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A Model of Bankruptcy Prediction: Calibration of Atman's Z-score for Japan

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Abstract

Early warning of financial distress is vital for bankruptcy prediction and the study of bankruptcy risk became of main interest for the various stakeholders of the financially distressed firms. This paper is a follow up of Altman (1968) Z-score, and more precisely a calibration for the Japanese setting. The motivation behind this study is that the model might deviate from the original observations due to the differences. The first difference arises from the accounting and financial divergences between the two countries, and more specifically between the US GAAP and JP GAAP (PriceWaterhouseCoopers, 2005). The second difference is with respect to recent financial developments, such as risk management tools, and differences in corporate governance between the JP and US. In the development of the model, the same methodology as in the original model is followed. Firstly, the model is calibrated for a Japanese setting. Secondly, validation tests are performed in order to assess the reliability and predictability of the model. Finally, the empirical evidence shows support for the calibrated model. Furthermore, it is recommended that the model has to be used only under the financial and accounting conditions of Japan.

Acknowledgements

Hereby, I would like to thank my colleague and good friend Marko Rado (Rado, 2013), for his help and support throughout this paper. The idea behind creating the two models (JP model discussed in this paper and the UK model discusses by Rado (2013)) was to contribute to the great research reputation of Erasmus University Rotterdam. This led to a great collaboration between us. First of all, in order to maximize efficiency and minimize the time loss we both took part in the data gathering process. Furthermore, we also worked together when it came to statistical modelling in SPSS and LaTex programming, both for the aforementioned reasons. It should be noted that the research part as well as the writing part were done on individual basis. While, the structure of the two papers may look alike (in terms of modelling and document output), the work was done on individual basis. The reader should be absolutely certain that the work carried out as well as the results of it are individual.

Furthermore, I want to thank my supervisor Dr. Nico van der Sar, or as Marko and me call him 'the Professor', for his encouragement, guidance and help during this process. Without his positive attitude and encouragement this thesis wouldn't have been possible.

Thank you,
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1 Introduction

Since the bankruptcy of the Compagnia dei Bardi[1] in 1344, the activity of predicting the bankruptcy has endured several changes, which were driven by the owners desire to keep their businesses afloat. Almost 700 years later, this turned out to be an achievable goal.

The recent economical events caused many firms to file for bankruptcy[2] and the study of risk and bankruptcy became of main interest for various stake holders in these firms (Aliakbari, 2009). Before facing this problem on a worldwide scale, the shareholders focus was mainly on minimising the risk, but due to the recent developments, and since bankruptcy affects the financial system by creating a vulnerable atmosphere for the economy, they start seeking ways of forecasting this malaises.

Altman (1968) Z-score is one model that can help the investors foresee the bankruptcy of a certain company. He analysed 33 publicly held US manufacturing bankrupt companies and their corresponding matches[3]. Furthermore, he based his research on five financial ratios: profitability, leverage, liquidity, activity, and solvency ratios, and by running a discriminant analysis on the data, he was able to develop a model that enhances bankruptcy prediction for publicly held US manufacturing companies. His model turned out to be highly significant, but the issue with it is that the model is only applicable for public US manufacturing companies. In order to analyse the Japanese financial environment, to forecast the bankruptcy of Japanese companies, as well as to see if the initial financial ratios are also applicable in this situation, the original Altman (1968) Z-score model must be calibrated. This issue is going to be addressed in this paper by using the same approach and methodology as Altman (1968). Firstly, the JP sample consists of 132 companies (66 bankrupt and 66 non-bankrupt) over a time span of 11 years (2000 - 2011). Secondly, their annual financial statements will be analysed in order to construct the financial ratios needed to perform the analysis. Lastly, in order to calibrate the model for Japan a multiple discriminant analysis will be run on the data. Furthermore, Rado (2013) perfectly calibrated the model for the UK setting.

The paper is structured as followed: Section 2 describes the results of past

[1]The Compagnia dei Bardi was a Florentine banking and trading company.

[2]As mentioned by Ikeda (2012), in Japan there is no aggregated bankruptcy and insolvency code as is in the US, and hence hereafter bankruptcy is refereed to the Bankruptcy Law, The Composition Law, The Corporate Reorganization Law, and The Commercial Code.

[3]The total sample was of 66 companies out of which 33 bankrupt.

research on both ratio analysis and bankruptcy prediction models, as well as the alternative view towards Altman (1968). Furthermore, the contribution of this paper to the existing literature will be discussed in the final part of the section. Section 3 provides an explanation for the theoretical framework used in this paper, and thus the multiple discriminant analysis will be introduced. Section 4 describes the financial data used in the model as well as main inputs of the model. Secondary data for publicly held Japanese manufacturing companies was gathered and then the financial ratios were built based on balance sheet information. Section 5 presents in more detail the model development and the analysis of the empirical results. After demonstrating the significance of the calibrated model, the implication of this result is analysed. Last but not least, Section 6 concludes the paper with a short summary of the main results. The limitations and further research are also discussed here.

2 Literature Review

Before digging deeper into the theoretical framework of this paper, it is necessary to define the terminology used, whilst having a look at the scientific literature covering this topic. As already mentioned in the introduction, this paper attempts to forecast the bankruptcy probability of a company by using financial ratios and a multiple discriminant analysis. The financial ratios are calculated by using balance sheet data for each company, while the discriminant analysis will further be conducted with the aid of statistical software. This section will start by first describing the results of several papers on the ratio analysis, then the findings on bankruptcy prediction by using the financial ratios, followed by an alternative view upon Altman (1968) work, and it will be concluded by presenting the contribution of this paper to the existing literature.

