the inventory liquidity are. As a result the rate of inventory turning into cash and account receivable is faster and its cashability is better. A faster inventory turnover means that a company sells faster and thus its probability of obtaining profit is higher. While if the inventory turnover slows down, it means that the amount of slack products in a company's inventory is increasing, the overstock problem is perhaps severe and too much assets are occupied by inventory.

Account receivable turnover (X_{13}) measures the average times a company's account receivable turns into cash in a year. Thus it is an indicator which reflects the rate of corporate accounts receivable turnover and management's ability to manage this account. Generally speaking, the higher the account receivable turnover, the faster the turnover into cash.

Growth Ability

Earning growth ratio (X_{15}) reflects the growth rate of the corporate profit margin. The **retained profit ratio (X_9)** reflects the financing strategy of a company. If a company thinks it is necessary to accumulate funds from inside to expand its operations, it can adopt a higher retained profit ratio.

Capital Structure and Financial Leverage.

Corporate capital structure is usually comprised of liabilities and equity capital. Without the protection of equity capital, creditors are rarely willing to provide loans. Financial leverage stands for the amount of liabilities which require constant payments. Taking advantage of financial leverage is usually called trading on equity, which means a company raises loans in order to obtain extra returns on its equity.

Asset liability ratio-total liabilities/total assets (X_6) is an indicator which reflects corporate capital structure and long term solvency. It illustrates what percent of a company's total assets is borrowed from creditors. This ratio can be used to measure management's ability to provide production and operation activities on funds provided by creditors. A low asset liability ratio shows that the proportion of self-owned asset is high and the proportion of liabilities is low, which provides a high safety in covering liabilities. But it does not mean that the lower the asset liability ratio the better the firm operates for all stakeholders. A too low ratio means that the operator is too conservative since when loan interest is lower than the rate of return on assets, shareholders can earn more in trading on equity at low interest. Of course, if the asset liability ratio is too high, i.e. the proportion of self-owned asset is too low, then the company may be over-expanded in operation and risks may occur in future. Creditors usually prefer this ratio to be as low as possible, as at a lower ratio a company is more secured to cover liabilities.

According to the experiences of western countries, this ratio should not be higher than 50 percent. If closes to 100 percent, it means a company is on the edge of bankruptcy. If over 100 percent, it means a company is insolvent and can be considered as reaching the warning line of bankruptcy. At present, the asset liability ratios of the majority of companies in China already exceed 50 percent and have often reached 70 percent. Considering the practical situation of China, the authors believe that the asset liability ratio is normal from 60 percent to 70 percent in China.

In addition, the liabilities to share capital book value ratio (X_4), market value of trading shares to total liabilities ratio (X_5) and book value of total shares to market value of total shares ratio (X_{10}) reflect the extent to which a company utilizes financial leverage as well as the unique structure of equity components of Chinese share-holding companies.

4.2 Model Building and Validity Test

4.2.1 Model building

After considering a large number of combinations of the 15 characteristic variables, the final model to capture the distress risk of Chinese companies included just four variables. To our surprise, these variable are very similar to Altman's Z"-score model (Altman and Hotchkiss, 2005) and the emerging market scoring model (Altman, et. al. 1995 and 2006)[8] . The four variables include X_6 , X_7 , X_8 , X_9 , and is of the form:

$$Z = 0.517 - 0.460x_6 + 9.320x_7 + 0.388x_8 + 1.158x_9 \qquad (4.3)$$

where x_6 = asset liability ratio (total liabilities/total assets);

x_7 = rate of return on total assets (net profit/average total assets);

x_8 = working capital to total asset ratio (working capital/total assets), where working capital equals current assets minus current liabilities;

x_9 = retained earnings to total assets ratio (retained earnings/total assets).

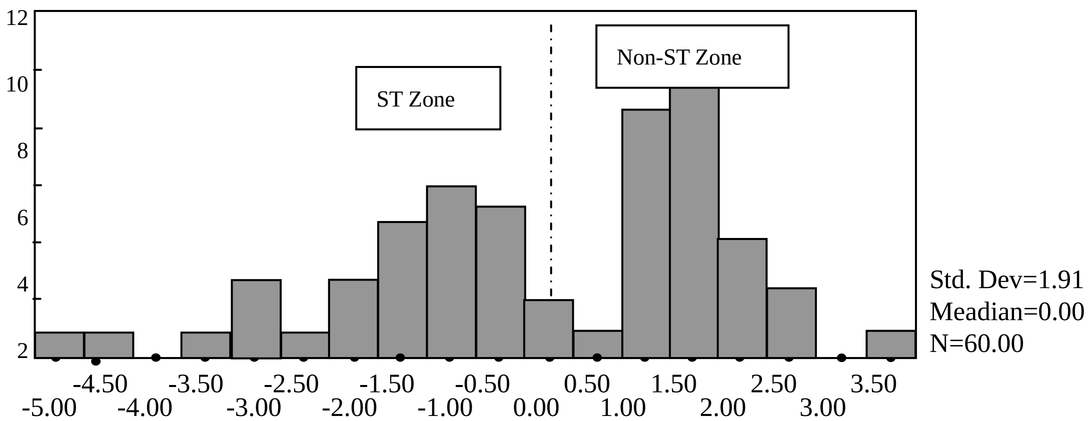
[8] These four varables include the working capital/TA, retained earnings/TA, EBIT/TA and net worth/Total liabilities.

