Erasmus University Rotterdam

Erasmus Universiteit Rotterdam
Erasmus School of Economics

Department of Business Economics

Section: Finance

Bachelor Thesis

Testing and calibrating the Altman Z-score for the U.K.

Author:
Marko Rado
344734

Supervisor:
Dr. Nico van der Sar

Abstract

Corporate bankruptcy is an important topic, especially since the wake of the recent crisis that trembled financial and monetary institutions. This paper extends on the well-known Altman Z-score model presented by Altman (1968) by calibrating it to the United Kingdom. The calibration is necessary because of the accounting and financial divergence between the UK and the United States. Some of the reasons for divergence are inter-country accounting differences, recent financial developments and differences in corporate governance between the UK and US. The point of view taken when creating the UK model is that Altman's model is still valid for the US, but there could be a better model predicting UK bankruptcies. First, the model is re-estimated using UK data. Then, secondary tests are performed to test the reliability and predictive power. Finally, the empirical evidence shows a remarkable support for the calibrated model and advocates its usage to companies operating in or working under the financial and accounting conditions of the UK.

Acknowledgements

The reason for writing this thesis is trying to contribute to the great research reputation of the Erasmus University Rotterdam. Being a Finance 1 tutor has motivated me to look beyond the standard scope of finance. Pondering over life and the future wealth that is awaiting us, my colleague Traian Gurău and I came to an idea of calibrating the Atlman Z-score to other world markets. Choosing which markets to focus on was not that difficult, since we asked ourselves: where are the current financial centres of gravity? By answering this question we had pinpointed our markets: US, UK and Japan. As we continued exploring the idea of starting up such a project, we wanted it to contribute to our *alma mater*. To this end we started writing our theses.

As this paper focuses on calibrating Altman's model to the UK, a truly wonderful paper by my colleague Gurău (2013) calibrates Altman's model to Japan. In writing this thesis there were some moments of academic collaboration between us. First of all, we did do the data collection together, as to increase the efficiency and minimize the time loss. Furthermore, we also programmed together when it came to statistical modelling in SPSS and the creation of the LaTeX code for the document output, again in the spirit of our university, to maximize efficiency and minimize opportunity costs. It should be noted, however, that the research performed and writing of the thesis were done on an individual level. While there is overlap at some degree regarding the modelling and document output and even some moments of academic brainstorming, the work was mainly done on an individual basis. Hence, it may be that the structure and methodology look similar to a certain degree, but the reader should be assured that the work performed and thus the specifics of the conclusions coming forth are individual.

Writing this thesis would be impossible without the support of the people around me. Especially, I want to thank my supervisor Dr. Nico van der Sar, or as Traian and me call him 'the Professor', who provided huge support in terms of motivation and academic knowledge during the thesis and over the years. His classes are great, his exams are tough and he is a great inspiration.

Finally I would like to conclude with a legal issue: any opinions expressed in this paper are those of the author and do not necessarily reflect or represent those of the Erasmus University Rotterdam.

Contents

List of Tables

1 Introduction

Accepting *status quo* is somewhat easy but academic and professional progress is founded on not only creating but also refining existing models and ideas. Such a stream of thought is applied when calibrating the Altman Z-Score model to the United Kingdom. The UK, once the world's financial center of gravity, is now sharing this title with, among others, the US and Japan. Nevertheless, still being a major player in the financial world, the UK has many firms who have been and nowadays still are evaluated by the Altman Z-Score model. The original model, using US data, is put forth by Altman (1968) and aims at predicting corporate bankruptcy[1]. While Altman proved in his paper that the model is highly accurate for the US, does this mean that it is also as accurate in an international setting? Is the model robust in predicting corporate bankruptcy in the UK? With the main question being, should and can one, taking into account country specific characteristics which can be traced back to company financials, calibrate the existing model?

The purpose of this paper is extending the Altman model by calibrating it to the UK. While there will be some deviations from the Altman model, the newly calibrated model, hereafter referred to as the UK model, will be theoretically based on the Altman model. This basically means that the new model will be constructed using the guidelines from Altman's ground breaking paper. The UK model will be constructed on the basis of several financial and economic ratios. Those ratios will be statistically analysed by first evaluating them in a univariate setting and then evaluating them in a multivariate setting using the multiple discriminant analysis (MDA) approach. This will yield the UK model, which is a one dimensional linear model predicting corporate bankruptcy one year prior to the event, having the same variables but different coefficients compared to Altman's model. The data employed to arrive at the UK model is, like Altman's, based on public manufacturing corporations.

The paper proceeds as follows. In Section 2, a literature review is presented with the relevant contributions so far and the contribution of this paper to the discussion of predicting corporate bankruptcy. Section 3 focuses on the theoretical framework concerning the model. Section 4 discusses the data, in-

[1] Bankruptcy within the UK does not have just a single law, as the law may differ over the different countries that are part of the UK. Hence in this paper when bankruptcy is mentioned it refers to the possible different country laws covering bankruptcy within the UK where necessary. But the main laws referred to when bankruptcy is mentioned in this paper would be the Insolvency Act 1986, the Insolvency Rules 1986 and the Enterprise Act 2002.

cluding a description of the ratios employed in this paper. Section 5 develops the UK model and presents empirical evidence testing its reliability and predictive power. Section 6 concludes, summarizing the findings and presenting the limitations of this paper.

2 Literature Review

Over the years, extensive research has already been done in the field of corporate bankruptcy. This paper uses the literature examined in the Altman (1968) paper as a starting point. This can be logically rationalized based on the fact that this paper and model presented are an extension of the aforementioned paper. The deviations from the original paper and its corresponding literature will be discussed after reviewing the literature in the Altman paper. Hence this section first presents relevant research leading up to this paper, then discusses the contribution of this paper to the existing literature in light of post Altman (1968) literature and finally presents alternative approaches.

2.1 Prior Altman (1968)

Identification of company malaises, both operating and financial, finds some of its foundations in ratio analysis. Before the advent of quantitative measures of business performance one would have employed specific firms which would supply creditworthiness information concerning other firms. As mentioned in Altman (1968), more information on the foundations of credit rating agencies and firm performance analytics is presented by Foulke (1961). As early as in the 1930's one would find studies concerning company failure. An important conclusion concerning financial ratios was reached by several studies at that time. This conclusion, evident from the work of Winakor and Smith (1935), stated that defaulting companies showed significant different ratio measurements than non-defaulting firms. Other studies like for example Hickman (1958) focused on the ratios of large asset-size firms that had problems with their fixed debt commitments. From here other studies evolved, like for example Beaver (1966) and Tamari (1966), both utilizing financial ratios analysis in a bankruptcy prediction setting. The latter study used a matched sample of bankrupt and non-bankrupt firms, comparing their respective ratios on an individual basis. Extending upon this, Altman (1968) brilliantly saw, using his words, "a definite potential of ratios as predictors of bankruptcy". While he did recognize that ratios assessing profitability, liquidity and solvency were among the most significant, he added that their rankings are unclear. To this end he advocated using the MDA method in order to perform a multivariate analysis rather than individually assessing the ratios in a univariate setting. This eventually led to the well-known Altman Z-score model, which this paper extends upon.