2.1 Ratio Analysis

As financial distress can lead to bankruptcy, early warning is extremely desirable, if not vital. Bankruptcy is defined as the inability of a person or business to repay its outstanding debt (Aliakbari, 2009). Aharony, Jones, and Swary (1980) argued in their paper that “An early warning signal of probable failure will enable both management and investors to take preventive measures [...]”. Hence, it comes as no surprise that the focus of bankruptcy studies shifted from ways to avoid it to predict it all together. Winakor and Smith (1935) found that there is a significant difference between the measurement of financial ratios of unsuccessful companies as compared to the financially healthy ones. In his paper, Beaver (1966) analysed individually a set of financial ratios for a sample of bankrupt firms, together with a sample of matching non-bankrupt firms. He found that the financial ratios of five years prior the bankruptcy have the ability to forecast the bankruptcy probability, and hence Beaver is considered to be the pioneer in constructing a bankruptcy prediction model. In his paper, Beaver (1966) built his model by using a framework similar to the model of gambling ruins [4]. Therefore, the company is regarded as "reservoir of liquid assets, which is supplied by inflows and drained by outflows. [...] The solvency of the firm can be defined in terms of the probability that the reservoir will be exhausted, at which point the firm will be unable to pay its obligations as they mature". What he meant by this is that as long as there are cash reserves a company will survive

2.2 Bankruptcy Prediction Models

In his paper, Altman (1968) advocated that the aforementioned studies clearly illustrate the prediction potential of a financial ratio analysis. Thus, he was motivated to pursue the construction of a model that can enhance the bankruptcy predictability by using the ratio analysis. Even though Altman (1968) used a multiple discriminant analysis to construct his model, there are others way to do so. Ohlson (1980) applied a Logistic regression methodology (Logit). He used a sample of 2163 companies [5] over a time period of six years (1970 - 1976). He found that the size of the company, its financial structure, its performance, and its current liquidity have prediction power one year before the bankruptcy. Moreover, the Logit models score indicates the default probability, whereas the score of an multiple discriminant analysis must be recalculated into the probability of default by using historical observations, and for this reason Lacerda and Moro (2008) also found it as a more attractive statistical technique. Based on this argument, Seaman, Young, and Baldwin (1990) were motivated to test the predictive power of the linear, quadratic, and logistic models; their results showed that the highest predictive power of 78% was scored by the quadratic dis-

[4] In this model it is assumed that net assets follow a random process with some fixed probability of a negative cash flow each period. Therefore, for a long period there is the probability for a continuity of negative cash flows, which in turn can lead to a negative value of the net assets.

[5] A number of 105 companies out of the 2163 were bankrupt.

criminant approach. Nonetheless, their results concerning the quadratic model contradict the ones of Frydman, Altman, and KAO (1985).

Another bankruptcy prediction model is the K&P model developed by Clark, Foster, Hogan, and Webster (1997). Due to the fact that the financial information used in the univariate approach lacks precision, this model attempts to use an analytical hierarchy process in predicting the bankruptcy. The model distributes the financial risk over four hierarchy levels and three financial categories. Furthermore, the financial risk is determined by four financial risk attributes: the asset utilization, the financial flexibility, the earning power, and the liquidity position (Clark et al., 1997). Shareholders, creditors, employees, rating agencies and so on put a lot of emphasis on the failure prediction models an to this end many other studies have been carried out over time (Aliakbari, 2009). For example, Hensher and Jones (2007) identified some econometric models, such as the mixed logit model, the nested logit model, latent class multinomial logit, and the error component logit model, as better models due to their significantly greater explanatory and statistical power as compared with widely used standard logit models (Jones & Hensher, 2007b) [6].

2.3 Alternative view on Altman's Z-score

Even though most of the above discussed papers consider Altman (1968) as one of the pioneers of the bankruptcy predictions model, there are still researchers that have a different view towards the Z-score model. Shumway (2001) and Campbell, Hilscher, and Szilagyi (2011) addressed the main criticisms against Altman's modelling and variable selection. Their approximately accumulated criticism against Altman concerns the aforementioned points. In his paper, Shumway (2001) put forth three major criticism against Altman (1968) work. The first one is with respect to the time frame used in the analysis. Therefore, Shumway (2001) advocates that single period models are inconsistent due to the fact that a firm's risk for bankruptcy changes over time, and its health is a function of its latest financial data and its age. The second criticism is with respect to the financial condition of the bankrupt firm. In his paper, Shumway (2001) states that as firms approach bankruptcy, their financial condition deteriorates, but Altman (1968) fails to acknowledge this aspect. Shumway (2001) concluded that due to the fact that Altman (1968) does not take into consid-

[6] In their four papers ((Jones & Hensher, 2004), (Jones & Hensher, 2007a), (Jones & Hensher, 2007b) & (Hensher & Jones, 2007)) they introduced the theoretical and econometric foundations of advanced models for predicting corporate bankruptcy.

eration companies that will go bankrupt in two or three years, companies with high values of *WORKING CAPITAL/TOTAL ASSETS* in a particular year that go bankrupt in the next year are neglected, and thus the test statistics will be inflated. The last criticism is towards the financial ratios used in the analysis. Shumway (2001) advocates that previous bankruptcy models[7] do not include several market driven variables that are strongly related to bankruptcy probability, such as the market size, the past stock returns and the idiosyncratic standard deviation of the stocks[8]. Furthermore, he states that most of the financial ratios used in the previous models turn out to be poor predictors. Based on his criticism and also on his model, Campbell et al. (2011) developed their own model, which turned out to outperform the Shumway (2001) model. They found that distressed stocks have highly variable returns and high market betas and that they tend to under-perform safe stocks more at time of high market volatility and risk aversion.

These alternative views do not mean that Altman (1968) Z-score model is wrong, but in fact they show that as timed passed by more advanced techniques, and hence more appropriate financial variables, for constructing the model were discovered. While the aforementioned papers focused on the development of a model with a higher predictive power, this paper comes as a support of the original Altman (1968) Z-score model by calibrating it for publicly held Japanese manufacturing companies. Even though the aforementioned critiques are notable, there are still shortcomings to the hazard model. The first shortcoming is with respect to the multicollinearity problem. As already stated by Balcaen and Ooghe (2004), the hazard models are subject to the problem of multicollinearity and hence correlations between the independent variables must be avoided. As can be seen from table Table 8 in Appendix B, there is strong correlation between the variables and for this reason the hazard model cannot be correctly implemented in this paper (Lane, Looney, & Wansley, 1986). The second shortcoming of the hazard models is that the calculation of the survival time is irregular. In other words, the hazard model does not make a distinction between the closing date of the annual account and the natural starting point of the bankruptcy process (Luoma & Laitinen, 1991).

