Data Envelopment Analysis of Corporate Failure for Non-Manufacturing Firms Using a Slacks-Based Measure

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Abstract: The problem of predicting corporate failure has intrigued many in the investment sector, corporate decision makers, business partners and many others, hence the intense research efforts by industry and academia. The majority of former research efforts on this topic focused on manufacturing companies with considerable assets commensurate with their size. But there is a dearth of publications on predicting non-manufacturing firms' financial difficulties since these firms typically do not have significant assets or, indeed, any need for them as their work does not rely heavily on assets as a key variable. Our research shows that the slack-based measure (SBM) DEA model has obvious advantages in predicting corporate financial stress.

Keyword: corporate failure; non-manufacturing company; predictions; data envelopment analysis (DEA); Altman's Z score.

1. INTRODUCTION

From the viewpoint of company management and individual investors, corporate health of a company is of critical importance as the firm's future is in the balance. A very valuable piece of information would be the knowledge that a for-profit organisation is headed for corporate financial stress or failure.

There are various methods used to predict corporate failure before actual financial stress appears, one of the most prevalent methods is to use financial ratios. In the past, a number of studies have been completed using the information from financial statements, particularly financial ratios to predict corporate failure (Beaver, 1967). A prominent method of predicting bankruptcy is the Altman Z score (Altman, 1968). Altman used Multiple Discriminant Analysis to create a model that uses basic financial ratios in a linear formula to give a score. This score is used to classify a company into one of the following three categories: at risk of corporate stress or failure, healthy, and the indeterminate status, a "grey area". The problem with these methods is that they were generalized for manufacturing firms, i.e. there was a major emphasis on the asset size of the firms involved (Grice & Ingram, 2001; Stephen, Keating, & al, 2004). In recent times, more companies are non-manufacturing and service-oriented firms and thus have less focus on the overall asset-size of the company.

As a supplement to his original model, Altman created another model that he named Altman Z" model (Altman, 2002) to cover the non-manufacturing sector. Then he tested the "Z" score on non-manufacturing firms and developed corresponding coefficients to make his original model suitable for companies including both manufacturing and non-manufacturing companies. Nevertheless, this model is still substantially based on asset size notwithstanding the fact that a large number of companies are mainly focused on service and their most important asset is their people and they do not have large real assets. It follows that an investigation of the Altman Z" model for the non-manufacturing sector is necessary and this is proposed in this study.

There are two main benefits to use DEA in predicting corporate failure for non-manufacturing firms. One is that analysts could select inputs and outputs flexibly depending on their actual needs, which allow us to eliminate, or at least de-emphasize, the "asset" factor for non-manufacturing firms. Another one is that DEA is a nonparametric method. Although parametric methodologies are widely used and offer desirable characteristics, they require prior parameter specifications (as does the Altman Z” model), which are rather complicated for ordinary users. It follows that if we can eliminate assets, or at least significantly reduce their influence, when selecting inputs and outputs for the non-manufacturing company. Then we could use the DEA score as a predictor of corporate financial health.

The remainder of this article is structured as follows: Section 2 reviews the previous methods in predicting corporate failure. Section 3 provides a discussion of the SBM model which we employ in the specific application we report on. Section 4 is an application of this approach to a real database, and we report the comparisons between the Altman Z” model and our SBM model. To conclude, Section 5 summarizes the research and provides additional discussion.

2. LITERATUREREVIEW

In 1968, Edward Altman attempted the first multivariate approach to bankruptcy prediction, which was named Multiple Discriminant Analysis (MDA)(Altman, 1968). To develop the model Altman took a sample of 66 corporations with 33 firms in the bankrupt group and 33 in the non-bankrupt group (Altman, 2002). A list of 22 potential ratios was compiled which were split into five standard ratio categories: liquidity, profitability, leverage, solvency and activity ratios. From the list of 22, five ratios were selected to be able to do the best overall job at collectively predicting bankruptcy. These were selected based on: (1) statistical significance of various potential functions while determining the relative contribution of each individual variable, (2) the correlation between the variables, (3) the predictive accuracy of various profiles and (4) judgement of the analysis (Altman, 1968). Then Altman’s multivariate model is as follows:

$$Z = 1.2T_1 + 1.4T_2 + 3.3T_3 + 0.6T_4 + 0.999T_5 \qquad (1)$$

Where

$$T_1 = \frac{WorkingCapital}{TotalAssets} \ ,$$

$$T_2 = \frac{Retained\ Earnings}{TotalAssets} \ ,$$

$$T_3 = \frac{Earnings\ before\ Income\&Taxes}{TotalAssets} \ ,$$

$$T_4 = \frac{MarketValueofEquity}{TotalLiabilities} \ ,$$

$$T_5 = \frac{Sales}{TotalAssets}$$

Altman also stated in his research that companies could be categorized into three zones by selected cut-off points, i.e. Safe (Z> 2.6), Grey (1.1 <Z< 2.6) and Distressed (Z< 1.1).

Based on Altman’s Z score approach, a large number of related studies were developed by employing different ratios (Deakin, 1972; Ohlson, 1980; Zmijewski, 1984; Hsieh, 1993; Grice & Dugan, 2001; Shumway, 2001; Grice & Ingram, 2001; Chava & Jarrow, 2004), of which the majority still focused on manufacturing companies. It follows that Altman proposed his lesser known Z” score method which mainly dealt with the non-manufacturing industry as follows:

$$Z" = 6.56T_1^{"} + 3.26T_2^{"} + 6.72T_3^{"} + 1.05T_4^{"} \qquad (2)$$

Where

$$T_1^{"} = \frac{WorkingCapital}{TotalAssets} \ ,$$

$$T_2^{"} = \frac{Retained\ Earnings}{TotalAssets} \ ,$$

$$T_3^{"} = \frac{Earnings\ before\ Income\&Taxes}{TotalAssets} \ ,$$

$$T_4^{"} = \frac{BookValueofEquity}{TotalLiabilities}$$

Altman revised the coefficients and items in the former Z score model to form a Z” score model. Even though the Z” score model is called the attempt to examine alternative industries compared with the former Z score model, it still has a major influence by the firms’ asset size. Given this, a non-parametric method, i.e. DEA which is flexible with respect to attribute selection is considered in this research.

Recently, DEA appears to be a suitable method in corporate failure prediction by comparing with various traditional methods (Premachandra, Chen, & Watson, 2011; Li, Crook, & Andreeva, 2014; Shetty, Pakkala, & Mallikarjunappa, 2012; Xu & Wang, 2009). These studies utilized different methods to compare to DEA emphasizing the predominance of DEA in corporate failure prediction. However, as alluded to above, none of the studies focuses on the failure prediction for non-manufacturing firms which have a small asset size compared to other industries, and deserve more consideration.

3. METHODOLOGY

Since the basic constant returns to scale CCR model (Charnes, Cooper, & Rhodes, 1978) appeared, DEA models' capabilities have been significantly extended to a broad approach, including both radial and non-radial models. While each DEA model has its uses, the CCR and BCC (Banker, Charnes, & Cooper, 1984) models are limited by the fact that they do not account for mix inefficiencies. In this case, the company under examination is not limited to "proportional attributes change", but is evaluated by the general deviation from the best performing firms. It follows that the SBM model (Tone, 2001), which accounts for mix inefficiencies is more suitable for the current study.

Unlike Altman's Z" score model, we use the DEA *efficiency score* instead of ratio values to measure the health status of a company. Hence, before using DEA to evaluate a group of DMUs' efficiency scores, we need to construct the DMU first. In order to compare the prediction accuracy with Altman's Z" score model, we select the inputs and outputs of the DMU by extracting them from Altman's ratios. All of the numerators of the ratios are considered to be outputs and the denominators are defined as inputs in the model. The ratios are split rather than being input directly as it has been shown that ratios used as inputs or outputs in DEA models can affect the validity of the results.