2.2 Post Altman (1968)

Even though the foundations of this paper lie in the insightful paper by Altman (1968), it does deviate slightly from it which in turn enables a significant contribution to the existing literature. One of the main points where this paper deviates from Altman's is geographical in nature. Compared to Altman's paper, where public US manufacturing firms are used, this paper uses a dataset comprised of public UK manufacturing firms. The reasoning behind using UK data is because if one were to use the Altman model in the UK, then one should use a properly calibrated Altman UK model. The importance of using UK data instead of US data is due to the underlying accounting and financial divergence between the UK and US, as is presented throughout this paper.

First addressing the accounting divergence, the accounting practices for depreciation and amortization of both countries differ. While there may be other diverging accounting practices, depreciation and amortization is directly impacting one of the underlying ratios that are being employed by the model. This ratio, later explained as the third variable of the model, has earnings before interest and taxes (EBIT) in its numerator. Compared to EBITDA, EBIT in itself is already treated for depreciation and amortization. Hence, when using the Altman model on firms in the UK, one implicitly assumes identical accounting principles concerning depreciation and amortization. According to PriceWaterhouseCoopers (2005), while both US GAAP and UK GAAP are similar to IFRS in terms of depreciation and amortization, there are differences concerning changes in the depreciation method and the maximum life of an intangible asset. While these differences will not cause a constant problem, since they are of an exceptional nature (change in method and useful life extension), they might skew the outcome of the model. The skewing might present itself by overstating/understating the financial ratios and in turn causing a biased outcome. This would be in line with the GIGO principle: Garbage In, Garbage Out. This term, frequently used in the field of computer science and financial modelling, refers to the fact that regardless of how good a model is, if the input is nonsense, the output will be too[2].

Second, there is the issue of differing financial possibilities nowadays. These possibilities and instruments allow users of them to manage company aspects which effectively change the firm's underlying probability of default. In support of and extension to this claim is Marin (2013), stating that the possibility of filing bankruptcy is lower for firms managing foreign currency risk. Furthermore, other research, such as Fehle and Tsyplakov (2005), points out that companies far from or deep into financial distress are less prone to initiate or change risk management instruments, while firms that are between these two extremes do. This basically can turn into a spiralling effect for financially distressed companies, which are disadvantaged of not using risk management instruments, hence making their position relatively worse and worse as time progresses. The possible problem with the Altman model, when applied to the UK, would be that the Altman model could understate the expected time until bankruptcy[3]. While the Altman model didn't take this aspect into account, the UK model will be adjusted appropriately. As will be seen later, this adjustment will be done implicitly due to the external financial and economic characteristics of the firms in the datasets. Another point that could be made in this sphere is that the grey zone[4] becomes greyer. As noted earlier, firms which use risk management instruments, more specifically managing foreign currency risk, have a lower possibility of default. Thus there could be some firms managing foreign currency risk who, according to Altman's model (which doesn't take into account risk management instruments), should have gone bankrupt but in reality aren't. Hence this process of potentially increasing the misclassification range corresponds to the aforementioned analogy of the grey zone getting greyer.

To summarize, the suggestion put forth above is constructing a model which would take account of these potential issues. This would basically mean constructing a model capable of taking into account the specific accounting and financial characteristics of the UK. In itself the Altman Z-score model is probably, as said before, influenced by US specific characteristics which in turn can

[2]It should be noted here that nonsense refers to the overstated/understated inputs causing a faulty output.

[3]This assumption is based on the following stream of thought: if the downward spiral would take place these firms would be hit by a multiplier effect. The more the firm stays in this spiral, the faster it would go downward performance-wise. So while the Altman model would still predict a correct classification at the very moment it is calculated, the moment a firm is hit by the multiplier effect its lifespan would be different than initially predicted.

[4]The grey zone or also brilliantly referred to as "zone of ignorance" by Altman (1968), is that range of Z-scores where misclassifications can be observed.

potentially not represent the UK firms to the fullest extent. To this end the UK model is proposed since it will extend upon the Altman model by strengthening it through elimination of the underlying US/UK divergence problems. While the divergence from the first look is not dramatic, it is nevertheless present and simply using the existing Altman Z-Score model on UK firms one would fall victim to potential external validity issues. Hence, the outcome of this paper will be a UK specific Altman Z-score model. To the best of my knowledge, such a model does not currently exist at the time of writing this paper. The proposed UK model will contribute to the existing literature by not only taking into account the divergence problems, but also taking on and modelling some of the criticism hurled at Altman's original model. Hence, the UK model will serve as a strengthened Altman Z-score bankruptcy prediction model specifically calibrated for the UK[5].

2.3 Alternative approach

Since the Altman Z-score model much research has been performed in the field of corporate bankruptcy, more specifically bankruptcy prediction. First, Deakin (1972) proposes an alternative model for predicting bankruptcy having a lead time[6] of three years. After this, the study of Wilcox (1973) presents a lead time of four years by empirically replicating a test similar to the one of Beaver (1966). An especially prominent paper by Merton (1974) concerns the theory of the risk structure of interest rates and is a foundation for many papers. Furthermore, contributing to the field of corporate bankruptcy is an interesting paper by Bharath and Shumway (2008) which assesses the accuracy and contribution of the Merton DD model which is based on the aforementioned Merton paper[7]. Moreover, in an insightful paper, Libby (1975) presented the results of a field study jointly assessing the predictive power of ratio information and the ability of users of it to interpret this data in a business failure prediction framework. Furthermore, an interesting paper by Altman and Loris (1976) uses a quadratic discriminant analysis in the determination of an early warning system, called FEWS (Financial Early Warning System). Using this system, potential problematic broker-dealer organizations can be detected before failure. With the

[5]For an excellent parallel model and discussion considering Japan, namely the Japan Altman Z-score, see Gurău (2013).

[6]Here lead time refers to the amount of years in advance a model can predict business failure.

[7]They found that the functional form suggested by the Merton model is useful for forecasting defaults.

knowledge of the aforementioned studies, Ohlson (1980) attempted an alternative approach to bankruptcy prediction modelling. Instead of utilizing MDA, Ohlson used a conditional logit model to provide probabilistic predictions of business failure. Indeed, the field of bankruptcy prediction is constantly evolving, especially around financially turbulent times where its models are warranted and desirable. In line with this academic progress, some studies in the nineties presented an interesting point of view where neural networks were used in a bankruptcy prediction setting (Tam, 1991; Wilson & Sharda, 1994)[8].