The aim of this paper is the calibration of the Altman Z-score model, meaning that the model might deviate from the original observations, and due to some

[7] And hence also a criticism on Altman (1968).

[8] Shumway (2001) used these variables, together with accounting ratios, to construct his so called "Hazard Model".

differences, the paper will contribute to the existing literature on the topic. The first difference arises from the geographical setting. While US companies were studied in the original model, this paper focuses on Japanese companies. Therefore, it is easily observable that the first difference arises from the accounting and financial divergences between the two countries, and more precisely between the US GAAP and JP GAAP (PriceWaterhouseCoopers, 2005). An important difference between the two accounting regimes is with respect to asset amortization. Under the US GAAP the assets are amortized only if it has a finite life, whereas under the JP GAAP the assets are amortized over the period stipulated by the corporate tax law on a straight line basis (PriceWaterhouseCoopers, 2005). The reason for mentioning this difference is that this will indirectly affect the financial ratios used in the model. One of the financial ratios is *EBIT/TOTAL ASSETS*, where *EBIT* stands for earnings before interest and taxes meaning that the earnings had already been adjusted for amortization.

The second difference is with respect to the financial instruments that a financially distressed company can adopt nowadays in order to increase its odds in the face of bankruptcy. As Fehle and Tsyplakov (2005) stated, companies that are in far from or deep into financial distress have a lower incentive to implement changes by using risk management tools than the companies that are in between these two extremes. Even though it might not seem obvious at a first glance why this posses a problem, there is in fact one. As will be discussed later in this paper, there is a grey zone or also know as "zone of ignorance"[9], where it is inconclusive whether a company faces the risk of bankruptcy or not. Since many firms adopt nowadays risk management tools in order to improve their financial status, the margins of the so called "zone of ignorance" are becoming larger, thus increasing the probability of having a misclassification problem.

The solution to the aforementioned issues is constructing a model which would take this matters into account. As already mentioned before, there is a high chance that the Altman (1968) model is influenced by the geographical conditions as well as by the lack, at that time, of the same risk management tools. To this end, the JP model is proposed since it will able to take care of the existing divergences between the two countries. The following sections will cover the methodological aspects of the paper, the analysis of the results and it will end with the conclusions and the limitations to the research.

[9]As Altman referred to it in his paper (Altman, 1968).

3 Theoretical Framework

The previous section cited several studies that made the analysis of a firm's condition prior to financial difficulties possible. Although one can correctly observe the bankruptcy predictability of the ratio analysis, the validity of the analysis may be questioned both in a theoretical as well as in a practical framework. Thus, one problem that is generally regarded with respect to the ratio analysis is that its methodology is univariate, meaning that is does not account for the joint effect of the ratios on the firm's status (Eivind, 2001). This may pose a problem because such an interpretation for ratio analysis may lead to either a faulty conclusion or to confusion in analysing the results.

3.1 Multiple Discriminant Analysis

Given the nature of the existing problem as well as the idea behind this paper, a new and more advance model must be applied. Therefore, the most appropriate statistical technique that can be at use here is a multiple discriminant analysis (MDA). Multiple discriminant analysis is similar to the multiple linear regression in the sense that it undertakes the same tasks in predicting an outcome. Nevertheless, there is a major difference between the two statistical techniques, hence the inadequacy of the multiple linear regression in the model. The multiple linear regression is limited to the cases where the dependent variable Y is a numerical value for given values of weighted combinations of the independent variables X. On the other hand, there are many issues of interest that are represented by categorical variables, such as trading status, employed/unemployed, bankrupt/non-bankrupt, whether a person is a credit risk or not, etc (Klecka, 1980).

This statistical technique is used in order to reduce the differences between variables in order to classify them into a set of broad groups and thus MDA creates an equation which will minimize the possibility of misclassifying cases into their respective groups or categories. More specifically, the MDA process transforms individual variables values to a single discriminant score, which then is used to classify the object (Altman, 1968). The form of the equation or function is:

$$(1) \quad Z = v_1 X_1 + v_2 X_2 + v_3 X_3 + ... + v_n X_n$$

where,

$Z =$ the discriminant score

$v_j =$ the discriminant coefficient or wheight for the variable

$X_j =$ the independent variable

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

3.2 Theoretical Evaluation of the MDA

There are several other reasons for why the MDA technique is used. Firstly, MDA allows to investigate the differences between the bankrupt and non-bankrupt firms on the basis of financial ratios, indicating which ratios contribute most to group separation. The descriptive technique successively identifies the linear combination of attributes known as canonical discriminant equations, which contribute maximally to group separation. Secondly, the predictive MDA addresses the question of how to assign new cases to groups. The MDA function uses a firm's score on the predictor variables to predict whether it is bankrupt or not (Klecka, 1980). Furthermore, the discriminant analysis reduces the user's space dimensionality. This can be explained with a simple example. Let G represent the initial number of groups, then MDA will reduce independent variables to $G-1$. Thus, since this paper considers G to be 2 (bankrupt and non-bankrupt), the amount of dimensions is estimated at 1 (Altman, 1968). Therefore, the multiple discriminant analysis is a tool for predicting group membership from a linear combination of variables.

The focus of this section was on explaining the methodological steps that are going to be implemented in this paper. After describing the process of the discriminant analysis and the discriminant function, its advantages were presented. In the next sections much emphasis will be put the construction of the model alongside the data gathering process. Furthermore, the paper will conclude by presenting a summary of the analysis and its main results, and the limitations to this research.