Due to data availability, EBIT is substituted for Operating Income which is also a valuable indicator of corporate health in DEA. Moreover, as one of the main purposes of the research, we need to see how accurately bankruptcy can be predicted regardless of asset size. Additionally, the attribute "Total Liabilities" was also removed and "Working Capital" was split into "Current Assets" and "Current Liabilities". To test the relevance of human capital, which is important to smaller non-manufacturing firms in our model, the number of employees and the number of shareholders were added to the model. The number of employees was added to introduce the measure of human capital (the most important "asset" in a non-manufacturing firm) as a contributor to the efficiency of a company. The number of shareholders was added because for many smaller non-manufacturing firms the shareholders have decision-making power and invest both time and money that contribute to the success of a firm. In this sense, the number of shareholders can also be seen as a reflection of the financial well-being of a company as viewed by the public.

Another problem we met was that many bankrupt companies had negative values in RE, OI and BVE, to which the SBM model was not applicable. Thus each output was split into positive and negative parts. For example, RE was split into RE^+ and RE^-, where RE^+ was defined as an output in its usual meaning, and, of course, RE^- was defined as an input. This method is essentially saying that RE^+ is an output and therefore should be made as large as possible to improve the company's operating efficiency. However RE^- is viewed as an input which would be minimized. Therefore the inputs/outputs of the model after revision are shown in the table 1.

Table 1: Inputs/Outputs classification

Outputs	Inputs
Current Assets (CA)	Current Liabilities (CL)
Positive Retained Earnings (RE^+)	Negative Retained Earnings (RE^-)
Positive Operating Income (OI^+)	Negative Operating Income (OI^-)
Positive Book Value of Equity (BVE^+)	Negative Book Value of Equity (BVE^-)
The Number of Shareholders (SH)	The Number of Employees (EM)

Generally, the calculation results obtained from DEA models are affected by the relationship between the number of DMUs and DMU dimensions, and this topic has taken a variety of forms in the DEA literature (Staat, 2001; Zhang & Bartels, 1998; Smith, 1997; Banker, Chang, & Cooper, 1996). Although we did attempt to use the normal SBM model, i.e. without orientation, to calculate the scores, the number of DMUs applicable to our study was between 23 and 42, which is somewhat limited, considering the above 10 attributes. The numbers of either bankrupt or non-bankrupt DMUs in each year were changed due to the lack of available financial data. We give the detailed description of the data in Section 4. As a result, many DMUs obtained an efficiency score of “1”, which was not very discriminatory in judging bankruptcy. Given this, we adopted a practical approach as the guidance in deciding the number of DMUs and DMU dimensions as follows (Cooper, Seiford, & Tone, 2007):

$$n \geq max\{m \times s, 3(m+s)\} \tag{3}$$

Where n, m and s are the numbers of DMUs, inputs and outputs respectively.

From the above equation, it can be observed that the number of DMUs in our case should be at least 30, however in most of the times the scale of DMUs was smaller than 30. It follows that we used the input-oriented SBM model in actual calculation to comply with the constraints in Eq. (3). Undoubtedly, the output-oriented SBM model should also be feasible and give satisfactory results. Furthermore, various studies concentrated on generating new data sets to overcome the problem of insufficient DMUs, for which we will not offer a detailed discussion here (Panagiotis, 2012; Sergio & Daniel, 2009; Staat, 2001).

4. APPLICATION TO BANKRUPTCY PREDICTION

As the DEA model incorporates all inputs and outputs together, and provides an efficiency score in the interval [0, 1] to describe the overall health status of a company, it is necessary to select two values in [0, 1] as cut-off points to categorize companies under examination into three zones, i.e. safe, grey and distressed, similarly to Altman’s models. Therefore, the data sample collected is divided into two groups. The first group is used to define appropriate cut-off points. Then we apply the input-oriented SBM model to the second group and compare the results with Altman’s method to validate our model.