Note that many financial ratios usually regarded as good indicators of financial crisis by mature markets are not included in our discriminant analysis, such as the stock market value to total liabilities ratio. It further shows that the current stock market value in China is not strongly correlated to company performance. The reason is that recent China stock prices are mainly driven by technical factors and liquidity, as well as their fundamentals.

4.3.2 Validation of the model and multicollinearity test

There are many approaches to validate the performance of a discriminant model. One is a back-substitution test. In this study, the results of back-substitution test indicated that the predictive accuracy of the established discriminant function reached 100 percent when classifying the 60 test samples. The two discriminant groups exactly fall into two sides of the spectrum (See Figure 4.1).

Figure 4.1 Distribution of Scores-Original Samples



A second approach is to examine some descriptive separation statistics, such as F-test, mean difference among groups, variance-covariance matrix equality test, and Kolmogorov-Smirnov Test (see Appendix A). Table 4.4 lists some primary descriptive statistics. The F-test shows all indicators are significant at least at the 2 percent level, which rejects the null hypothesis that the means of the two groups are equal and indicates there exists significant differences in characteristic variables between these two groups. As shown in Table 4.4, the mean of the liability ratio of “ST” companies (x_6) is up to 75 percent while that of non-ST companies is only 42 percent. For the other three indicators that reflect asset operation efficiency, i.e. x_7, x_8, x_9, “ST” companies are all negative values, while non-ST companies are all positive.

Table 4.4 Statistic description of discriminant function

Variables	Coefficients	Means of ST Companies n=30	Means of non-ST companies n=30	Wilks' λ	F Value	DF		Sig
Constant	0.517							
x_6	-0.46	0.7507	0.4169	0.578	42.417	1	58	0.000
x_7	9.32	-0.1671	0.1236	0.294	139.134	1	58	0.000
x_8	0.388	-0.3607	0.2675	0.704	24.386	1	58	0.00
x_9	1.158	-0.3261	0.2149	0.765	17.831	1	58	0.000

Found in table：$F_{1.60(a=0.001)}=12$

As to the multicollinearity test for the constructed model, we use TOL (Tolerance) and VIF (Variance Inflation Factor) to test multicollinearity (see Table 4.5). The expression is:

$$TOL_J = 1 - R_j^2 = 1/VIF_J \qquad (4.6)$$

where R_j^2 is the determinant coefficient R^2 of X_j to the other k-1 independent variables. When TOL is small, it is concluded that multicollinearity exists. A general criterion is that a high multicollinearity exists when VIF is over 10 or TOL is smaller than 0.1.

Table 4.5 Statistical test of multicollinearity

Model variables	VIF	TOL	Model dimension	Eigen value	Conditions index	Variance Proportions				
						Constant	X_6	X_7	X_8	X_9
			1	2.465	1.000	0.01	0.01	0.03	0.02	0.02
X_6	2.162	0.463	2	1.626	1.231	0.02	0.01	0.00	0.04	0.03
X_7	2.227	0.449	3	0.731	1.836	0.01	0.00	0.46	0.05	0.01
X_8	3.618	0.276	4	0.138	4.221	0.00	0.00	0.07	0.88	0.92
X_9	4.170	0.240	5	0.0399	7.861	0.97	0.98	0.44	0.01	0.02

It can be noted that in the statistical result, the VIF of each variable in the model is smaller than 10 and TOL is over 0.1, which indicates no problem of multicollinearity. In each step of the discriminant analysis, the problem of multicollinearity has been considered in model building. Wilks' lambda of each variable is calculated and the variable with smallest such value enters into the model. The variable with significance of the F statistic at the 0.05 level enters into the model while the one with significance greater than 0.10 level is excluded from the model.

4.3 Determination of the Cutoff Point

The dividing line of discriminant values in the original sample is apparent. Note that the non-ST companies in the original sample are all chosen from the top 50 companies in 1998's securities rankings and the results that we find are quite reasonable. We wish to obtain, however, similar results when we use the model to conduct a discriminant analysis for a new and random sample of healthy firms. In order to verify the discrimination effect of the model and to determine a more robust cutoff point, we use two different samples, i.e. 21 "ST" companies and 39 randomly chosen non-ST companies for out-of-sample testing. The discriminant function (4.2) is used to calculate Z-scores of these 60 companies (See table 4.6). The result shows that out of a total of 60 "ST" companies in the original and holdout samples, all 60 have Z_{China}-scores less than 0.5 and 84 percent less than or equal to zero. In non-ST companies, there are 63 (91 percent of the total sample) with Z_{China}-scores higher than 0.5 and 75 percent over 0.9. Summing up, for the results of the original sample and also the new sample, 0.5 appears to be the best dividing line. We therefore developed the following pragmatic empirical discriminant criteria:

(1) Firms with Z_{China}-scores less than 0.5 ($Z<0.5$) are classified as technically distressed companies ("ST" companies);

(2) Firms with Z_{China}-scores over 0.5 and less than 0.9 ($0.5<Z<0.9$) are classified as potential distress companies and close watch is required;

(3) Firms with Z_{China}-scores over 0.9 ($Z>0.9$) are classified as financially healthy companies.