4 Data Description

4.1 Data Requirements and Data Gathering

After citing the relevance of the past studies for this paper, as well the theoretical framework that will be employed, light must the shed on the data analysed. For the purpose of an empirical investigation of the Altman (1968) model and in order to assess the effectiveness of the financial ratios to predict bankruptcy, secondary data for both bankrupt and non-bankrupt public Japanese manufacturing companies over a time span of 11 years (2000 - 2011) has been gathered. Thus, the names of the public companies that went bankrupt as well operated for the period 2000 - 2011 has been collected using the Bloomberg Terminal[10]. This specific time period was chosen for capturing the effects of the burst of two financial bubbles as well a full recovery period on the worldwide economy. Since this paper matches bankrupt firms to the non-bankrupt firms, the number of the non-bankrupt firms in the analysis must be equal to that of the bankrupt firms. Therefore, in the initial, raw phase there were 77 Japanese companies that went bankrupt and 2143 non-bankrupt Japanese companies.

As mentioned in the previous section, one of the steps in performing the MDA analysis of this model is constructing the financial ratios for each company (Altman, 1968). Therefore, balance sheet values for working capital, retained earnings, EBIT, market value of equity, sales, and total assets are gathered using the Bloomberg Terminal. Furthermore, due to the reporting style only the final year is of significance for this paper, meaning that the relevant input data is the latest reporting accounted for by the firm, taken at year-end. After the data for the aforementioned financial indicators is compiled, a data cleaning step must be taken in order to ensure the validity as well as the reliability of the analysis. Therefore, 5 companies out of the 77 bankrupt ones were purged on the ground that they were either missing essential data or had no data at all. This correction reduced the bankrupt sample to 72 firms.

In order to arrive to the final sample of firms, a stratified random sampling procedure has been applied. This procedure involves the division of the population into strata, which are formed based on the members shared attributes or characteristics. Therefore, the data is stratified by year, which permits the non-bankrupt firms to be matched to the bankrupt ones in the latest reporting

[10] The reasons for using the Bloomberg Terminal as a source for the secondary data are its validity and reliability. What is meant by this is that Bloomberg Terminal is used world wide by every financial institution and hence it is the best choice.

year of the latter, and thus allowing for a direct comparison between the two groups (Field, 2009). After performing this step in SPSS, the final sample is comprised of 66 bankrupt firms and 66 non-bankrupt firms, summing up to a total of 132 companies. The corresponding firms and their names are presented in Appendix A.

Another problem at hand is the assessment of the data requirements. Having taken care of the matching problem, as well as purging the detrimental details (such as missing information), the next step is meeting both the financial and the economical requirements needed for an analysis of bankruptcy. As mentioned before, there are several balance sheet variables used for the model and since this paper is a calibration for Japan of Altman (1968) model, these variables are going to be used in order to construct the financial ratios used in the initial model. In Altman's view there are five ratios that contribute to the bankruptcy predictability of the company, and they are classified in: profitability, leverage, liquidity, activity and solvency ratios. Thus, the model used in this paper is explained below:

$$Z = \alpha + v_1 X_1 + v_2 X_2 + v_3 X_3 + v_4 X_4 + v_5 X_5 \tag{2}$$

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

4.2 Financial Ratios

X_1 - *Working capital/Total assets.* The Working capital/Total assets ratio is a financial ratio which measures the liquid assets of a firm with respect to the firm size (total capitalization). The working capital is a measurement of a firm's efficiency as well as its short-term financial health, and it is given by the difference between current assets and current liabilities. In the case of a constant financial distress, the firm in cause will experience a decrease in the current assets with respect to the total assets. Hence, this ratio is positively related to the financial health of a company, meaning that a bankrupt company will have a low value, while a high value will be attributed to the healthy company. Furthermore, both Altman (1968) as well as Merwin (1942) considered this ratio as the best indicator of ultimate discontinuance (Altman, 1968).

X_2 - *Retained earnings/Total assets.* This measure of cumulative profitability is also considered to be a measure of firm's age. This is due to the fact that a young firm is considered to not have had enough time to grow and build up their cumulative earnings. Therefore a relatively young firm will have a low *RETAINED EARNINGS/TOTAL ASSETS* ratio, which may be argued that there is a higher probability that the discriminating process will classify the firm as a bankrupt one than an older one. But since a firm is more prone to failure and thus to bankruptcy in the earlier years of its existence (Altman, 1968), this ratio is used in the model. Moreover, this ratio is lower for bankrupt firms because they are not able to retain their earnings, in contrast with a non-bankrupt firm which has a high *RE/TA* ratio.

X_3 - *Earnings before interest and taxes/Total assets.* The *EBIT to Total Assets* ratio can be seen as an indicator of how effectively a company is using its assets to generate earnings before its contractual obligations are met. This ratio is, in essence, a measurement for the true productivity of a firm. Thus, if the earnings of a firm are bigger with respect to its assets, and hence a higher ratio value, than that the company is using its assets efficiently. The EBIT/TA ratio is an indicator of bankruptcy due to the fact that the assets power of a financial distressed firm is low, which in turn affects the firms profitability.

X_4 - *Market value of equity/Total liabilities.* This is a measure of a company's financial leverage and shows what proportion of equity and debt the company is using to finance its assets. The ratio is composed from two variables: the market value of equity, which is equal to the market value of all shares of stock, both preferred and common, and the company's liabilities. This form of outside financing enables a company to experience potentially higher earnings than otherwise. Furthermore, it also shows how much a company's assets can decline in value before the liabilities exceed the assets and it goes into bankruptcy (Altman, 1968).

X_5 - *Sales/Total assets.* The *SALES/TOTAL ASSETS* ratio is a financial ratio that shows the amount of sales generated for every dollar worth of assets. It basically measures the firm's efficiency at using its assets in generating sales and revenue. Therefore, a distressed firm will experience a decrease in its sales, and thus leading to a lower value of the ratio.

As stated in the beginning of this part, these financial ratios will be used to make qualitative statements about the going concern of the selected Japanese firms. Thus, this part introduced the data gathering and the data processing, as well as the financial ratios that will be used in model, while Section 5 will explain the model development and the results, followed by the conclusion in Section 6.

5 Model Development and Empirical Results

This section is discussing the model development as well as the results of the analysis. Firstly, an univariate model for each financial ratio is presented. This is done in order to emphasise the predictive power of each ratio individually. Secondly, the multiple discriminant analysis for the Japan will be introduced and explained. Last but not the least, the paper will cover three validation methods for the model.