4.1. Data Acquisition

The data that we utilized was collected through Mergent Online database (Mergent, 2011), a professional company which mainly focused on filing bankrupt companies in North America dating back to the 1980s selected by SIC (Standard Industrial Classification) codes. The list of companies was narrowed down to those classified as non-manufacturing or service-based firms. These companies must also have filed for bankruptcy between the years of 2000 and 2006. The reason for these dates was that more recent filings would be more easily obtained, and more easily compared to current companies. Bankruptcy filings from 2007 to present were not selected due to the economic recession taking place; hence, it was decided that the data could not reflect the real situation in that period. The companies considered to be bankrupt during that period could be more so for external reasons, which was not the main purpose of the current research.

For each bankrupt company, financial data was collected for up to 5 years before the date of bankruptcy being filed, as it was shown that there was potential to predict bankruptcy up to 5 years in advance (Beaver, 1967; Charles, 1942). Some companies did not have a full 5 years data and thus only had the number of years before bankruptcy collected. Whenever it was possible to identify them, the companies that had filed for bankruptcy but did not fail were excluded from the study. Many of these companies filed for bankruptcy for reasons other than complete insolvency, some liquidation were due to legal issues and others because they were suffering financial distress, filed in an attempt to reorganize and restructure their corporate strategy and alleviate their situation. Data from the full Balance Sheets, Income Statements, Cash Flow Statements and Retained Earnings were collected. From the Balance Sheet, current assets, total assets, current liabilities, total liabilities, retained earnings and shareholders’ equity values were extracted. From the Income Statement, the operating profit was calculated using the formula Net Sales – Cost of goods – Expenses. The number of employees and number of shareholders were also collected.

Once the data was collected for the bankrupt companies, healthy companies were then found. A healthy company was chosen for every bankrupt company based on SIC number and on the years of health. Healthy companies had to be in existence for at least 5 years after the bankruptcy of their bankrupt counterpart. Healthy companies also must not have filed for bankruptcy during the time that they are being compared to the bankrupt counterpart. The same financial data was collected for a healthy company as the bankrupt counterpart within the same years. For example, if a bankrupt company filed bankruptcy in 2002, financial data was collected for 1997-2001. The healthy company would have to have been in existence and not to have filed for bankruptcy between the years of 1996 to 2006. In some cases a suitable healthy match could not be found and thus the number of bankrupt companies exceeds the number of non-bankrupt ones.

The numbers of bankrupt and non-bankrupt companies used for the first group to determine cut-off points are shown in Table 2. And the numbers of bankrupt and non-bankrupt companies for the second group are listed in Table 3.

Table 2: Number of companies in group 1

Year before Bankruptcy	Number of Bankrupt Companies	Number of Non-bankrupt Companies
1	40	29
2	34	28
3	31	26
4	32	24
5	26	23

Table 3: Number of companies in group 2

Year before Bankruptcy	Number of Bankrupt Companies	Number of Non-bankrupt Companies
1	42	35
2	38	34
3	39	34
4	32	30
5	26	27

4.2. Results Analysis

The companies in group 1 were evaluated by an input-oriented SBM model for five years, but the results are not shown because of the limited space in this paper. Once each company was assigned an efficiency score, a measure of bankruptcy status had to be determined. For each year every possible cut-off point was tested at an increment of 0.05 from 0 to 1 to determine the bankrupt and non-bankrupt classification accuracy at those potential cut-off points. Figure 1 shows the accuracy percentages vs. the cross points for the first year. For example for a cut-off point of zero, no bankrupt companies are classified as bankrupt and all non-bankrupt companies would be classified as non-bankrupt. Along with the increasing cut-off values, the accuracy for non-bankrupt companies is increasing, but the accuracy for bankrupt companies is, decreasing. The only point which we should choose to maintain highest accuracy for both bankrupt and non-bankrupt companies is the cross over point of the two curves. Here that point would be 0.55, where the bankrupt and non-bankrupt accuracies are 67.50% and 68.97% separately.