Table 4.6 Z-score distribution statistics

Original sample (Group one)	Discriminant score (Z-score)	New sample (Group two)	Total sample
non-ST companies(n=30)		non-ST companies (n=39)	69
29	>0.9	23	
0	>0.5-0.9	11	
1	>0.3-0.5	5	
ST companies(n=30)		ST companies(n=21)	51
0	>05-0.9	1	
0	>0.3-0.5	2	
1	0-0.3	5	
29	<0.0	13	
Total sample n=60		Total sample n=60	120

4.4 Accuracy of Follow-up Prediction

Bankrupt companies usually experience a deterioration period from potential distress to final bankruptcy. So predicting corporate potential distress as early as possible can definitely earn time for the regulator or investor, or, indeed, management of the distressed firm itself, to avoid further damage. Therefore, it is important to show how long our prediction model will be able to accurately predict financial distress before it actually happens. To test the accuracy of the financial distress model in follow-up predictions, we conducted predictive analysis for 30 "ST" companies in the original sample five years prior to "ST". See Table 4.7 for results.

Table 4.7 Prediction results of the distress model five years prior to "ST" announcement ("ST" companies in original sample)

Year before distress (ST)	Right prediction	Wrong prediction	Prediction accuracy（%）
1 n=30	30	0	100
2 n=30	26	4	87
3 n=30	21	9	70
4 n=30	18	12	60
5 n=27	6	2l	22

Our results indicate that this model is able to predict fairly accurately up to four years prior to financial distress. However, we recommend that the most effective or accurate usage of this model is the two-year horizon (87 percent accuracy). The "ST" penalty was given by CSRC to those companies who suffered losses for two consecutive years. An effective prediction model should have accurate prediction power of at least three or four years, which could provide two years for observation before the first loss occurred.

In addition, the variations of the characteristic financial means of the "ST" companies and "non-ST" companies indicate the gradually deteriorating process of company finance (see

Table 4.8). As the "ST" year approaches, the financial means of the variables exhibit unfavorable symptoms and the differences between the two groups are expanded. For instance, the liability ratio (x_6) of "ST" companies rises up to 75 percent one year prior to "ST" announcement from 57 percent three years prior. However, during the same period, the ratios of non-ST companies varied slightly, mostly below 50 percent. The other three indicators show the same trend.

Table 4.8 Mean and standard deviation statistics of characteristic financial indicators of two group companies three year prior to ST announcement

Financial indicator \ Years prior to ST	Group	3	2	1
X_6 Total liabilities/ total assets	ST companies	0.5665(0.1835)	0.6066(0.1846)	0.7507(0.2180)
	Non-ST companies	0.4906(0.1699)	0.4441(0.1424)	0.4169(0.1767)
X_7 Net profit/average total assets	ST companies	-0.0101(0.0931)	-0.0747(0.1931)	-0.1671(0.1251)
	Non-ST companies	0.1227(0.0721)	0.1157(0.0517)	0.1236(0.0507))
X_8 Working capital/total assets	ST companies	0.0385(0.20093)	0.0158(0.2074)	-0.3608(1.4205)
	Non-ST companies	0.1765(0.1627)	0.2814(0.1803)	0.2675(0.1680)
X_9 Retained profits / total assets	S ST companies	0.0253(0.1190)	0.1190(0.1031)	-0.3261(0.6366)
	Non-ST companies	0.1075(0.0732)	0.1544(0.0993)	0.2149(0.2951)

*numbers in the brackets are standard deviations

5 Four-Factor Credit Rating Model for China Listed Companies

Based on the model developed in Section 4, we can assign a credit rating based on the Z_{China}-Scores of each company.

5.1 Sample and Data Source

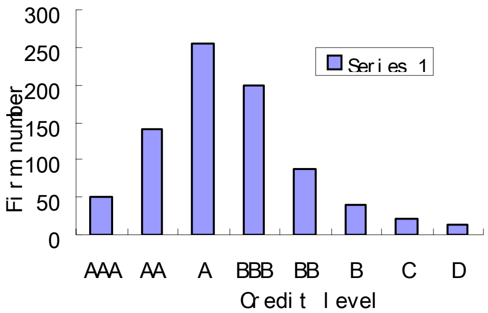
The sample in this study covered 8 years and was divided into two phases. The first phase covered years from 1998 to 2002, where there were 811 companies in 1998, 902 in 1999, 1051 in 2000, 1124 in 2001, and 1199 in 2002. The second phase covered years from 2003 to 2005, where there were 1250 companies in 2003, 1342 in 2004 and 1340 in 2005. Data sources came from Shenzhen GuoTaiAn Information Technology and Tinysoft Finance Analysis Database. We used financial data from balance sheet, income statement and cash flow statements. Z_{China}-Scores of these listed companies were calculated according to equation (4.3).