5.1 Univariate Analysis

In conformity with Altman (1968) methodology, the individual predictive power of the financial ratios is done by applying an analysis of variance (ANOVA) F-test, which will allow the test on the equality of variances (Altman, 1968). The F-test follows a F-distribution and it's testing hypothesis for this case are:

H_0 : All means are equal

H_1 : At least one mean is different from the others

Testing these hypotheses will allow one to draw conclusions about the means of the two groups. Thus, if the null hypothesis is rejected, it can be concluded that there is a significant difference in means of the bankrupt and non-bankrupt firms. Furthermore, testing these hypotheses will allow inferences to be made about the individual discriminating power. A summary table with each ratio's F-test values is presented bellow:

Table 1: F-test summary table

Variables	F-statistics
X1	129.477*
X2	42.263*
X3	23.819*
X4	56.230*
X5	0.224

* Significant at the 0.05 level.

As can be observed from the table, the results are similar to Altman (1968) in the sense that the first four variables are statistically significant, while the last variable turns out not to be. Ratios X_1 to X_4 are significant at a 5%[11] confidence interval, whereas ratio X_5, with an p-value of 0.636 is not even significant at a 10% confidence level. These results indicate that there is an extremely significant difference between the groups for variables X1 through X4, while variable X5 does not show a significant difference between the groups. Furthermore, based on the values from the table, the null hypothesis of equal means is rejected at a 5% significance level for the variables X_1 to X_4 , whereas the null is not rejected for X_5.

5.2 Multiple Discriminant Analysis

As already mentioned in the previous sections, one useful technique in arriving to both significant and explanatory results is the multiple discriminate analysis. After performing the necessary steps in SPSS (Field, 2009), the below presented equation reflects the model for the Japanese companies.

[11] A 5% significance level is used throughout this paper.

$$Z = -0.833 + 1.880X_1 + 0.489X_2 + 0.118X_3 + 0.081X_4 + 0.125X_5 \tag{3}$$

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

This is the final output of the model provided by SPSS. It represents a calibration for Japan of the initial Altman (1968) Z-score. It is necessary to mention again that this model is only applicable for public, manufacture Japanese firms. The model has all its variables positive leading to conclusion that the higher the input number the higher the Z-score, which is in accordance with the financial ratios' explanation from Section 4.

The goal of a discriminant analysis is to predict a group membership, so the first step in examining the results is to check whether there are any significant differences between groups on each of the explanatory variables. This is done by using the group means and ANOVA results data, which are presented in the tests of equality of group means table in Appendix B (Table 11). The reason for taking this step is that if there is no significant difference between groups, the analysis would not be worthwhile (Klecka, 1980). A basic idea about the variables can be attained by inspecting the group means and standard deviations. For instance, the mean difference between X_2 and X_3 depicted in Appendix B (Table 10) suggest that these may be good discriminators as the difference is large.

After having obtained both the coefficients numbers and the proof that there are significant group differences, the overall significance of the discriminant model is further discussed. One frequent test statistic used in the multivariate analysis of variance is the Wilk's Lambda, and it is a measure of the class centres separation as well as of the proportion of variance. If a small proportion of the variance is explained by the independent variable then it can be advocated that there is no effect from the grouping variable (in this case the financial ratios) and the groups (in this case bankrupt and non-bankrupt) have no different mean values (Klecka, 1980). Furthermore, Wilk's Lambda can be regarded as a multivariate generalization of the univariate F-distribution. The SPSS output for a MDA analysis already gives a summary output table for Wilk's Lambda[12], which is presented below:

Table 2: Model significance: Wilks' lambda

Wilks' lambda	Chi-square	Degrees of freedom	Significance
0.443	103.942	5	0.000

The value for Wilk's Lambda is all the time a number between 0 and 1. Furthermore, the lower the value the higher the model's ability to discriminate, thus more separation between the groups. The first column in the table shows the value of Wilk's Lambda, which in this case is 0.443. This number represents the proportion of the total variability that is left unexplained (Klecka, 1980). Even though, at the first glance, this might seem a rather large number, it still shows that there is an effect from the grouping variable and that the groups have different mean values. Furthermore, it must be interpreted together the Chi-square test with its corresponding degrees of freedom. Given the p-value of the Chi-square test of 0.000, it can be concluded that the discriminant model is highly significant at a 5% significance level.

A further way of interpreting the discriminant analysis results is to determine the range of where the misclassification problem might be present. This "zone of ignorance", as Altman (1968) called it, is determined using the group centroids of the predictor variables, and the explanation is as follows: the score of the non-bankrupt companies is at the right of range and the score of the bankrupt companies is at the left of the range, leaving all the inconclusive observations in the range.

Table 3: Group centroids

Status	Centroids
Bankrupt	-1.114
Non-bankrupt	1.114

Table 3 presents the centroids for the two groups. Once the value of the Z-score of a certain company is either smaller than the bankrupt group centroid

[12] The full output is presented in Appendix B (Table 12).

or bigger than the non-bankrupt group centroid then the company is allocated to one of the two groups. The meaning of the Z-scores of the companies that neither smaller than -1.114 nor bigger than 1.114, is that these companies will be stopped in the “zone of ignorance”. Out of all the allocated companies the minimum and the maximum Z-scores will represent the lower and the upper bound of the “zone of ignorance”, which are $[-2.59, 1.39]$ respectively.

5.3 Model Validation

The final step in analysing the model is its validation. The validation process is carried out by implementing three testing strategies. Firstly, the model is tested in the initial sample, which will allow conclusions about the predictive power of the model to be drawn. Secondly, the original Altman (1968) model will be tested on the Japanese data. The aim of the second strategy is to test the power of Altman (1968) model in Japan. Finally, the new and excellent model for UK exerted by Rado (2013) will be tested in the JP sample, which will reveal the power of Rado (2013) model in a JP setting.

The first validation strategy addresses the predictive power of the JP model and thus the initial sample is used in this testing strategy. The model is a MDA analysis performed on the JP data and the Z-score is its result. Then using the corresponding “zone of ignorance” interval the firms are placed either in the bankrupt group or in the non-bankrupt group. Table 4 presents the comparison of the predicted statuses with the actual statuses.