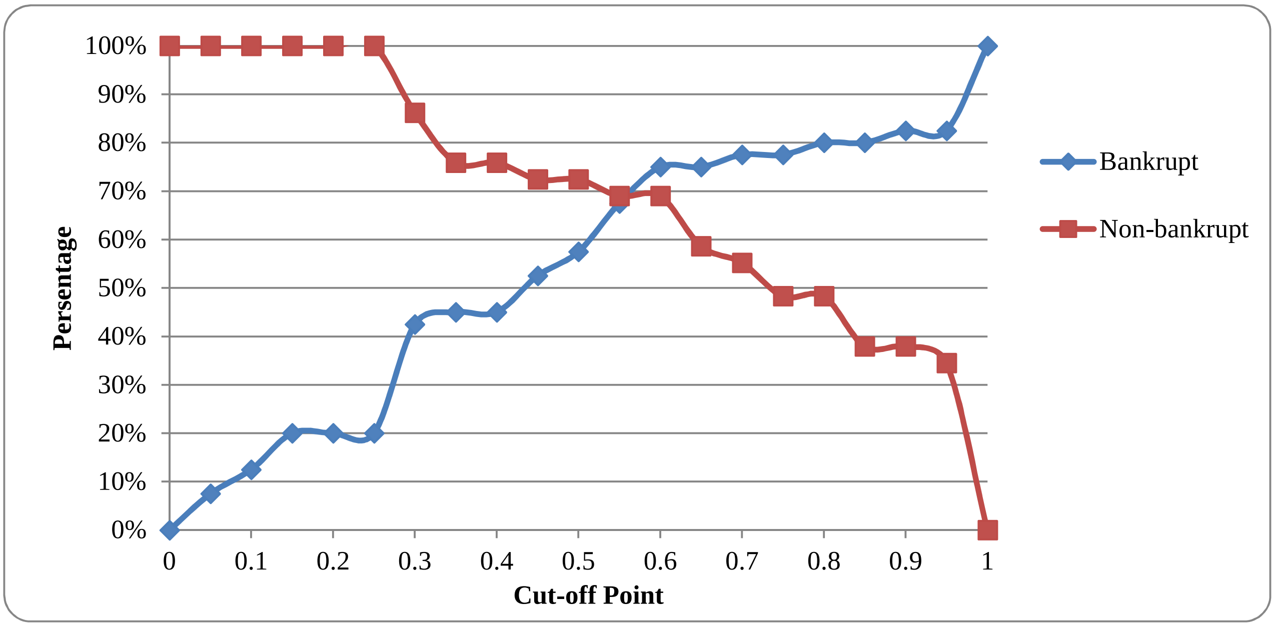

Figure 11: Bankrupt classification accuracy on year 1

To categorize all the companies into three zones, i.e. safe, grey and distressed, we need to choose two cut-off points. If we plot the curve of total accuracy which correctly categorized both bankrupt and non-bankrupt companies in Figure 2, we can find two points gaining relatively higher total accuracy around the point 0.55. One point is 0.5 located at left with 63.77% overall accuracy. Here the bankrupt companies have a classification accuracy of 57.50% and the non-bankrupt companies have a classification accuracy of 72.41%. This point is thus considered to be the bottom cut-off point to discriminate between "distress" and "grey" zones. In the same way, we could fix the top cut-off point 0.6, where the total accuracy obtains another high value. At this point, the classification accuracy for bankrupt companies is 75.00%, and for non-bankrupt companies the classification accuracy is 68.97%. It follows that this point is regarded as the boundary to separate "grey" and "safe" zones.