5.2 Rating Method

Z-scores of sample companies from 1998 to 2002 were calculated first with equation (4.3). Then sample companies in 1998 are rated by the percentage of firms in each rating category on a global basis method, as follows: According to the criteria stipulated in Basel II New Economy Accord (2004), credit rating minimally needs to be divided into seven non-defaulted levels, such as AAA, AA, A, BBB, BB, B, C as well as a minimum of one default rating, the D level. Meantime, according to the current situation of listed companies, those with Z-scores over 0.5 (non-ST companies) are classified as BBB level or above (i.e. investment level), while those with Z-scores less than 0.5 (ST companies) are classified as below BBB (i.e. speculative level). Also, the Z-score interval of each level is defined as shown in Table 5.1 and Figure 5.1. Based on these Z-score intervals, listed companies in 1999, 2000, 2001 and 2002 are rated.

Table 5.1 Credit rating of listed companies in 1998

Level	Z-score interval	Number of Firms	Percentage
AAA	Z⩾1.8	51	6.29%
AA	1.3⩽Z<1.8	142	17.51%
A	0.9⩽Z<1.3	256	31.57%
BBB	0.5⩽Z<0.9	200	24.66%
BB	0⩽Z<0.5	87	10.73%
B	–1⩽Z<0	40	4.93%
C	–2⩽Z<–1	22	2.71%
D	Z<–2	13	1.60%



5.3 Analysis of Credit Ratings

Using the method mentioned above, we obtained credit ratings of listed companies from 1998 to 2002 (Table 5.2). The results show that during 1998 to 2002, the credit levels of listed companies of BBB or above are over 60 percent in all years; respectively 80 percent for 1998, then 75.8 percent, 76.9 percent, 65.5 percent, and 60.1 percent for 1999 to 2002. On the one hand, this indicates that the overall credit of Chinese listed companies was good based on our classification, but deteriorated fairly significantly over this first sample period.

As shown in Figure 5.2, the overall ratings exhibit a normal distribution with slight skewness tilts to the right. This can be explained by the fact that the entry regulation of listed companies in China was getting more and more stringent over the past few years, which set very strict constraints, such as, size, performance, management team, and governance structure. Such policy prevented questionable companies from entering the securities markets. Meantime, China's economy continued to prosper at an astonishing speed of over 10 percent GDP growth per year, which supported most of the companies to have excellent performance on both the financial statements and stock prices.

On the other hand, we found that, except in 2000, the percentage of listed company credit levels at BBB or above increased slightly compared to the previous year, the percentage in other years exhibited a decreasing trend, especially in 2001 and 2002 when D rated companies increased dramatically from 2.2 percent to 3.5 percent respectively. Chinese stock prices in this period were in a bearish mode and the major reasons were:

1. The Asian financial crisis broke out in 1997, which affected the Chinese economy and led to decreasing export, inadequate domestic needs, and reduced investment. GDP growth rate slowed by one percent and therefore companies' performance deteriorated, liquidity tightened, credit levels dropped and firms found it more difficult to obtain the capital they needed.
2. Because of the perceived lack of sustainable growth power in Chinese listed companies, as well as some deficiency in regulation, such as, transparency, market access, trade management, and information disclosure, some questionable companies were listed which led to unstable credit levels of listed companies.
3. In 1999, GDP growth rate in China increased to 8 percent while in other years such value was below 8 percent. This indicated a relatively healthy macro economic environment and stability relative to most other countries during the Asian Financial Crisis. Due to these factors, the overall credit rating of listed companies in 2000 increased slightly, instead of decreasing.

Table 5.2 Credit rating of listed companies from 1998 to 2002

Credit level	1998		1999		2000		2001		2002	
	Firm number	Percent	Firm number	Percent	Firm number	Percent	Firm number	Percent	Firm number	Percent
AAA	51	6.3%	39	4.3%	24	2.3%	10	0.9%	12	1.0%
AA	142	17.5%	99	11.0%	97	9.2%	66	5.9%	50	4.2%
A	256	31.6%	282	31.3%	290	27.6%	208	18.5%	183	15.3%
BBB	200	24.7%	264	29.3%	397	37.8%	452	40.2%	475	39.6%
BB	87	10.7%	145	16.1%	160	15.2%	252	22.4%	307	25.6%
B	40	4.9%	45	5.0%	48	4.6%	82	7.3%	97	8.1%
C	22	2.7%	14	1.6%	17	1.6%	29	2.6%	33	2.8%
D	13	1.6%	14	1.6%	18	1.7%	25	2.2%	42	3.5%
Total	811	100.0%	902	100.0%	1051	100.0%	1124	100.0%	1199	100.0%