Table 4: Validation test: Initial Sample

		Predicted			Correct	Total	% Correct	% Error
		B	NB	Type I	63	66	95.45%	4.55%
Actual	B	63	3	Type II	60	66	90.9%	9.1%
	NB	6	60	Total	123	132	93.18%	6.82%

As can be inferred from the table, there are three cases of misclassification for the non-bankrupt firms, leaving a total of 63 bankrupt firms which were in fact predicted bankrupt by the model. This gives a model accuracy of almost 96% in predicting the bankruptcy. Secondly, out of 66 non-bankrupt companies, 60 were classified correctly, meaning that there is 91% accuracy in classifying a company as non-bankrupt. These results, indirectly show that the calibration for Japan of the Altman (1968) model is indeed superior to the original Z-score model for the given data set.

The second strategy applied is the testing of the Altman (1968) Z-score on the JP data. This is done by applying the Altman's Z-score model and its corresponding range in a JP setting. This strategy implies that a new Z-score will be calculated for each firm from the sample and then assigned to one of the two groups. Table 5 presents the comparison of the predicted statuses with the actual statuses.

Table 5: Validation test: Altman (1968) Model

		Predicted	
		B	NB
Actual	B	63	3
	NB	2	64

	Correct	Total	% Correct	% Error
Type I	63	66	95.45%	4.55%
Type II	2	66	3%	97%
Total	65	132	49.23%	50.78%

As can be seen from the table above, the percentage of correctly classified companies is 49.23 percent. Furthermore, the percentage of correct classified bankruptcies is 95%, whereas the percentage of correct classified non-bankruptcies is only 3%. When compared to the first strategy, one can observe a significant difference between the two approaches. In the first strategy, the percentage of correctly classified companies is 93.18% while the second strategy has only a 49% predictability power. Furthermore, Type I and especially Type II error are relatively larger compared to the first strategy. This results lead to the conclusion that the model for Japan truly outperforms the original Altman Z-score with respect to the predictability of bankruptcy for publicly held Japanese manufacturing companies.

The third strategy assesses the predictive power of the Rado (2013) UK model, within a JP setting. This is done by applying the Rado (2013) Z-score and its corresponding range on the JP data. This strategy implies that a new Z-score will be calculated for each firm from the sample and they are assigned to one of the two groups. Table 6 presents the comparison of the predicted statuses with the actual statuses.

Table 6: Validation test: Rado (2013) Model

		Predicted	
		B	NB
Actual	B	2	64
	NB	3	63

	Correct	Total	% Correct	% Error
Type I	2	66	3%	97%
Type II	3	66	4.8%	95.2%
Total	5	132	3.9%	96.1%

As can be seen from the table above, the percentage of correctly classified companies is 3.9. Furthermore, the percentage of correctly classified bankruptcies is 3, while the percentage of correctly classified non-bankruptcies is 4.8. When compared with the first strategy, the total number of correctly classified companies of these two strategies is very small, while its total error is much larger. This results lead to the conclusion that the model for Japan truly outperforms the one for UK in terms of classifying JP public manufacturing companies employed in this paper.

This section presented the model development as well as the results of the analysis. Firstly, an univariate model for each financial ratio was discussed. This was done in order to emphasise the predictive power of each ratio individually. Secondly, the multiple discriminant analysis for the Japan was both introduced and explained. Last but not the least, this section covered three validation methods for the model. The next and final section will present the conclusions that can be drawn from the model, together with the limitations of the paper.

6 Conclusion

6.1 Concluding Remarks

The aim of this paper was to calibrate the Altman Z-score model with respect to publicly held Japanese manufacturing companies. The analysis was conducted on a sample of 132 publicly held Japanese manufacturing companies. This paper has started with a literature review describing all relevant scientific literature concerning ratio analysis, bankruptcy prediction models and alternative views towards Altman (1968) Z-score. Furthermore, a discriminant analysis model was proposed to assess the calibration of the Z-score model for Japan. In order to calibrate the original Altman (1968) Z-score for Japan, several steps were implemented. First, secondary data for both publicly held bankrupt and non-bankrupt Japanese manufacturing companies was collected. Moreover, five financial ratios were constructed by using the secondary data: profitability, leverage, liquidity, activity and solvency ratios. Second, a discriminant model (MDA)[13] was developed. This model transforms individual variables values to a single discriminant score, which is then used to classify the object. Third, three validation tests were performed in order to prove the reliability and predictive power of the model. Last but not the least, the calibrated model turned out

[13]Multiple Discriminant Analysis.

to be highly significant and it is recommended to be used to companies operating in or working under the financial and accounting conditions of Japan. The idea behind the model is that the bankrupt and non-bankrupt public Japanese manufacturing companies are discriminated against. Moreover, as the previous section explained, the model is only applicable for JP companies and this can be observed from the superiority that the calibrated model has over the original Altman (1968) Z-score and the recalibration for UK under the JP setting. This model was created as a support for the already existing bankruptcy prediction models, and to this extend it is advisable not to be used as the main predictive model, but more as a confirmation of the already known results.

6.2 Limitations of the paper

Even though the model proved to be significant, there are limitations to the model that reduce its predictive power. First there is number of bankrupt firms. Due to the fact that the data gathering process implied the utilisation of the Bloomberg terminal, the data available was limited [14]. Furthermore, this paper lacked the necessary funds and data sources which created some data restrictions. Thus, an improvement to this study will be to include more Japanese bankrupt companies. Second, there was a problem with the already existing data, in the sense that for some companies parts of the required data was either missing or not existing at all. This problem forced for some data to be purged and it also made it impossible for some validation techniques to be performed. A possible solution to this would be that in further research upon the model more data sources should be included. Another limitation is represented by the statistical package used in the analysis. In Altman (1968) original model, there was no intercept present in the equation, whereas in the calibrated model, there is. In his 2000 paper, Altman advocated that the reason for such an occurrence might be do the statistical package used in constructing the model (Altman et al., 2000). A fourth limitation is the type of companies used. This paper focused only publicly held manufacturing firms. Thus, further research should be performed in order to analyse the privately held companies, and if possible, a model that can predict bankruptcies in both public and private sectors should be created. The fifth limitation of the model is with respect to its depth. Therefore, further analysis should be conducted in order to either add

[14] As mentioned earlier, the reason for using Bloomberg Terminal to maximize convergence to the financial industry.

more financial ratios to the model concerning an increase in its predictability or if possible to create JP specific ratios.