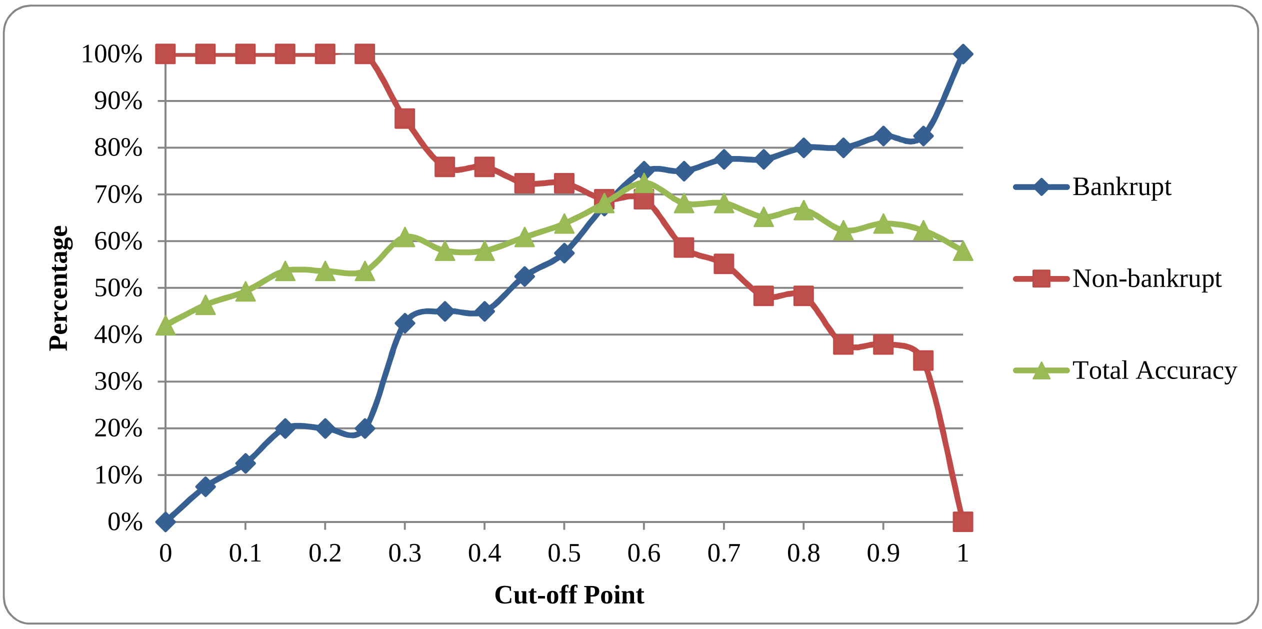

Figure 2: Selection of cut-off points for year 1

However, this is only the process to select cut-off points for one year before bankruptcy. In the same way, we can plot the bankrupt and non-bankrupt percentage curves for the other four years before bankruptcy as shown in Figure 3. As we are more concerned about the classification accuracy for bankrupt companies than non-bankrupt, we will shift these points up. By comparing the values over the 5 years, the finalized cut-off points are indicated in Table 4.

Table4: Cut-off points for SBM model

Interval	Classification
$\theta \geq 0.80$	Safe Area
$0.65 < \theta < 0.80$	Grey Area
$\theta \leq 0.65$	Distress Area