Figure 5.2 Credit rating of listed companies from 1998 to 2002

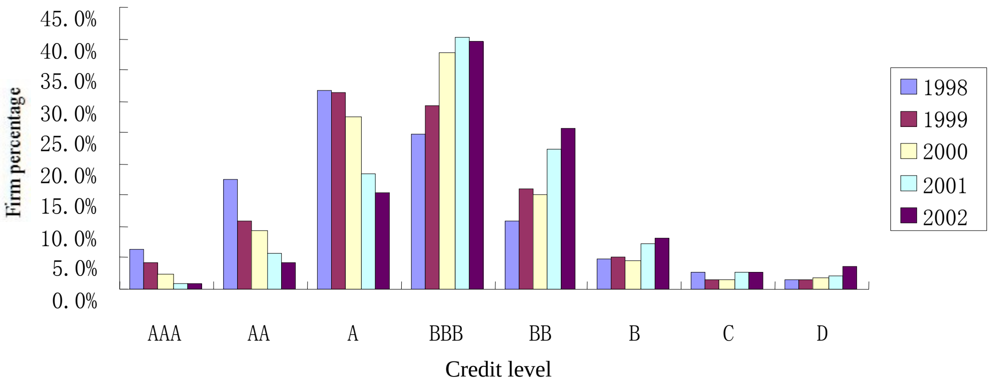


Table 5.3 Credit rating of Chinese listed companies from 2003 to 2006

Level	Z-score interval	03		04		05		06	
		Firms	Percent	Firms	Percent	Firms	Percent	Firms	Percent
AAA	Z≥1.8	15	1.20%	38	2.83%	33	2.46%	51	3.49%
AA	1.3≤Z<1.8	72	5.76%	73	5.44%	76	5.67%	125	8.56%
A	0.9≤Z<1.3	185	14.80%	203	15.13%	166	12.39%	228	15.61%
BBB	0.5≤Z<0.9	454	36.32%	462	34.43%	426	31.79%	470	32.17%
BB	0≤Z<0.5	360	28.80%	378	28.17%	386	28.81%	416	28.47%
B	-1≤Z<0	19	1.52%	91	6.78%	126	9.40%	100	6.84%
C	-2≤Z<-1	12	0.96%	35	2.61%	50	3.73%	34	2.33%
D	Z<-2	133	10.64%	62	4.62%	77	5.75%	37	2.53%
Total		1250	100%	1342	100%	1340	100%	1461	100%

From Table 5.3, the overall performance of listed companies from 2003 to 2005 was decreasing, worse than in previous years. However, it bounced back in 2006 reflecting that the economy was booming since 2005, and so did the stock market. Table 5.2 shows that the percentages of credit levels of listed companies at BBB or above were all over 60 percent from 1998 to 2002 with the highest up to 80 percent, which indicated a wonderful overall performance in such period. However, the percentage of listed companies rated at BBB or above was all below 60 percent from 2003 to 2005, rising to close to 60 percent in 2006. Also the percentage of potential financial distress companies that were rated from BB to D from year 2003 to year 2006 was 41.92 percent, 42.18 percent, 47.69 percent, and 40.19 percent, respectively. From such trend, it is easy to see that the economy rebounded since 2005.

Based on average of listed companies' credit levels from 1998 to 2002, we obtained the distribution of annual credit levels (See Figure 5.3).

Figure 5.3 Credit level variance of listed companies from 1998 to 2002

The above Figure indicates that the variances of Chinese listed company credit levels were significant and mainly on the BBB level due to regulation factors, such as, listing rules and quality or trustworthiness of accounting information. The BBB level is the cutoff point between investment grades and speculative grades. Companies falling into BBB level or below will result in closer monitoring from regulators. Investors may suffer losses from the down-grading or the potential ST announcement, or even delisting if situation is not be improved. For this reason, when getting close to the BBB level, the majority of listed companies may take action to change their management in order to improve performance so that the credit quality can be upgraded. Down-grading or ST status means the firm needs to operate with higher costs; for example, a higher interest rate or higher collateral.

Some companies might be labeled as risky, and under close monitoring, the Regulator might step-in to audit its financial status. If fraudulent information is found, it will be disclosed to the public. If the situation of such firms could not be improved, the final result is delisting. Corporate governance is an increasingly serious issue in Chinese firms today and the attitude of senior management oftentimes will determine where the company will migrate when rated BBB. If shareholders apply pressure and management also wants to improve the situation, the credit rating of such firms might improve. Otherwise, the situation might deteriorate. Such behavior would cause the credit level of listed companies to fluctuate around BBB.

5.4 Credit Rating Analysis of “ST” Companies

As mentioned above, “ST” companies are the ones with unsatisfactory performance and deteriorating financial status. If the rating model could identity which companies were below the BBB level or have a trend that is moving towards such level even just a year before the ST announcement, then such model would be very useful and valuable. In this study, we chose 29 companies with “ST” announcements in 2002 and 37 companies with “ST” announcements in 2006 and conducted Z_{China} score credit rating analysis from 1998 to 2002 (See Table 5.4) and from 2002 to 2006 (See Table 5.5).

