A Method Study of Financial Distress Prediction

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Abstract. This paper simply introduces the main problems in financial forecast that we are facing in our country. Based on this, some general forecasting methods and techniques of financial distress are listed and analyzed. The main issues that should be considered in the process of predicting the financial distress are presented. Finally, a prediction method of financial distress, named modified sample matching method, is proposed in this paper.

Keywords: Financial Distress Prediction; Sample Matching Methods, Modified Sample Matching Methods

1. Introduction

China's stock market has developed for nearly two decades, facing severe stock market boom or crash. As the star shares of listed companies are converted into junk stocks frequently and suddenly, many investors gradually lost confidence in the stock market and listed companies. Although they are facing a crisis of confidence and trust that many experts have disputed too much, they have the consensus. One of them is that the quality of listed companies in China is too poor to maximize the shareholders' value. In other words, regarding all the listed companies in China as a whole, they are in the state of damaging shareholder value almost every year. The future development of the damage-type companies is uncertain. On one hand, their financial position may be recovered, re-creating value for shareholders; on the other hand, it may further deteriorate and eventually fall into financial difficulty. Actually, many factors impact the financial rehabilitation or deterioration of these companies. Many scholars have been studying how to use the company's financial position, governance and protection of investor' interests to predict changes in the company' future financial position [1-3]. For the managers of listed companies, the study not only supplies the decision-making basis to improve management, enhance corporate, and prevent the financial crisis, but also provides policy basis for the governmental departments to develop monitoring quality of listed companies, protect the interests of small investors, and maintain the healthy development of capital markets [4]. Some scholars have established a single-variable prediction model, assuming that cash flow/total debt, total assets net profit margin and asset-liability ratio have the great effect in predicting financial failure. It is simple and easy to operate this model, however, a single indicator that reflected the content is often limited and could not explain the financial situation. If investigating a number of indicators simultaneously, the result of the identity problem has a different interpretation [5]. The multivariate model, which is resulting in solving the shortcoming of single-variable model, is an econometric model based on the development variable, such as linear probability model, linear identification model and logit model. Some scholars have used the linear probability model in the analysis of bank failures [5, 6]. The calculation of the model is simple, but it can predict the possibility of financial crisis only between 0 and 1. Actually, the calculated Y values may fall outside the range, so it is rare to use in financial distress prediction of the actual studies.

2. The classical methods of financial distress prediction

With the development of the computer and information technology in recent years, researchers apply the artificial neural networks, expert systems, genetic algorithms, and many other analytical methods and techniques to the prediction of financial distress studies. Some of predictive methods commonly used are as follows:

(1) In the late half of the 1990s, literatures of neural network analysis techniques applied to corporate distress prediction appeared substantially [6]. Although the neural network discriminant model is a great innovation in research methods, the actual effect is too unstable. For example, COATS and FANT identify 47 financial-crisis companies and 47 normal companies by the neural network model, resulting in 91% of predictive accuracy rate that is significantly higher than 72% by the multiple discriminant. Some scholars

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have predicted the financial crisis of U.S. companies and banks through the analysis method of neural network, achieving certain results. However, some scholars believe that neural network model with MDA has no significant predictive results, compared with the LOGISTIC. At present, the artificial neural network model is still used in corporate failure prediction frequently.

(2) Charitou and Trigeorgis built up the discriminant model of financial crisis by the discriminant model of financial crisis by the relevant variables of B-S option pricing model, and compared the 139 U.S. companies between 1983 and 1994 for the test and finally found that the options variables, such as the face value of debt, the market value of current assets, and the entrepreneurial standard deviation, have a significant effect on predicting the insolvency. However, the basic approach of the study is still based on the test of Logisit regression. It only introduces the option factor of the variable design, and has little contribution to the actual theory [1].

(3) In 1988, Messier and Hansen introduced the expert system (ES) to the field of financial distress prediction for the first time. They explored and compared the applications of ES in the field of credit analysis from the perspective of knowledge acquisition. The result of the data from 71 companies have showed that the ES is better than the Linear Discriminant Analysis (LDA), Group Decision Making Methods, etc. While the correct classification rate of LDA is 57 in the test samples, ES is 87 .5, and is more stable than that of Group Decision Making Methods.