While Altman (1968) is one of the most frequently quoted papers when it comes down to corporate bankruptcies, it is also a paper that has received criticism. Some of the relevant criticism is presented in the remainder of this subsection. A paper, put forth by Shumway (2001), develops a hazard model and exerts critiscism against Altman. Furthermore, another paper, presented by Campbell, Hilscher, and Szilagyi (2011), follows a similar line of reasoning as Shumway, but outperforms Shumway and extends upon it by also applying their method to portray an interesting evaluation of the underperformance of distressed stocks. Their roughly aggregated critique against Altman's paper is concerning the modelling and the ratios employed. The first criticism is the modelling aspect where they advocate that hazard models are more appropriate than static models in bankruptcy prediction. They point out that by using a hazard model all information is processed in estimating the bankruptcy assessment, because the hazard model can take into account year to year changing financials of firms and each firm's period at risk. While these are interesting points, there are some shortcomings to the hazard model that may call into question the case they have against Altman.

More specifically as put forth by Balcaen and Ooghe (2004), there are two relevant disadvantages of the hazard model. The first one is that hazard models are vulnerable to the issue of multicollinearity, as stated by Balcaen and Ooghe (2004), and that one should avoid strong correlations (Lane, Looney, & Wansley, 1986). As can be seen from Appendix B (Table 8), there are some strong correlations. The second disadvantage is the timing specifics during the modelling. Applying a hazard model one implicitly assumes that the reporting date of the annual reports is considered as the natural starting point of bankruptcy (Luoma & Laitinen, 1991).

The second criticism is lodged against the ratios employed by Altman. They

[8]While in the former study the focus is set solely on the prediction of bank bankruptcy, the latter model, also using neural networks, focuses on firm bankruptcies.

advocate the use of more market-driven ratios and Shumway, for example, even proposes some that according to his paper are more significant in predicting bankruptcy. While it is an interesting point that can be evaluated further in a Z-score setting, this paper focusses on replicating Altman's model for the UK. Meaning that this paper calibrates the exact same variables the business world is accustomed to as a first step, but nevertheless advocates that further steps should be taken as further research.

3 Theoretical Framework

In the first part of the previous section, several studies were presented that utilized ratio analysis. These studies emphasized their contribution in such a way that they focused on individual signals contributing to bankruptcy. While their contributions are significant, these studies are univariate in nature and one may question to what extent they should be used. Their individual step-wise univariate approach is questionable because it is vulnerable to not capturing the full effect in terms and possible interaction between the individual variables. Nevertheless, this paper recognizes their significance by appropriately extending upon their findings through modelling their measures. Hence this paper builds a model where their individual work is emphasized in a group setting. This basically means utilizing their research by analysing their individual ratios simultaneously. To achieve this type of multivariate modelling one has to determine the specific multivariate modelling approach to use and evaluating this model theoretically within this particular setting by contrasting potential advantages and disadvantages.

3.1 Modelling approach

In achieving the above advocated modelling, this paper implicitly questions the univariate methodology by presenting a multivariate approach to the traditional ratio analysis. The specific type of multivariate approach employed is the multiple discriminant analysis (MDA)[9]. MDA is a statistical technique classifying observations, based on their individual characteristics, into one of beforehand specified groups. It has a large potential in the bankruptcy prediction field and, as is observable from the literature review, MDA and similar models became rather popular in a bankruptcy prediction setting since the publication of

[9]This approach is successfully used by Altman (1968) and replicated in this paper.

the Altman (1968) paper[10]. Moreover, MDA is a versatile modelling technique which is easily applicable to many sciences[11]. Furthermore, MDA is particularly used when prediction is warranted for a qualitative dependent variable consisting of two or more, a priori determined, groups (paper specific: predictively allocating firms based on their ratios as either bankrupt or non-bankrupt).

To construct this MDA model several steps have to be taken. First, as was shortly mentioned before, explicit groups have to be formed. This paper considers 2 mutually exclusive groups, or more specifically group classifications, namely bankrupt and non-bankrupt. Second, data has to be collected composed of bankrupt and non-bankrupt observations of firm financials. Third, MDA then attempts to establish a linear combination, an equation, which minimizes the probability of misclassifying firms into one of the two above mentioned groups. This equation can then be used to classify, with a certain accuracy, firms into one of the two group classifications. The output of the equation is a Z-score of the following linear form[12]:

$$Z = \alpha + v_1 X_1 + v_2 X_2 + v_3 X_3 + ... + v_n X_n \tag{1}$$

where,

$Z =$ discriminant score

$\alpha =$ the constant

$v_j =$ discriminant coefficient

$X_j =$ independent variable

and where $j = 1, 2, 3 ... n$

[10] It should be noted though that while MDA was relatively unpopular in the field of bankruptcy prediction, it was already utilized in a financial setting. More precisely, it was already applied in consumer credit evaluation and investment classification, as can be seen from (Durand, 1941; Myers & Forgy, 1963) and Smith (1965), respectively.

[11] For example, taxonomic problems were approached by the use of MDA as is observable from Fisher (1936). For an excellent re-cap of studies utilizing MDA see Cochran (1964).

[12] The variables have the same letters as the Altman paper for simplicity and consistency. Furthermore, the theoretical model has a constant, but as Altman (2000) mentions, the statistical package used in this paper causes a constant, standardizing the later mentioned cut-off score at zero (if sample sizes of the two groups are the same).

3.2 Theoretical evaluation

The theoretical evaluation regarding the use of MDA is presented in the remaining part of this section. The first advantage of using MDA is the discriminating ability inherent in the approach itself. In terms of this paper, it allows one to discriminate, with a certain accuracy, between bankrupt and non-bankrupt firms. A second advantage of using MDA is its multivariate approach. While the univariate approach considers the firm characteristics individually, MDA considers the characteristics simultaneously as well as capturing their interaction. This allows MDA to eliminate potential misclassifications and ambiguities which were present in the above discussed traditional academic works. An additional advantage of using MDA in this setting is the reduction of the user's space dimensionality. It is basically reduced from the amount of independent variables to $G - 1$, where G represents the number of beforehand determined groups[13]. Thus, the amount of dimensions is estimated at 1 since this paper considers G to be 2 (bankrupt and non-bankrupt). While this approach has its upsides, a potential downside lies hidden in the variable selection process. One may advocate that the list of variables analysed might have an underlying problem of correlation or (multi)collinearity. On the one hand, this may seem as a disadvantage where the researcher has to be extra careful in selecting the variables. On the other hand, the disadvantage can turn into an advantage: if correctly performed, the model can yield a relatively small amount of variables which has the possibility of revealing a lot of information. In conclusion, reviewing the aim of this paper, the nature of the problem, the above mentioned advantages and the potential disadvantage, MDA is chosen as the most suitable statistical technique for this research[14].

4 Data

This section discusses the theoretical aspects and practical methodology employed in the data selection. The theoretical aspects of data selection employed for the most part in this paper follow very closely the paper by Altman (1968), while in other parts necessary deviations are present. The sample selection process starts with assessing and fulfilling the requirements of the model. The

[13] For the mathematical computations and steps taken to arrive at this point refer to (Bryan, 1951; Rao, 1952).

[14] An alternative approach is utilizing a multiple regression analysis. While theoretically it could be used in this setting, it should be very carefully designed and interpreted.

model requires a dataset to be composed of an equal number of bankrupt and non-bankrupt firms over a certain time period with fundamental data for every point in time. The first step would thus be getting the names of public manufacturing firms that went bankrupt and still operate for the period 2000-2011. This specific period was chosen as it captures a full business cycle[15] and probably incorporating the effect that the European Union might have had.