Table 5.4 Credit ratings of companies with ST announcement in 2002 (N=29)

Credit level	2002		2001		2000		1999		1998	
	Firm number	Percent	Firm number	Percent	Firm number	Percent	Firm number	Percent	Firm number	Percent
D	8	28.57%	9	32.14%	1	3.57%	0	0	1	3.57%
C	5	17.86%	8	28.57%	1	3.57%	2	7.14%	3	10.71%
B	8	28.57%	7	25.00%	13	46.43%	5	17.86%	3	10.71%
BB	6	21.43%	4	14.29%	4	14.29%	11	39.29%	6	21.43%
BBB	1	3.57%	0	0	4	14.29%	6	21.43%	8	28.57%
A	0	0	0	0	3	10.71%	1	3.57%	3	10.71%
AA	0	0	0	0	1	3.57%	2	7.14%	2	7.14%
AAA	0	0	0	0	1	3.57%	1	3.57%	2	7.14%

The results in Table 5.4 show that amongst the companies with an “ST” announcement in 2002, almost all were classified as below the BBB level by our proposed model in the same year or one year earlier than ST was announced. The percentages of those classified at a D level are 28.57 percent in 2002 and 32.14 percent in 2001 and accounted for the largest percentage in all credit levels. In two, three and four years prior to ST announcement, that is, 2000, 1999, 1998, although the percentage of companies classified as BBB or below was decreasing by year, the percentage was still significant: 82.14 percent, 85.71 percent, and 75 percent, repectively.

The credit level with the largest percentages in 2000 was B (46.43 percent) in 1999 BB (39.30 percent), and in 1998 was BBB, (28.57 percent). In addition, our study found that during the three years prior to “ST” announcement, there were 17 companies with credit levels that decreased year by year, which accounted for 60.7 percent of the total number of distressed companies. After monitoring credit rating migration for “ST” companies in five years prior to the announcement of ST, the rating given by the model was low and decreasing year by year. Such prediction basically matched the actual situation. Also, our analysis indicated that in the four years prior to ST announcement, our rating method not only identified low credit quality as “ST” companies, but also reflected that the trend of credit quality of such companies was decreasing.

Table 5.5 Credit ratings of companies with ST announcement in 2006 (N=37)

Credit level	2006		2005		2004		2003		2002	
	Firm number	Percent	Firm number	Percent	Firm number	Percent	Firm number	Percent	Firm number	Percent
D	2	5.41%	8	21.62%	5	13.51%	0	0	1	2.70%
C	2	5.41%	14	37.84%	8	21.62%	1	2.70%	1	2.70%
B	8	21.62%	14	37.84%	16	43.24%	0	0	2	5.41%
BB	22	59.46%	1	2.70%	8	21.62%	26	70.27%	18	48.65%
BBB	3	8.11%	0	0	0	0	10	27.03%	12	32.43%
A	0	0	0	0	0	0	0	0	3	8.11%
AA	0	0	0	0	0	0	0	0	0	0
AAA	0	0	0	0	0	0	0	0	0	0

In order to test if the credit rating model that we developed is robust in different time periods of forecasting, we conducted another test that covered years from 2002 to 2006. Table 5.5 shows that Chinese listed companies credit variation from year 2002 to 2006 was significant and mainly fell on the BB level – 48.65 percent, in 2002. The economy from year 2002 to 2004 deteriorated due to several reasons, such as, SARS, and 15 firms rated BBB and A disappeared in 2004. The percentages of those classified at a D level are 2.70 percent in 2002, 13.51 percent in 2004, 21.62 percent in 2006, and 5.41 in percent in 2006, which indicated that 2004 and 2005 were two tough years for Chinese firms.

After monitoring credit rating fluctuations for "ST" companies for five years prior to their announcement of ST, the rating given by the model was low and decreasing year by year. Companies that fell below the BBB grade would warrant attention from regulators to give more strict monitoring. Based on the past experience, firms may even suffer ST announcement or even delisting if the operation of such companies could not be improved. For such reason, when the rating gets close to BBB, listed companies could take action to improve or even change management in order to manage a financial turnaround. Therefore, the results indicated that the model can be used to help investors forecast which firms might be in trouble in the future and to avoid making poor investment decisions.

5. Conclusions

Our model was tested by two data sets covering the period from 1998 to 2006. The model was able to identify the potential distress of Chinese companies with satisfactory accuracy even three years prior to their distress, i. e., Special Treatment (ST). Our model is very similar to that of the Z"-Score emerging market model's four-variable version. One of the four variables (WC/TA), is identical and three (NP/ATA), (RE/NP) and (TL/TA) are close variations on the three that were used in the earlier model.

Appendix A: Kolmogorov-Smirnov Sample Data Test

This is a goodness-of-fit test which examines whether the sample set is subject to designated theory distribution. Posit that $F_n(x)$ is a good estimation of the unknown population distribution function $F(x)$, and select test statistic Z=max[$F_n(x)-F_0(x)$]. If the sample is subject to the designated distribution, i.e. $F(x)=F_0(x)$, the observed value of Z should be small, otherwise, the null hypothesis could be false. This study tests whether the sample is subject to normal distribution. See table 4.2 for test results.

The Kolmogorov-Smirnov test[9], *Z values of* X_2, X_4, X_6, X_7, X_{11}, X_{12}, X_{14} and X_{15} are all small with significance level over 5 percent, which is basically in accordance with a normal distribution. The Z values of other indicators, i.e. X_1, X_3, X_5, X_8, X_9, X_{10} and X_{13}, are large with significance level mostly at 0.000, rejecting the null hypothesis of complying with the normal distribution hypothesis.