(4) Some scholars, based on the z-score method and ZETA method, added a new variable and industry factors and then proposed the amendatory ZETA method, which selected financial indicators by observing two groups of companies whose finance is in good or difficult condition. The model uses the Fisher criterion to establish the linear figuring function $Z = \lambda_0 + \sum_{i=1}^{k} \lambda_i X_i$. Some scholars use the Logit and Probit regression method to establish a predictive model: $\ln \frac{P_i}{1-P_i} = \alpha + \beta X_i$, in which the dependent variable is the natural logarithm of the possibility of financial crisis in the company i to $P_i / 1 - P_i$, and X_i is a group of micro-financial ratios of the company i that can test out the financial characteristics in the company, and P_i is the probability of financial crisis on the condition of X_i that has been given. One of the significant advantages of this model is that it converts the probability of the financial distress in (0, 1) interval into the real axis, overcoming the shortcoming of the linear probability model [7].

(5) Multidimensional scaling (MDS) provides an alternative for the current failure prediction model. Compared with the traditional methods of analysis, the result of MDS is easy to understand and overcome the limitation of traditional methods that are readily impacted by the extreme observation data. After the analysis, the MDS map makes both the failing companies and the successful ones fall into different regions, and the map can be explained further by using the standard multivariate statistical analysis methods. MDS method can accomplish through conventional method, understanding and analyzing the clear reason of dividing the companies into health or problem ones , thus enabling all levels of managers to analyze by the method of multivariate statistical analysis [8].

(6) Single-variable discriminant analysis method. The bankruptcy prediction, carried out by the Fitzpatrick, is the first financial distress prediction. Long before, Fitzpatrick had found that the two indicates--- net profit/shareholders' equity and shareholders' equity/ liabilities—have the greatest distinguishing ability among all the indicators. The main research methods were the empirical analysis and comparison of a series of financial ratio between the failure companies and normal companies, because of the lack of the advanced statistical and computational tools. This situation lasted until the early 1960s, and then the study of discrimination of financial risk went into the systematic stage. In 1966, William came up with a univariate analysis method and a single rate model, that is, using the single financial ratio to predict corporate financial distress. He found that the best discriminant variables were working capital flow/liabilities (identified 90% of the companies successfully one year before the companies going bankrupt) and net profit/total assets (the successful rate of identification in the same stage is 88%).

(7) Statistical methods. The statistical models are established by Multi- discriminant analysis (MDA), logistic regression, nearest neighbor method, and classification and regression tree. The first two are parameter method and the latter two are non-parametric methods. Both MDA and Logistic regression are multivariate statistical methods. The fundamental way is to classify new samples, according to some types of

training samples that have been known and the established discriminate function (model). The greatest advantage of these two methods is the characteristics obvious explanation and the existing defects is the extremely strict preconditions. For example, both of them are sensitive to the multi-collinearity between variables, and MDA requires the data to obey the multivariate normal distribution and other data covariance.

(8) Cross-validation. The m recross-validation means that sample with n volume is divided into m groups which are disjoint randomly, each of which has n/m samples. Training the classifier with (m-1) samples of groups and using the remaining sample of group as test classifier of test set, the validation can get a test error, and the process is repeated to guarantee each one in the m groups have been tested at least once. The average corresponding test error of each group in m is regarded as the classifier to test error over the entire sample set. Cross-validation can reduce the estimating bias, thereby evaluating the model more objectively [9].

(9) Multivariate discriminant analysis method. Altman (1968), the U.S. financial expert, used the multiple linear discriminant model to study the bankruptcy of company firstly. Based on the scare of industry and assets, he selected 33 pairs of non-bankrupt companies for the 33 bankrupt companies, regarding the five variables of the rate of working capital assets, retained earnings assets ratio and total asset turnover ratio as the discriminant variables and resulting in the Z-value, the probability of judging the total deterioration of corporate finance. Later, Altman and others proposed a more accurate predicting model of corporate financial difficulties, ZETA model. However, they did not introduce the specific methods of operating this model in details because they provide the service with payment.