4.1 Data requirements

Having decided upon the time period the next step is assessing the data requirements. The data requirements will present themselves as financial and economic requirements needed when analysing corporate bankruptcy. As seen from the aforementioned studies there is a high amount of significant variables indicating firm problems. Altman (1968) considered five ratios jointly doing the best job in bankruptcy prediction, which belonged to the following categories: liquidity, profitability, leverage, solvency, and activity. Since this paper calibrates the model advocated by Altman, the variable selection is in line with Altman's paper. Thus, the discriminant function presented in this paper is constructed as follows:

$$Z = \alpha + v_1X_1 + v_2X_2 + v_3X_3 + v_4X_4 + v_5X_5 \quad (2)$$

where,

Z = discriminant score

α = the constant

v_j = discriminant coefficient, where $j = 1, 2, 3, 4, 5$

X_1 = Working capital/Total assets

X_2 = Retained earnings/Total assets

X_3 = Earnings before interest and taxes/Total assets

X_4 = Market value of equity/Total liabilities

X_5 = Sales/Total assets

[15] 2000 being in the midst of the dot-com bubble, with the remaining years being a recovery leading up to the credit crisis in 2008 and with the start of a recovery again in the following years.

4.2 Ratios

X_1 - *Working capital/Total assets.* The first ratio advocated by Altman (1968) is a liquidity ratio. Its numerator, working capital, is the difference between current assets and current liabilities. Thus looking at the variables that this ratio is made of, one may correctly note that this ratio is taking into account liquidity and size aspects. More specifically, it is a liquidity ratio because it reflects the net liquid assets in relation to the total capitalization. The use of this ratio is not only advocated by Altman, but also supported by Merwin (1942) where the net working capital to total assets ratio is the foremost rated indicator of cessation. With this ratio one would expect a negative relation with bankruptcy or a positive relation with non-bankruptcy, as decreasing working capital relative to total assets is a liquidity indicator of operating losses which in turn affects a firm negatively.

X_2 - *Retained earnings/Total assets.* The second ratio advocated by Altman (1968) is a (cumulative) profitability ratio. Interestingly, this is a "new" ratio that was proposed by Altman himself. Next to profitability, age is also taken into account when this ratio is used. The implicitly considered age characteristic of this ratio can be understood better with the example put forth by Altman: A lower *Retained earnings/Total assets* ratio is expected for younger firms because they did not have time to grow and build up their cumulative profits. Hence one may correctly expect that younger firms will, *ceteris paribus*, more probably be classified as bankrupt relative to older firms[16]. With this ratio one would expect a negative relation with bankruptcy or a positive relation with non-bankruptcy, as negative profits, which affect a firm negatively, decrease retained earnings relative to total assets.

X_3 - *Earnings before interest and taxes/Total assets.* The third ratio advocated by Altman (1968) is a solvency ratio. Insolvency takes place, from a bankruptcy point of view, when the total liabilities are higher than the fair valuation of a company's assets, with value established by the earnings power of the assets. It basically measures the productivity of a company's assets, ignoring leverage and taxes effects. This can be seen when decomposing the ratio to its variables it is built from: the numerator EBIT and the denominator total assets. EBIT in this setting provides the earnings power assessment of the assets, which is a determinant of a company's ultimate existence. Hence this

[16]While this may be seen as more discriminating against younger firms, it is exactly the point. In the early years of a firm, the tendency of failure is greater as shown by Dun&Bradstreet (1966).

ratio can be appropriately used in assessing a firm's continuation. With this ratio one would expect a negative relation with bankruptcy or a positive relation with non-bankruptcy, as decreasing EBIT relative to total assets is a solvency indicator of decreasing earnings power of the assets which in turn affects a firm negatively.

X_4 - *Market value of equity/Total liabilities.* The fourth ratio advocated by Altman (1968) is a leverage ratio. This ratio can be broken down into its variables: liabilities and market value of equity, which is calculated as the total market value of all shares of stock (common and preferred). It basically shows when the firm will become insolvent, in terms of how much a company's value (in terms of market value of equity plus liabilities) can decrease before the company value will be exceeded by liabilities. This can be explained by the following example: if a firm has liabilities of £1 million and a market value of equity of £5 million, it can endure a five-sixth decrease in value before insolvency. Albeit, a firm with an equity value of £500 thousand and liabilities of £1 million could endure a one-third decrease in value before insolvency. With this ratio, one would expect a negative relation with bankruptcy or a positive relation with non-bankruptcy, as decreasing market value of equity relative to total liabilities is a leverage indicator of decreasing solvency which in turn affects a firm negatively.

X_5 - *Sales/Total assets.* The fifth ratio advocated by Altman (1968) is an activity ratio. This ratio, usually employed by management, is key in handling competitive situations and reflects the sales yielding capability of a company's assets. With this ratio one would expect a negative relation with bankruptcy or a positive relation with non-bankruptcy, as decreasing sales to total assets is an activity indicator of decreasing sales which in turn affects a firm negatively.

4.3 Data gathering

Having established the needed ratios, the next step is gathering the specific firm names. Using the Bloomberg Terminal[17], a data output of bankrupt and non-bankrupt UK public manufacturing firm names, ranging from 2000 to 2011, is created. Since this paper matches non-bankrupt firms to bankrupt firms, bankrupt firms are used for determining the final amount of non-bankrupt firms.

[17] For this step and any data requirement henceforth, a Bloomberg Terminal has been used to gather the data, unless stated otherwise. The reason for just using the Bloomberg Terminal in this paper is in order to simplify the usage of the UK model to most financial firms, as most of them if not all have access to a Bloomberg Terminal. Hence by using it, this paper converges to a maximum possible extent to the financial industry.

The raw number of UK public manufacturing firms that went bankrupt during the above period, as provided by the Bloomberg Terminal, equals 58. Furthermore, the number of active public UK manufacturing firms over all these years, as provided by the Bloomberg Terminal, amounts to 1173.

After gathering the names of the firms, the next step is gathering the balance sheet data. Due to the reporting style of the data source, the fundamental data is at year-end. This means that if a firm went bankrupt, the fundamental data employed is the last fundamentals reported by the firm, taken at year-end. After compiling a dataset for both bankrupt and non-bankrupt firms a data-cleaning step is undertaken to ensure the matching process is efficient. The data-cleaning entailed removing bankrupt firms that either are missing essential data or have no data at all. This step decreased the number of bankrupt firms to 42. The next step is matching the non-bankrupt firms to the bankrupt ones.

To match the firms a stratified random sampling procedure is applied. This procedure is chosen because it allows for random sampling at *a priori* determined requirements. The firms are stratified by year, allowing non-bankrupt firms to be matched to bankrupt firms in the latest reporting period provided by the bankrupt firms. Thus, it takes the current macro-economic sentiment into account affecting firms industry wide. Hence, developing the model by discriminating between the bankrupt and non-bankrupt firms during the same reporting period, does not omit the potential effect the economy has on a certain firm's fundamentals. After stratified random sampling the firms[18], the final sample size measured 35 bankrupt and 35 matched non-bankrupt firms, summing up to a total of 70 firms which are presented in Appendix A (Table 7).