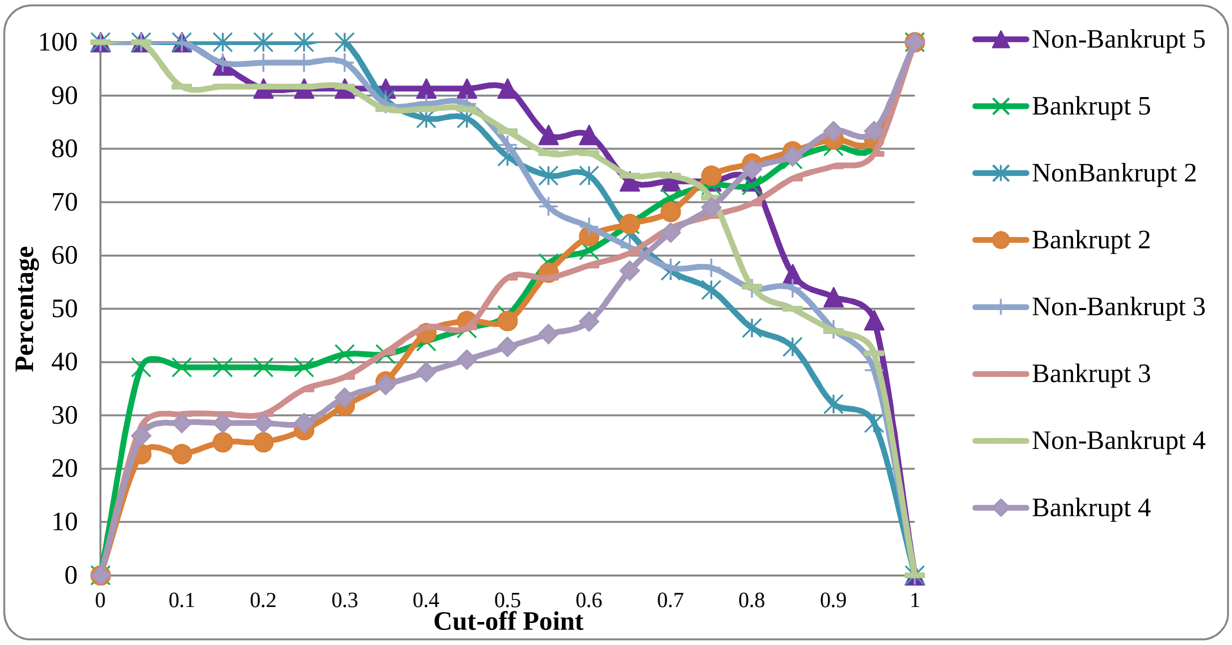

Figure 3: Cut-off points from year 2 to 5 before bankruptcy

Then we calculate the SBM efficiency scores for all companies in group 2. Based on the cut-off points that we obtained from group 1, the classification accuracy of group 2 is estimated as shown in Table 5. Moreover, the classification accuracy results for group 2 can also be obtained by Altman's Z" model, which are shown in Table 6. By comparing the calculation results of Table 5 and Table 6, we find out that some fields of the classification accuracies by SBM may be lower than Altman's model. However, most of the fields obtained by SBM exhibit abetter performance than Altman's model. If we investigate the overall classification accuracy including both bankrupt and non-bankrupt companies, and plot the results in Figure 4. It is apparent that the SBM is significantly better than Altman's model. Moreover, the longer before bankruptcy, the higher accuracy SBM could provide.

Table 5: Classification accuracy of group 2 by determined cut-off points

Year	1	2	3	4	5
Bankrupt accuracy	78.6%	57.9%	46.2%	53.1%	38.5%
Non-bankrupt accuracy	62.9%	61.8%	73.5%	66.7%	70.4%
Total accuracy	71.4%	59.7%	58.9%	59.7%	54.7%
Bankrupt accuracy including grey area	85.7%	68.4%	69.2%	78.1%	57.7%
Non-bankrupt accuracy including grey area	77.1%	88.2%	88.2%	93.3%	81.5%
Total accuracy including grey area	81.8%	77.8%	78.1%	85.5%	69.8%
Total bankruptcy	53.3%	36.1%	30.1%	30.7%	28.3%
Total non-bankrupt	36.4%	45.8%	50.7%	43.6%	56.6%
Total within grey area	10.4%	18.1%	19.2%	25.8%	15.1%

Table 6: Results of Altman Z" model on group 2

Year	1	2	3	4	5
Bankrupt accuracy	77.8%	59.1%	50.0%	41.5%	35.1%
Non-bankrupt accuracy	47.5%	52.5%	55.0%	52.5%	63.9%
Total accuracy	63.5%	55.9%	52.4%	46.9%	49.3%
Bankrupt accuracy including grey area	88.9%	86.4%	70.5%	70.7%	83.8%
Non-bankrupt accuracy including grey area	60.0%	72.5%	75.0%	75.0%	88.9%
Total accuracy including grey area	72.9%	69.1%	59.5%	60.5%	67.1%
Total bankruptcy	61.2%	45.2%	39.3%	34.6%	30.1%
Total non-bankrupt	29.4%	34.5%	44.1%	46.9%	52.1%
Total within grey area	11.8%	23.8%	20.2%	25.9%	36.9%