Hypothesis testing of equal sample means for 15 variables in different groups, i.e.:

H_0: The mean of X_i in group 0 (ST group) is equal to that of X_i in group 1(Non-ST group)

H_1: The mean of X_i in group 0 is not equal to that of X_i in group 1

The test statistics are Wilks' λ and F statistic. Wilks' λ statistic is sometimes called U statistic. For two groups, when variables are considered separately, λ is the ratio of sum of squares within groups to total sum of squares, i.e.:

$$\text{Wilks' } \lambda = \frac{Sum\ of\ Squares\ Within\ groups}{Total\ Sum\ of\ Squares} = \frac{SSW}{SST} \tag{4.1}$$

where $SSW = \sum_{i=1}^{2}\sum_{a=1}^{n_i}\left(x_{ia} - \overline{x_i}\right)^2$; $SST = \sum_{i=1}^{2}\sum_{a=1}^{n_i}\left(x_{ia} - \overline{x}\right)^2$;

n_i is the sample size of group i.

If the means of all observation groups are the same, λ is equal to 1. A large λ indicates the means of different groups are basically the same while a small λ indicates there are differences.

For the test of equal means between two samples, F statistic value is:

$$F = \frac{MSB}{MSW} = \frac{SSB/1}{SSW/(n-2)} \tag{4.2}$$

[9] This is a goodness-of-fit test which examines whether the sample is subject to a designated normal distribution. Posit that Fn(x) is a good estimation of the unknown population distribution function F(x) and select test statistic Z=max(Fn(x)-F0(x). If the sample is subject to the designated distribution, i.e.,F(x)=Fo(x), the observed value of Z should be small, otherwise, the null hypothesis could be false. This study tests whether the sample is subject to a normal distribution.

$$\text{where} \quad SSB = \sum_{i=1}^{2} n_i \left(\overline{x_i} - \overline{x}\right)^2$$

If the significance level is too low, the null hypothesis that the means of all groups are equal will be rejected. See Table 4.2 for test results.

Table 4.2 Test result for equal sample mean

Variables	Wilks' λ	F statistic	df1	df2	Significance
X_1	.971	1.742	1	58	.192
X_2	.983	1.004	1	58	.321
X_3	.966	2.043	1	58	.158
X_4	.961	2.367	1	58	.129
X_5	.987	.745	1	58	.392
X_6	.578	42.417	1	58	.000
X_7	.294	139.134	1	58	.000
X_8	.704	24.386	1	58	.000
X_9	.765	17.831	1	58	.000
X_{10}	.999	.044	1	58	.835
X_{11}	.909	5.785	1	58	.019
X_{12}	.710	23.711	1	58	.000
X_{13}	.907	5.952	1	58	.018
X_{14}	.930	4.383	1	58	.041
X_{15}	.847	10.472	1	58	.002

The test results indicate that X_6, X_7, X_8, X_9, X_{12} and X_{15} reject the null hypothesis that the sample means between group 1 and group 2 are equal at significance level α=0.01, which indicates that there exists significant differences in these indicators between financial distress companies and non-distress companies. While the λ values of X_1, X_2, X_3, X_4, X_5, , X_{10}, $X_{11,}$ X_{13} and X_{14} are relatively large, indicating that the means of these indicators between financial distress companies and non-distress companies are not statistically different.

Appendix B: The correlation matrix of 15 variables is shown in Table 4.3. From the correlation matrix we found that many indicators did not have strong correlations among each other; except X_1 and X_8 (0.960), X_9 and X_8 (0.839), X_9 and X_1 (0.831). Therefore, X_1, X_8 and X_9 exhibit high correlations among each other.

Table 4.3 Correlation matrix

	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}	X_{14}	X_{15}
X_1	1.000	.125	.017	-.082	.056	-.056	.102	.960	.831	.064	.073	.078	.021	.046	.046
X_2	.125	1.000	-.003	.073	-.020	.123	.024	.105	.117	-.173	.196	-.009	.088	.025	.045
X_3	.017	-.003	1.000	-.012	.063	-.039	.050	.090	.014	.053	-.090	.056	-.066	-.097	.043
X_4	-.082	.073	-.012	1.000	-.303	.383	-.138	-.103	-.098	-.418	.307	.122	.123	.150	.109
X_5	.056	-.020	.063	-.303	1.000	-.529	.156	.089	.105	.440	-.170	.108	-.149	-.054	.000
X_6	-.056	.123	-.039	.383	-.529	1.000	-.431	-.126	-.162	-.537	.257	-.235	.072	.095	.161
X_7	.960	.105	.090	-.103	.089	-.126	.102	1.000	.839	.172	.044	.115	-.027	-.012	.005
X_8	.073	.196	-.090	.307	-.170	.257	-.089	.044	.083	-.285	1.000	.100	.062	.298	.100
X_9	.831	.117	.014	-.098	.105	-.162	.086	.839	1.000	.138	.083	.195	-.033	.026	-.047
X_{10}	.064	-.173	.053	-.418	.440	-.537	.207	.172	.138	1.000	-.285	.137	-.096	-.110	-.006
X_{11}	.102	.024	.050	-.138	.156	-.431	1.000	.102	.086	.207	-.089	-.222	-.106	-.076	.058
X_{12}	.078	-.009	.056	.122	.108	-.235	-.222	.115	.195	.137	.100	1.000	-.043	.017	.006
X_{13}	.021	.088	-.066	.123	-.149	.072	-.106	-.027	-.033	-.096	.062	-.043	1.000	.294	.071
X_{14}	.046	.025	-.097	.150	-.054	.095	-.076	-.012	.026	-.110	.298	.017	.294	1.000	.241
X_{15}	.046	.045	.043	.109	.000	.161	.058	.005	-.047	-.006	.100	.006	.071	.241	1.000

References

Altman, E.I. 1968. Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy, Journal of Finance (23), September, 189-209.