(10) The regression of logic and probit. Multiple discriminant analysis models have strict assumptions, for example, multivariate normal distribution of multi-variable, multi-variable covariance and multiple variables of indicators such as average variable vector, covariance, priori probability and misclassification cost must have been known. However, most financial ratios of companies could not satisfy these requirements in fact. What's more, if the dummy variables appear, the assumption of joint normal distribution could not be established completely, and the Z-value would lose its clear meaning. To overcome these limitations, the researcher of financial difficulties have introduced the regression method of logit and probit since the late 1970s. The method simplified the problem as calculating the probability of financial distress in some periods , while the certain properties (presented by financial ratios) of the company has been known. If the calculated probability is greater than the setting split points, we can judge that the company will have financial distress during this period.

3. The method of financial distress prediction

Sample design process of financial distress prediction involves how to determine the sample group of financial distress company, how to determine the controlling factors of matching criteria, how to allocate the number of individuals between the two groups of sample, etc. We believe that we should take into consideration the following four aspects when determining the research on the company samples which are engaged in financial difficulties.

(1) To determine the sample group of companies in financial distress. Studying whether the establishment of sample is right or not directly relates to the rationality and application value of research achievement. The primacy standard is whether the financial position of selected companies is in accordance with the defined concept of financial distress.

(2) To determine the period of companies in financial distress. As we all know, the market interest rates, price indices, business cycles and other exogenous variables have a significant effect on the forecasting accuracy of the prediction model. The financial distress of companies always happen within the relevant period. From what we can read in existing literature, most studies only take into account achieving sufficient number of individual samples in determination of the study period. However, because of the different surroundings of companies in different years, the financial ratios of companies will inevitably be influenced by time- span- related factors, such as the macroeconomic situation and economic cycles. If we are unaware of the problem and do not deal with it when building the model, then the research result will obtain the bias because of the timing difference of the data. The bias will reduce the external validity of the model application.

(3) To consider the size of the company. The study of Altman assesses the effect of the scale factors on selecting sample in detail. He removed the samples of both small companies (total assets are less than million) and huge companies. These kinds of companies are not suitable to predict model generally, because Altman thought that the report data in the small companies is incomplete and the probability of the huge company's bankruptcy is extremely small [10].

(4) Requirements for the integrity of sample data. Zmijewski test the sample selection biases because of data integrity standard in selecting samples. He believed that the previous studies had regarded data integrity as the standard of selecting samples, damaging the premise of statistic technology in the process of establishing a predictive model. The requirements of random sampling and the companies in financial distress are more likely to provide incomplete data. The model based on complete data ignores this information and undoubtedly underestimate the probability of bankruptcy. His research showed that this bias does exist, but the model revised by him has not been improved significantly on the statistical significance and overall prediction accuracy.

4. Modified method of sample matching

Previous financial distress prediction studies generally required distressed and non-distressed companies matching in the industry and scale, the reasons are as follows:

(1) The difference of industries makes the comparison between different industries become impossible.

(2) Although other conditions are the same, the companies with different sizes have different probabilities of financial distress.

In order to control the factors of industry and size, we can base on the companies in financial distress, and then look for matching sample among other four types of companies. The rules are as follow:

(1) Having the same industry with the companies in financial distress (using the Commission's Industry Classification Standard—the first date of industry classification code.)

(2) If the options in the same industry are more than one, we should choose the company closest to the total assets and financial distress in the T year; If the company which has the closest total assets has matched with other companies, we should choose the second closest one, and so on. According to the above two rules, we should remove the samples that could not match the company. As a result, we can get 5 types of companies and each type has 27 companies. Using the ratio of 2:1, we divide the sample into model samples and test samples. The former is used for training the model, and the latter is used for testing the model prediction.

5. Conclusion

This paper studies the general forecasting methods and techniques of financial distress and presents the main issues that should be considered in the process of predicting the financial distress, and also proposes a method to improve the prediction for financial distress.

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