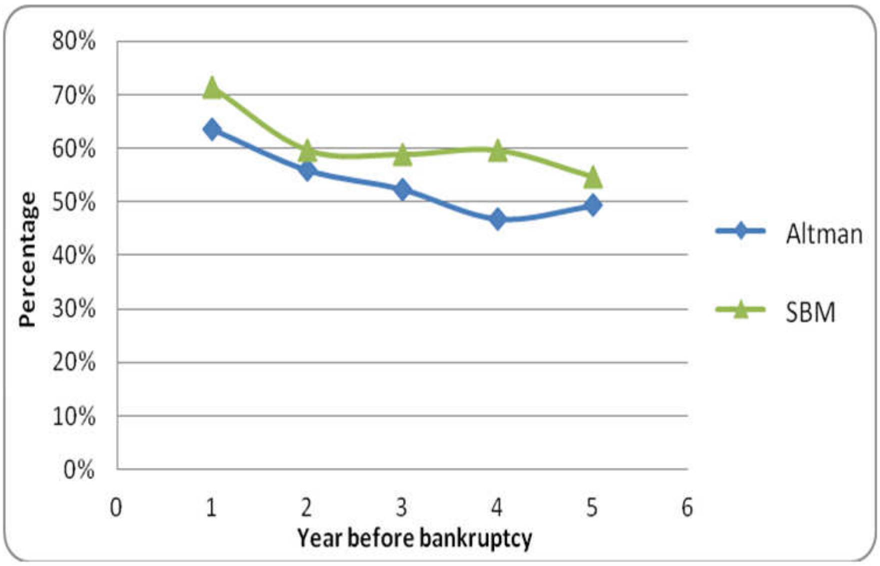

Figure 4: Total classification accuracy comparison between Altman & SBM

5. CONCLUSION

This research surveyed the related literature in bankruptcy prediction, stretching from Beaver’s univariate model to Altman’s Z” model, then proposed the approach of utilizing a nonparametric method, i.e. the SBM model in DEA, to predict corporate failure. To deal with negative factors in this study, we split such factors into positive and negative parts, which could be a viable option when needed in DEA analyses. Based on the methodological revision to SBM, we also validate our method by two groups of bankrupt and non-bankrupt firms. The second group is examined with the cut-off points obtained from the first group.

The overall accuracy of the SBM model was obviously higher than that of the Altman Z’’ model, which showed that the total assets or liabilities of a company were actually not necessary in predicting bankruptcy, and that SBM could be a more appropriate method in corporate failure prediction. The results are significant for companies such as non-manufacturing or retail companies which do not own a large investment in assets, and not suitable for using Altman’s Z” model. The overall classification results showed that Altman Z” model had a good prediction accuracy in the close years before bankruptcy, but still lower than the SBM model developed here, which, in fact, shows a dramatically higher accuracy than Altman’s Z” model, unveiling a company’s health status in advance, which should be more important for company management (they could change the course of the firm before too late) or investors or lenders (where they could force a change in management, or simply withdraw their investment while there is time).

This research has many useful conclusions but, as usual, there are suggestions for further work, including: (1) employing alternate DEA models or constraint conditions, particularly using the Assurance Region model which would put more restrictions on the variable weights and may obtain more meaningful results; (2) prediction accuracy may be affected by different approaches to selecting inputs/outputs, therefore different or other, related financial factors may bring higher prediction accuracy; (3) due to the lack of available data, the number of DMUs used in this study was insufficient for a more comprehensive assessment of the model. With a larger number of DMUs, the cut-off points will become more realistic and accurate for bankruptcy prediction; (4) innovative approaches to determine the cut-off points could be explored. The trial and error approach is simple and intuitive, however a different and more statistically sound method should be developed. Decision trees were considered but not employed, however this and could be considered for future research.

Either previous univariate models or Altman’s Z and Z” models mostly focused on firm asset size, and used parametric methods, i.e. weighted sum of asset based items, which resulted in a more likely empirical cut-off points selecting process, but not a data based reality. It follows that the DEA technique, a non-parametric method, could solve the problem resulting in a rather practical approach to predict corporate failure, especially for non-manufacturing firms. In closing, we hope that this research will be insightful and informative for future researchers.

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