5 Model Development and Empirical Results

This section starts by pre-testing the individual ratios, then develops the final UK model and finally performs some validation tests on the UK model.

5.1 Pre-modelling

Adhering to the testing sequence of Altman (1968), the first test would be to test for the discriminating ability of the ratios on an individual basis. This is

[18] With a cut-out rate of 1/6 due to the low number of bankrupt firms.

done by performing an analysis of variance (ANOVA) F-test. The F-test allows for a test on the equality of variances. More specifically, its hypotheses are:

H_0 : All means are equal

H_1 : At least one mean is different from the others

Looking at the hypotheses would allow to statistically test whether, per ratio, the means in bankrupt and non-bankrupt firms differ or not. This would allow for inferences about their individual discriminating ability. While the full-fledged statistical output concerning the F-test is presented in Appendix B (Table 10), a summary is presented in the following table:

Table 1: F-test summary table

Variables	F-statistics
X1	12.736**
X2	6.350*
X3	5.048*
X4	4.607*
X5	1.097

* Significant at the 0.05 level.

** Significant at the 0.01 level.

As can be seen from the table above, the results are very similar to Altman (1968) in terms of which variables are significant. Ratios X_1 to X_4 are all individually significant at the 5% level, with X_1 being significant at the 1% level, meaning that the null hypothesis of all means are equal is rejected for each variable individually[19]. Furthermore, X_5 is insignificant even at the 5% level, meaning that the null hypothesis of all means are equal cannot be rejected.

[19] A significance level of 5% is used throughout this entire paper.

5.2 Model building

After performing all necessary steps in SPSS, the following equation reflects the final UK model:

$$(3) \quad Z = -0.381 + 1.136X_1 + 0.022X_2 + 0.247X_3 + 0.017X_4 + 0.014X_5$$

where,

Z = discriminant score

X_1 = Working capital/Total assets

X_2 = Retained earnings/Total assets

X_3 = Earnings before interest and taxes/Total assets

X_4 = Market value of equity/Total liabilities

X_5 = Sales/Total assets

The model above contains the calibrations necessary for it to be effectively used in the UK. It is usable specifically for public UK manufacturing firms. The model has all of its ratio variable coefficients being positive, leading to an inference that the larger the output the less likely bankruptcy becomes. This can be seen by looking at the reasoning in the previous section, concerning the theoretical expectations of individual variables[20]. While the ratio variable coefficients are positive, the constant is negative. This is most probably a statistical requirement that may have occurred in order to standardize the cut-off score at zero.

After having established the coefficients of the model, the next step is checking the significance of the UK model. To this end a type of F-test of mean differences is employed, more specifically Wilks' lambda. It is a measure of the ability of the model to separate cases (individual firms) into groups (bankrupt vs. non-bankrupt). The eventually calculated lambda value will range between 0 and 1, and the lower the lambda the higher the discriminatory ability of the model. To be more specific: a value of 0 means that means differ, while a value of 1 means that means are the same. After performing the necessary steps in SPSS, the full output is presented in Appendix B (Table 11) and the following

[20] See Section 4.2, where the ratio variables are examined theoretically on an individual level.

table summarizes the findings:

Table 2: Model significance: Wilks' lambda

Wilks' lambda	Chi-square	Degrees of freedom	Significance
0.827	12.473	5	0.029

The table above is a practical representation of the aforementioned theoretical explanation of Wilks' lambda. The first column of the table represents the value of Wilks' lambda, which in this case is 0.827. While at the first look this may look relatively high, one should also take into account the accompanying Chi-square test with its corresponding degrees of freedom. When taken together, the final conclusion concerning the significance of the model is that the model is significant at the 5% significance level.

The following practical step would be determining the range where misclassification may occur. The rationale behind this is providing a cut-off for the UK Z-score which enables it, up to a certain point, to be generalized. The cut-off is a range where above it means the firm is rather improbably facing bankruptcy. Below the cut-off range would mean that bankruptcy in the following year is very probable. And finally, within the range is the "zone of ignorance". This "grey zone" is determined with the use of the MDA model centroids, which are:

Table 3: Group centroids

Status	Centroids
Bankrupt	-0.451
Non-bankrupt	0.451

By using the centroids one can establish "checkpoints" to spot individual Z-scores that pass them. Once a Z-score of a certain firm in the sample passes these "checkpoints", it becomes marked. In order to be marked, the firms' Z-scores have to pass it in a negative direction, meaning that bankrupt firms with Z-scores above their centroid and non-bankrupt firms with Z-scores below their centroid become marked. Out of all these marked firms the minimum and maximum Z-score are taken, which then represent the lower and upper bound of the range of the "grey zone", respectively. Utilizing this process, the "grey zone" of the UK model is represented by the following range: $[-1.57, 1.46]$.

5.3 Post-modelling tests

The final step in this section is assessing the predictive power of the model. In order to achieve this, three testing environments are created. These environments include: 1) testing the model in the initial sample, 2) testing the predictive power of the Altman (1968) model in the UK sample, 3) testing a new and excellent model for Japan put forth by Gurău (2013) in the UK sample. The first environment is created to test the predictive power of the model in the initial setting. Within this environment one tests the power of the UK model in predicting bankruptcies in a UK setting. With the second environment one tests the power of the Altman Z-score model in predicting bankruptcies in a UK setting. Finally, with the third environment, one tests the power of the Gurău Japan model in predicting bankruptcies in a UK setting. These environments are discussed individually in the order in which they are initially presented above.

The first environment assesses the predictive power of the UK model. This testing environment uses the initial sample while employing the UK model with its corresponding range criterion. The environment takes all firms in the UK sample and calculates their individual UK model Z-scores. Then using the range criterion obtained above these firms are then classified to a predicted status as either bankrupt (B) or non-bankrupt (NB). Finally, the predicted statuses are compared to the actual statuses and the findings are summarized in the following table:

Table 4: Validation test: initial sample

		Predicted	
		B	NB
Actual	B	30	5
	NB	8	27

	Correct	Total	% Correct	% Error
Type I	30	35	85.7%	14.3%
Type II	27	35	77.1%	22.9%
Total	57	70	81.4%	18.6%

As can be seen from the table above, the percentage of correctly classified firms is 81.4 percent. Furthermore, the percentage of correctly classified bankruptcies is 85.7 percent, while the percentage of correctly classified non-bankruptcies is 77.1 percent. These numbers are relatively high when compared to the other environments, while the Type I and II errors are relatively small compared to the other environments. This indirectly confirms that the UK model truly outperforms the original Altman Z-score and the Gurău Japan model in terms of classifying UK public manufacturing firms, for the given dataset.