This paper presented the calibration of Altman (1968) Z-score model for Japan. It was proven that this model is highly significant in predicting the bankruptcy and it also showed its superiority in explaining a Japanese company bankruptcy with respect to Rado (2013) UK model and to the original Altman (1968) model. Furthermore, the model can be seen as a proof of the usefulness of the initial Altman (1968) model and as a model belonging to the same group of bankruptcy models. As stated before, it is advocated that the model should be used only to reinstate the conclusions already obtained by implementing other models. Moreover, the financial data used in constructing this model contains the effects of the financial crisis. The JP model can be used to predict corporate bankruptcy up to one year up front for publicly held JP manufacturing firms during a crisis and non-crisis period.

To sum up, this paper was concerned with a practical application of the Z-score model on countries other than the US by showing that financial ratios have predictive power in assessing the bankruptcy probability in a Japanese setting. Bankruptcy risk is a central and highly debated issue nowadays, and this study has shown that stakeholders should strive to implement as many risk management tools as possible. Of course, some companies will be saved only by implementing this tools. Hence, it is important to stress out that, in order to avoid such circumstances, bankruptcy has to be forecasted as earlier as possible.

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A Appendix: Names and tickers

Table 7: Firm names and ticker symbols

Bankrupt		Non-bankrupt	
Ticker	Name	Ticker	Name
1754 JP Equity	TOSHIN HOUSING	1831 JP Equity	SEKISUI HO HOKU
1772 JP Equity	TOHOKU ENTERPR	1841 JP Equity	SANYU CONSTRUCTI
1779 JP Equity	MATSUMOTO KENKO	2112 JP Equity	ENSUIKO SUGAR
1785 JP Equity	NANABOSHI CO LTD	2311 JP Equity	EPCO CO LTD
1786 JP Equity	ORIENTAL SHIRAIS	2397 JP Equity	DNA CHIP
1797 JP Equity	FUJIKI KOMUTEN	2676 JP Equity	TAKACHIHO KOHEKI
1800 JP Equity	TONE GEO TECH CO	2766 JP Equity	JAPAN WIND DEVEL
1804 JP Equity	SATO KOGYO	2817 JP Equity	GABAN CO LTD
1806 JP Equity	AC REAL ESTATE C	3587 JP Equity	PRINCI-BARU CORP
1818 JP Equity	NISSAN CONSTRUCT	3600 JP Equity	FUJIX LTD
1825 JP Equity	ECO-TECH CONST	3706 JP Equity	TOKAI PULP & PAP
1836 JP Equity	DAI NIPPON CONST	3723 JP Equity	NIHON FALCOM
1839 JP Equity	MAGARA CONSTRUCT	3841 JP Equity	JEDAT INC
1845 JP Equity	MORIMOTO CORP	4502 JP Equity	TAKEDA PHARMACEU
1851 JP Equity	OHKI CORP	4557 JP Equity	MED & BIO LABS
1858 JP Equity	INOUE KOGYO	4564 JP Equity	ONCOTHERAPY SCIE
1874 JP Equity	SATOHIDE CORPORA	4572 JP Equity	CARNA BIOSCIENCE
1886 JP Equity	AOKI CORP	4770 JP Equity	ZUKEN ELMIC INC
1889 JP Equity	AOMI CONST	4973 JP Equity	JAPAN PURE CHEMI
1902 JP Equity	YAMAZAKI CONSTRU	5945 JP Equity	TENRYU SAW MFG
1908 JP Equity	SAMPEI CONSTRUCT	5979 JP Equity	KANESO CO LTD
1917 JP Equity	NISSEKI HOUSE IN	6134 JP Equity	FUJI MACHINE MFG
1920 JP Equity	SHOKUSAN JUTAKU	6149 JP Equity	ODAWARA ENGINEER
1962 JP Equity	ERGOTECH CO LTD	6274 JP Equity	SHINKAWA
2219 JP Equity	TAKARABUNE CORP	6307 JP Equity	SANSEI CO LTD
2318 JP Equity	CREST INVESTMENT	6337 JP Equity	TESEC CORP
2356 JP Equity	TCB HOLDINGS COR	6346 JP Equity	KIKUKAWA ENTERPR
2473 JP Equity	GENESIS TECH	6348 JP Equity	JAPAN MARINE TEC
2808 JP Equity	SANBISHI CO LTD	6416 JP Equity	KATSURAGAWA ELEC
3115 JP Equity	TESAC CORP	6418 JP Equity	JAPAN CASH MACH
3206 JP Equity	NANKAI WORSTED	6445 JP Equity	JANOME SEWING