Altman, E.I. 1989. Measuring Corporate Bond Mortality and Performance. Journal of Finance, September, pp.909-922.

Altman, E.I., 1984. The success of the business failure prediction models: An international survey. Journal of Banking and Finance 8, 171-198.

Altman, E.I., R. Haldeman and P. Narayanan. 1977. ZETA Analysis, A New Model to Identify Bankruptcy Risk of Corporations, Journal of Banking & Finance, 1, June, 29-54.

Altman, E.I. and Anthony Saunders. 1998. Credit risk measurement: development over the last 20 years, Journal of Banking & Finance, 21, 1721-42.

Altman, E.I., J. Hartzell and M. Peck. 1995. Emerging Market Corporate Bonds: A Scoring System, N.Y. Salomon Brothers, May and Emerging Market Review, Summer 2006.

Altman, E.I. and P. Narayanan. 1997. An International Survey of Business Failure Classification Models in F. Choi, International Accounting and Financial Handbook, NY, John Wiley & Sons.

Altman, E.I. and Edith Hotchkiss 2005. Corporate Financial Distress and Bankruptcy, 3rd ed., J. Wiley & Sons, Jersey City, NJ.

Asquith,Paul,David W.Mullins Jr.and E.D.Woff.1989. Original Issue High Yield Bonds: Aging Analysis of Defaults, Exchanges and Calls" Journal of Finance, September, 923-953.

Aoxiang Pan, 1999. Financial Statement Analysis. Economic Science Press, Beijing, China.

Beaver,W 1967.Financial Ratios as Predictors of Failure, Journal of Accounting Research 4 (suppl.) 71-111.

Chen,Qing.1999. Evidence Analysis on Financial Distress of Listing Companies. Accounting Research 4, pp.31-38. (Chinese Journal).

Chen, Xiao. Chen, Zhihong. 2000. Corporate Financial Distress theory, methodology and Application. Investment Study.2, pp.125-126. (Chinese Journal).

China Securities. Various issues in 2000. (Chinese Journal).

Deakin, E.B. 1972. A Discriminant Analysis of Predictors of Business Failure, Journal of Accounting Research, March.

Dewing, H.S. 1952. The Financial Policy of Corporations. New York: Ronald Press.

Donaldson, G. 1969. Strategy for Financial Mobility. Boston, Mass.: Harvard University Press.

Edminster, R.A. 1971. Financial Ratios and Credit Scoring for Small Business Loans, Journal of Commercial Bank Lending, September.

Fisher, R.A. 1936. The Use of Multiple Measurements in Taxonomic Problems, Annals of Eugenics, No. 7, September.

Gilbert,L.R., K.Menon, and K.B.Schwartz. 1990. Predicting Bankruptcy for Firms in Financial Distress. Journal of Business Finance and Accounting. Spring. 161-171.

Gao, Shangquan and Chi, Fulin 1996. The Chinese Securities Market. Foreign Languages

Press, Beijing.
H.Y. Izan. 1984. Corporate distress in Australia, Journal of Banking and Finance. 8, 303-320.
Jarrow, R.A., D. Lando and S.M. Turnbull. 1997. “A Markov Model for the Term Structure of Credit Risk Spreads,” Review of Financial Studies, 10, no. 5, 481-523.
KMV Corporation 1995. Introducing Credit monitor, Version 4 and the KMV EDF Credit Measure. 2000. San Francisco: KMV Corporation.
Lau, A. 1987. A Five-state Financial Distress Prediction Model. Journal of Accounting Research, Spring, 127-138.
Lin, Hong-Chi 1997, A study of the ability of cash flow data in predicting financial distress for Taiwan’s food processing industry, Dissertation, Nova Southeastern University.
Newton, G.W. 1975. Bankruptcy and Insolvency Accounting. New York:The Ronald Press.
Ross, Stephen A. Westerfield, Randolph W. and Jeffrey F. Jaffe, 2005. Corporate Finance. 7th edition, McGraw-Hill Companies.
Scott, James. 1981, The probability of bankruptcy-a comparison of empirical predictions and theoretical models, Journal of Banking and Finance 5, 317-344.
Wilcox J. 1972. A Prediction of Business Failure Using Accounting Data. Journal of Accounting Research. Vol.ii.
Wu, Shilong and Lu, Xianyi. 2001. Financial Distress Prediction Model for Chinese Trading Firms. Economic Research Journal. 6, pp.46-55. (Chinese Journal).
Zhang, Ling. 2000. Financial Distress Early Warning Model. Quantitative and Technical Economics. (3) 49-51 (Chinese Journal).