The second environment assesses the predictive power of the Altman Z-score model, put forth by Altman (1968), within a UK setting. This testing environment uses the initial sample while employing the Altman Z-score model with its corresponding range criterion. The environment takes all firms in the UK sample and calculates their individual Altman Z-scores. Then using Altman's range criterion these firms are then classified to a predicted status as either bankrupt (B) or non-bankrupt (NB). Finally, the predicted statuses are compared to the actual statuses and the findings are summarized in the following table:

Table 5: Validation test: Altman (1968) model

		Predicted	
		B	NB
Actual	B	28	7
	NB	31	4

	Correct	Total	% Correct	% Error
Type I	28	35	80%	20%
Type II	4	35	11.4%	88.6%
Total	32	70	45.7%	54.3%

As can be seen from the table above, the percentage of correctly classified firms is 45.7 percent. Furthermore, the percentage of correctly classified bankruptcies is 80 percent, while the percentage of correctly classified non-bankruptcies is 11.4 percent. These numbers are relatively lower compared to the first environment, while the Type I and II errors are relatively larger compared to the first environment. This indirectly confirms that the UK model truly outperforms the original Altman Z-score in terms of classifying UK public manufacturing firms, for the given dataset.

The third environment assesses the predictive power of the Gurău Japan model, put forth by Gurău (2013), within a UK setting. This testing environment uses the initial sample while employing the Japan model with its corresponding range criterion. The environment takes all firms in the UK sample and calculates their individual Japan model Z-scores. Then using Gurău's range criterion these firms are then classified to a predicted status as either bankrupt (B) or non-bankrupt (NB). Finally, the predicted statuses are compared to the actual statuses and the findings are summarized in the following table:

Table 6: Validation test: Gurău (2013) model

		Predicted	
		B	NB
Actual	B	4	31
	NB	6	29

	Correct	Total	% Correct	% Error
Type I	4	35	11.4%	88.6%
Type II	29	35	82.9%	17.1%
Total	33	70	47.1%	52.9%

As can be seen from the table above, the percentage of correctly classified firms is 47.1 percent. Furthermore, the percentage of correctly classified bankruptcies is 11.4 percent, while the percentage of correctly classified non-bankruptcies is 82.9 percent. When analysing by checking the totals, the number of correctly classified bankruptcies is relatively lower compared to the first environment, while the total error is relatively larger compared to the first environment. This indirectly confirms that the UK model outperforms the Japan model in terms of classifying UK public manufacturing firms, for the given dataset.

6 Conclusion

6.1 Concluding remarks

The goal of this paper was calibrating the Altman Z-score model to UK data. First, the model was re-estimated using UK data. Having performed the necessary statistical steps, the paper presented a final discriminant model. This model has a goal of discriminating to the best extent between bankrupt and non-bankrupt public UK manufacturing firms. The model in itself is linear, which allows for it to be fairly easy comprehended. The model is built up of ratios that can be readily taken out from either balance sheet data or advanced data service providers. Furthermore, the UK model is also calibrated, to a certain extent, to the recent tumultuous financial period. By discriminating and calibrating to the type of financials that are present in a full business cycle, the model is up to a certain point robust to potential volatile economic sentiments. Hence the UK model can be used to predict corporate bankruptcy for public UK manufacturing firms during crisis and non-crisis periods, one year prior to bankruptcy. Then, secondary tests were performed for reliability and predictive power. The UK model outperforms the other alternative models (Altman and Japan) and its usage is advocated when analysing the default likelihood of companies working under a UK setting. Finally, the empirical evidence shows a remarkable support for the calibrated model and advocates its usage to companies operating in or working under the financial and accounting conditions of the UK. It should be clear that this model is not to be used solely when analysing company default, but it should be used rather as an addition to other models. This should be clear though, as this model, like any other model in its field, is meant as a support in analyses of company malaises and not as a *panacea*.

6.2 Limitations

While this paper tries to fulfil many aspects and requirements of firm bankruptcy analysis, there are some limitations to the work performed. First, there is the number of bankrupt firms. As this paper mainly used the Bloomberg Terminal to gather data, to maximize convergence to the financial industry as was mentioned before, the extent to which data was available was limited. The number of bankrupt firms could have been larger by utilizing more data sources readily available to the potential end-users of this model. But as funds and sources were limited, this paper had some data restrictions. The suggestion for further research would be to increase the number of data sources. Second there is the aspect of not having available the full financials of some companies. While, as was shown, some companies were identified as bankrupt, they were nevertheless missing data. This lack of data was in the form of missing ratio inputs and these companies had to be removed. Furthermore, some validation techniques could not be properly used due to the missing data. A possible solution that can be taken into account in further research is triangulating needed data by increasing the number of data sources readily available to the potential end-users of this model. A third limitation would be the type of software employed. This paper tried to replicate the original Altman (1968) model as much as possible, but the statistical software used barred it from replicating the model exactly. While the UK model does theoretically and to a certain extent statistically replicate the Altman Z-score model, there is a minor difference in the modelling. The Altman model did not have a constant, but as stated by Altman (2000), this is due to a divergence in the statistical package employed. If further research aims to perfect the UK model, in terms of replicating the original model to the maximum extent, then another statistical package should be experimented with. A fourth limitation is the type of companies analysed. In this paper the analysis was performed on public UK manufacturing firms. Further research could be performed on either privately held companies, or by trying to make the model work for other type of companies. A fifth limitation where future research could expand upon is the depth to which this analysis is done. While this paper tried to replicate the Altman model, future research could venture off further than this. Further research could perhaps focus more on the other, not analysed, ratios or even build UK specific ratios, if such could be created and deemed necessary.

References

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, *23*(4), 589–609.

Altman, E. I. (2000). Predicting financial distress of companies: Revisiting the Z-score and ZETA models. *Stern School of Business, New York University*.

Altman, E. I., & Loris, B. (1976). A financial early warning system for over-the-counter broker-dealers. *The Journal of Finance*, *31*(4), 1201–1217.

Balcaen, S., & Ooghe, H. (2004). Alternative methodologies in studies on business failure: Do they produce better results than the classical statistical methods? *Vlerick Leuven Gent Management School Working Papers*(16).

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research*, 71–111.

Bharath, S. T., & Shumway, T. (2008). Forecasting default with the Merton distance to default model. *Review of Financial Studies*, *21*(3), 1339–1369.

Bryan, J. G. (1951). The generalized discriminant function: Mathematical foundation and computational routine. *Harvard Educational Review*, *21*(90-95), 125–126.

Campbell, J. Y., Hilscher, J. D., & Szilagyi, J. (2011). Predicting financial distress and the performance of distressed stocks. *Journal of Investment Management*.

Cochran, W. G. (1964). On the performance of the linear discriminant function. *Technometrics*, *6*(2), 179–190.

Deakin, E. B. (1972). A discriminant analysis of predictors of business failure. *Journal of Accounting Research*, *10*(1), 167–179.

Dun&Bradstreet. (1966). *The failure record through 1965: A comprehensive failure study by location, by industry, by age, by size, by cause.* Dun & Bradstreet, Incorporated.

Durand, D. (1941). Risk elements in consumer installment lending. *Studies in Consumer Installment Financing*, *8*, 105–142.

Fehle, F., & Tsyplakov, S. (2005). Dynamic risk management: Theory and evidence. *Journal of Financial Economics*, *78*(1), 3–47.

Fisher, R. A. (1936). The use of multiple measurements in taxonomic problems. *Annals of Eugenics*, *7*(2), 179–188.

Foulke, R. A. (1961). *Practical financial statement analysis* (5th ed.). McGraw-Hill.

Gurău, T. (2013). *A model of bankruptcy prediction: calibration of Altman's Z-score for Japan.* (Bachelor Thesis, Erasmus University Rotterdam, Erasmus School of Economics)

Hickman, W. B. (1958). *Corporate bond quality and investor experience.* Princeton University Press.

Lane, W. R., Looney, S. W., & Wansley, J. W. (1986). An application of the Cox proportional hazards model to bank failure. *Journal of Banking & Finance*.

Libby, R. (1975). Accounting ratios and the prediction of failure: Some behavioral evidence. *Journal of Accounting Research*, *13*(1), 150–161.

Luoma, M., & Laitinen, E. K. (1991). Survival analysis as a tool for company failure prediction. *Omega*.

Marin, M. (2013). Can financial risk management help prevent bankruptcy? *Journal of Finance and Accountancy*, *12*, 1–18.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance*, *29*(2), 449–470.

Merwin, C. L. (1942). *Financing small corporations in five manufacturing industries, 1926-36.* NBER.

Myers, J. H., & Forgy, E. W. (1963). The development of numerical credit evaluation systems. *Journal of the American Statistical Association*, *58*(303), 799–806.

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*, *18*(1), 109–131.

PriceWaterhouseCoopers. (2005, August). *Similarities and differences - A comparison of IFRS, US GAAP and UK GAAP.*

Rao, R. C. (1952). *Advanced statistical methods in biometric research.* John Wiley & Sons, Inc., New York and Chapman & Hall, Ltd., London.

Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model. *The Journal of Business*, *74*(1), 101–124.

Smith, K. V. (1965). Classification of investment securities using MDA. *Institute Paper*, *101*.

Tam, K. Y. (1991). Neural network models and the prediction of bank bankruptcy. *Omega*, *19*(5), 429–445.

Tamari, M. (1966). Financial ratios as a means of forecasting bankruptcy. *Management International Review*, *6*(4), 15–21.

Wilcox, J. W. (1973). A prediction of business failure using accounting data. *Journal of Accounting Research*, *11*, 163–179.

Wilson, R. L., & Sharda, R. (1994). Bankruptcy prediction using neural networks. *Decision Support Systems*, *11*(5), 545–557.

Winakor, A., & Smith, R. (1935). Changes in the financial structure of unsuccessful industrial corporations, bulletin no. 51. *Bureau of Business Research, University of Illinois*.

A Appendix

The following table shows the names and ticker symbols of, respectively, the bankrupt and non-bankrupt firms used in this paper:

Table 7: Firm names and ticker symbols

Bankrupt		Non-Bankrupt	
Ticker	Name	Ticker	Name
0624470D LN Equity	EAGLE-I HOLDINGS	ADB PZ Equity	ADNAMS PLC-CL B
2967759Q LN Equity	ASW HOLDINGS	AKT LN Equity	ARK THERAPEUTICS
582427Q LN Equity	ALBERT FISHER	ANTO LN Equity	ANTOFAGASTA PLC
ACR LN Equity	ABBEYCREST PLC	ATD LN Equity	BIOSEEK PLC
AER LN Equity	AERTE GROUP PLC	AVCT LN Equity	AVACTA GROUP PLC
AXE LN Equity	AXEON HOLDINGS	BVS LN Equity	BOVIS HOMES GRP
BSLA LN Equity	BLACKS LEISURE	BWY LN Equity	BELLWAY PLC
CDE LN Equity	CONDER ENVIRON	CDY LN Equity	CASDON PLC
CLPTQ US Equity	CELLPOINT INC	CGS LN Equity	CASTINGS PLC
CUS LN Equity	CUSTOMVIS PLC	CHH LN Equity	CHURCHILL CHINA
CVE LN Equity	CULVER HOLDINGS	CRA LN Equity	CORAC GROUP PLC
DNK LN Equity	DANKA BUS SYSTEM	GFM LN Equity	GRIFFIN MINING
ELT OF Equity	ELTON GAMES LTD	GLE LN Equity	GLEESON (MJ) GP
EPI GR Equity	EMISSION & POWER	HSM LN Equity	HEATH (S) & SONS
ETE LN Equity	EURO TELECOM PLC	IMM LN Equity	IMMUPHARMA PLC
EVOP PZ Equity	EVERGREEN OIL PL	JEL LN Equity	JERSEY ELECTRICI
FIH LN Equity	FISH PLC	MGNS LN Equity	MORGAN SINDALL G
FOS LN Equity	FORTRESS HLDGS	MPE LN Equity	M P EVANS GROUP
GTON LN Equity	GARTON ENGINEER	NAR LN Equity	NORTHAMBER PLC
HAMP LN Equity	HAMPSON INDS	OXB LN Equity	OXFORD BIOMEDICA
HLL LN Equity	HILL STATION PLC	RNWH LN Equity	RENEW HOLDINGS
HRD LN Equity	HARDY AMIES PLC	ROR LN Equity	ROTORK PLC
IDD LN Equity	ID DATA GROUP PL	SCE LN Equity	SURFACE TRANSFOR
LAN LN Equity	LAND OF LEATHER	SIA LN Equity	SOCO INTL PLC
LGM LN Equity	LONGMEAD GROUP	SMJ LN Equity	SMART & CO CNTRC
MDX LN Equity	MELDEX INTERNATI	SNG LN Equity	SYNAIRGEN PLC
MIC LN Equity	MICAP PLC	SPR LN Equity	SPERATI (CA)
NGG LN Equity	NEXTGEN GROUP PL	TFW LN Equity	THORPE (F.W.)
OKD LN Equity	OAKDENE HOMES	TON LN Equity	TITON HLDGS PLC
PLG LN Equity	PLAYGOLF HOLDING	TPS CN Equity	TURBO POWER SYST
PLM LN Equity	PLASMON PLC	TW/ LN Equity	TAYLOR WIMPEY PL
RVA LN Equity	RENOVA ENERGY PL	WNS LN Equity	WENSUM COMPANY
SCK LN Equity	SNACKHOUSE PLC	WODA LN Equity	WOOD (ARTHUR)LON
VDS LN Equity	VIVIDAS GROUP PL	WTB OF Equity	WEETABIX LTD-A
WAGN LN Equity	WAGON PLC	WYN LN Equity	WYNNSTAY GROUP

B Appendix

Relevant SPSS output:

Table 8: Pooled Within-Groups Matrices

		X1	X2	X3	X4	X5
Correlation	X1	1.000	.730	.695	.289	-.229
	X2	.730	1.000	.898	-.050	.077
	X3	.695	.898	1.000	-.184	.126
	X4	.289	-.050	-.184	1.000	-.377
	X5	-.229	.077	.126	-.377	1.000

Table 9: Input information: analysis case processing summary

Unweighted Cases		N	Percent
Valid		70	100.0
Excluded	Missing or out-of-range group codes	0	0.0
	At least one missing discriminating variable	0	0.0
	Both missing or out-of-range group codes and at least one missing discriminating variable	0	0.0
	Total	0	0.0
Total		70	100.0

Table 10: Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
X1	.842	12.736	1	68	.001
X2	.915	6.350	1	68	.014
X3	.931	5.048	1	68	.028
X4	.937	4.607	1	68	.035
X5	.984	1.097	1	68	.299

Table 11: Model significance test: Wilks' lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
UK model	.827	12.473	5	.029

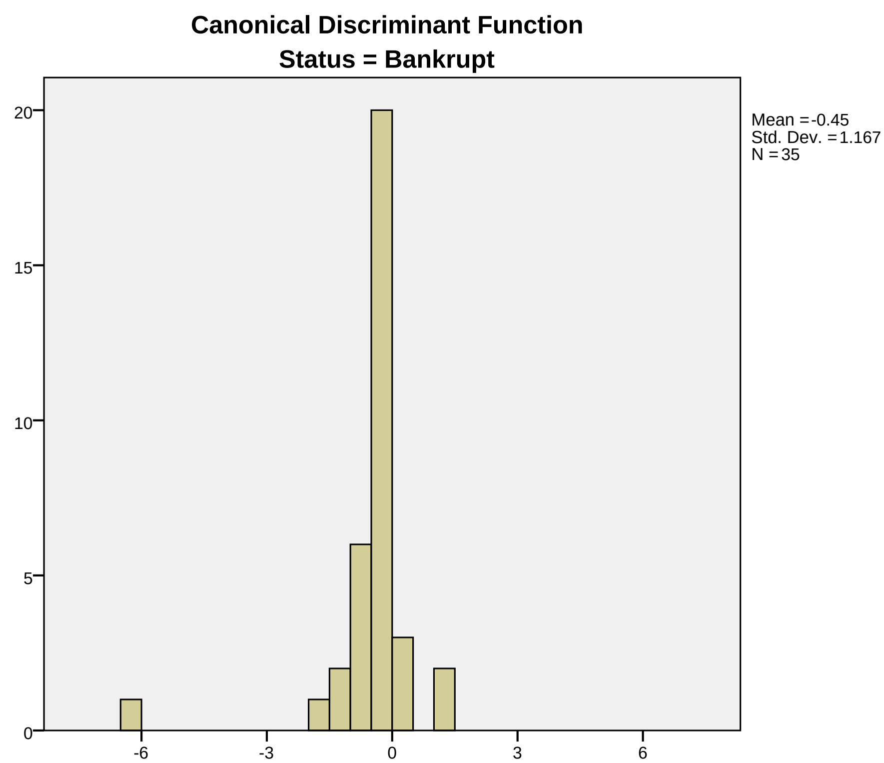
Table 12: Model development: canonical discriminant function coefficients

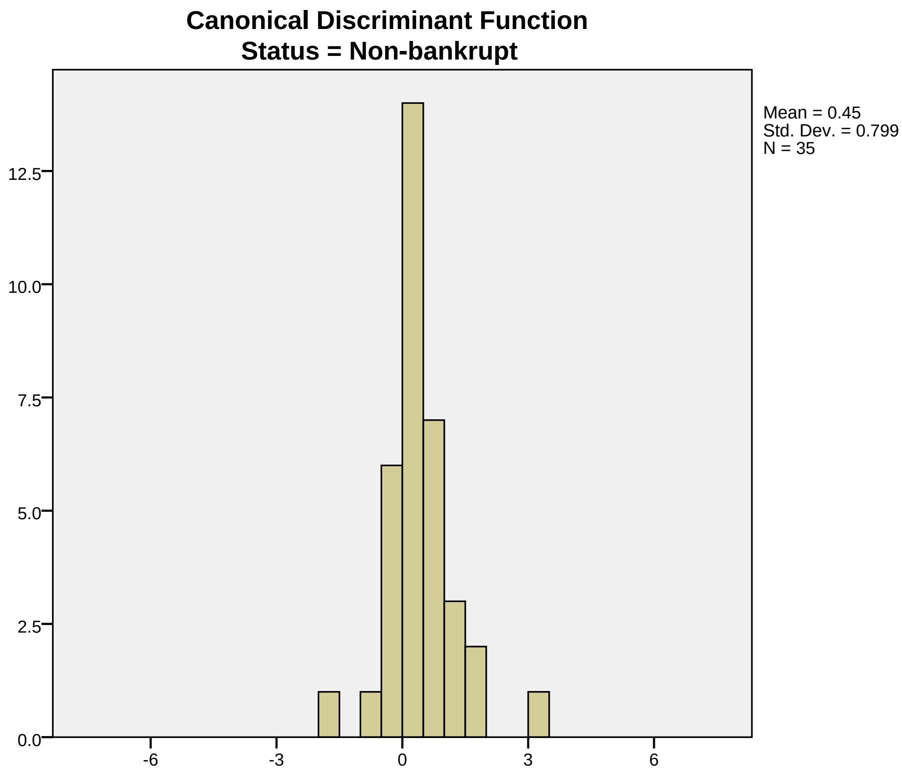
Variables	Coefficients
Working capital/Total assets	1.136
Retained earnings/Total assets	.022
Earnings before interest and taxes/Total assets	.247
Market value of equity/Total liabilities	.017
Sales/Total assets	.014
(Constant)	-.381

Unstandardized coefficients.

Table 13: Descriptive statistics

Status		Mean	Std. Deviation	N	
				Unweighted	Weighted
Bankrupt	X1	-.056218019843065	.780226589560117	35	35.000
	X2	-1.859824944833340	4.052587080859560	35	35.000
	X3	-.272781238183453	.620620775692169	35	35.000
	X4	5.039548660235460	14.695865439580300	35	35.000
	X5	1.098630978064190	.946936706324159	35	35.000
Non-bankrupt	X1	.472654426532880	.399880001986591	35	35.000
	X2	.025862719667876	1.781661382594470	35	35.000
	X3	-.022708241850288	.220035671074815	35	35.000
	X4	16.807779384471100	28.917022757880000	35	35.000
	X5	.866494213925087	.906683631909679	35	35.000
Total	X1	.208218203344907	.670595806131915	70	70.000
	X2	-.916981112582734	3.249417588097930	70	70.000
	X3	-.147744740016871	.479073796911404	70	70.000
	X4	10.923664022353300	23.528313995153100	70	70.000
	X5	.982562595994638	.927682309231961	70	70.000


Canonical Discriminant Function
Status = Bankrupt
20
15
10
5
0
-6
-3
0
3
6
Mean =-0.45
Std. Dev. =1.167
N =35


Canonical Discriminant Function
Status = Non-bankrupt
Mean = 0.45
Std. Dev. = 0.799
N = 35
12.5
10.0
7.5
5.0
2.5
0.0
-6
-3
0
3
6