3304 JP Equity	TOSCO CO LTD	6654 JP Equity	FUJI ELECTRIC
3870 JP Equity	NIPPON KAKOH SEI	6718 JP Equity	AIPHONE CO LTD
4790 JP Equity	GRACE CORP	6721 JP Equity	WINTEST CORP
5562 JP Equity	JAPAN METAL-CHEM	6769 JP Equity	THINE ELECTRONIC
5917 JP Equity	SAKURADA CO	6786 JP Equity	REALVISION INC
5925 JP Equity	SAKAI IRON WORKS	6806 JP Equity	HIROSE ELECTRIC
5926 JP Equity	AG AJIKAWA CORP	6820 JP Equity	ICOM INC
6106 JP Equity	HITACHI SEIKI CO	6833 JP Equity	NIDEC-READ CORP
6114 JP Equity	SUMIKURA INDUST	6834 JP Equity	SEIKOH GIKEN CO
6216 JP Equity	KOTOBUKI IND	6836 JP Equity	PLAT'HOME CO LTD
6275 JP Equity	ISEKI POLY-TECH	6857 JP Equity	ADVANTEST CORP
6290 JP Equity	SES CO LTD	6875 JP Equity	MEGACHIPS CORP
6304 JP Equity	MAKI MANUF CO	6888 JP Equity	ACMOS INC
6359 JP Equity	AWAMURA MANUF CO	6914 JP Equity	OPTEX CO LTD
6394 JP Equity	OYE KOGYO CO LTD	6920 JP Equity	LASERTEC CORP
6660 JP Equity	INNEXT CO LTD	6929 JP Equity	NIPPON CERAMIC
6667 JP Equity	SHICOH	6954 JP Equity	FANUC CORP
6671 JP Equity	ARM ELECTRONICS	7443 JP Equity	YOKOHAMA GYORUI
6813 JP Equity	NAKAMICHI CORP	7447 JP Equity	NAGAILEBEN CO
6851 JP Equity	OHKURA ELECTRIC	7466 JP Equity	SPK CORP
6868 JP Equity	TOKYO CATHODE	7503 JP Equity	IMI CO LTD
6927 JP Equity	HELIOS TECHNO HD	7587 JP Equity	PALTEK CORP
7104 JP Equity	FUJI CAR MFG	7748 JP Equity	HOLON CO LTD
7286 JP Equity	IZUMI INDUSTRIES	7865 JP Equity	PEOPLE CO (TOYS)
7306 JP Equity	MARUISHI CYCLE	7874 JP Equity	LEC INC
7881 JP Equity	NISSO INDUSTRY	7974 JP Equity	NINTENDO CO LTD
7884 JP Equity	HONMA GOLF CO	8068 JP Equity	RYOYO ELECTRO
7910 JP Equity	DANTANI CORP	8112 JP Equity	TOKYO STYLE CO
7934 JP Equity	MELX CO LTD	8150 JP Equity	SANSHIN ELEC CO
8024 JP Equity	SILVER OX INC	9650 JP Equity	TECMO LTD
8146 JP Equity	KOSUGI SANGYO CO	9816 JP Equity	STRIDERS
8169 JP Equity	TAKARABUNE CO LT	9883 JP Equity	FUJI ELECTRONICS
8858 JP Equity	DIA KENSETSU CO	9955 JP Equity	YONKYU CO LTD
8911 JP Equity	SOHKEN HOMES CO	9962 JP Equity	MISUMI GROUP INC
8939 JP Equity	DAIWASYSTEM CO	9995 JP Equity	RENESAS EASTON C

B Appendix: SPSS output

Table 8: Pooled Within-Groups Matrices

Pooled Within-Groups Matrices						
		X1	X2	X3	X4	X5
Correlation	X1	1.000	.399	.236	.243	-.093
	X2	.399	1.000	.615	-.032	-.093
	X3	.236	.615	1.000	.126	-.026
	X4	.243	-.032	.126	1.000	-.145
	X5	-.093	-.093	-.026	-.145	1.000

Table 9: Input information: analysis case processing summary

Unweighted Cases		N	Percent
Valid		132	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		132	100.0

Table 10: Descriptive statistics

Status		Mean	Std. Deviation	N	
				Unweighted	Weighted
1	X1	-.150850713044618	.387556381741887	66	66.000
	X2	-.277435310457261	.524056827776698	66	66.000
	X3	-.036559292600727	.092051796828415	66	66.000
	X4	.251258374701198	.373672477405010	66	66.000
	X5	.979323671021467	.457377049629283	66	66.000
2	X1	.576281152070763	.345413899404021	66	66.000
	X2	.303404590823221	.502220349840738	66	66.000
	X3	.045202907854692	.100248490628738	66	66.000
	X4	7.409404359279040	7.746145501597000	66	66.000
	X5	.903318454210763	1.220402600594660	66	66.000
Total	X1	.212715219513072	.516639027764641	132	132.000
	X2	.012984640182980	.588563584643256	132	132.000
	X3	.004321807626983	.104283119885627	132	132.000
	X4	3.830331366990120	6.538287039778240	132	132.000
	X5	.941321062616115	.918836353028409	132	132.000

Table 11: Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
X1	.501	129.477	1	130	.000
X2	.755	42.263	1	130	.000
X3	.845	23.819	1	130	.000
X4	.698	56.230	1	130	.000
X5	.998	.224	1	130	.636

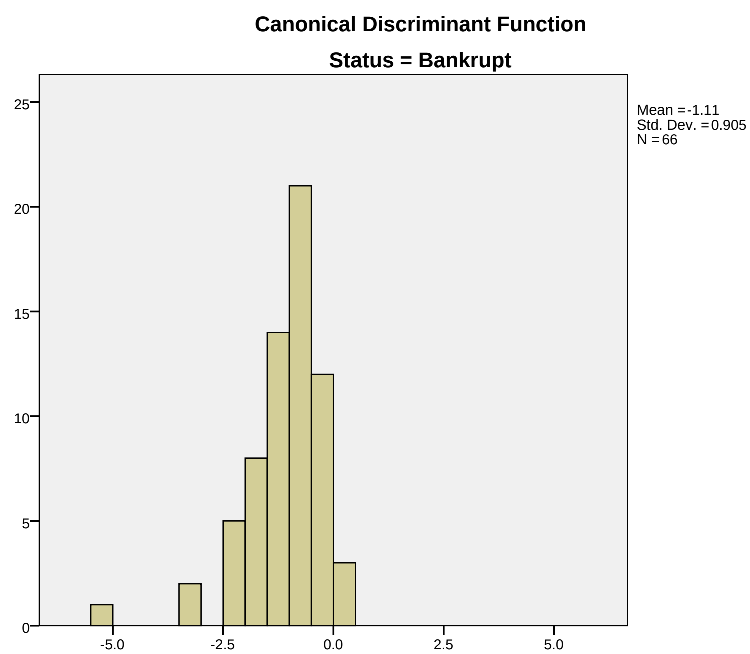
Table 12: Model significance test: Wilks' lambda

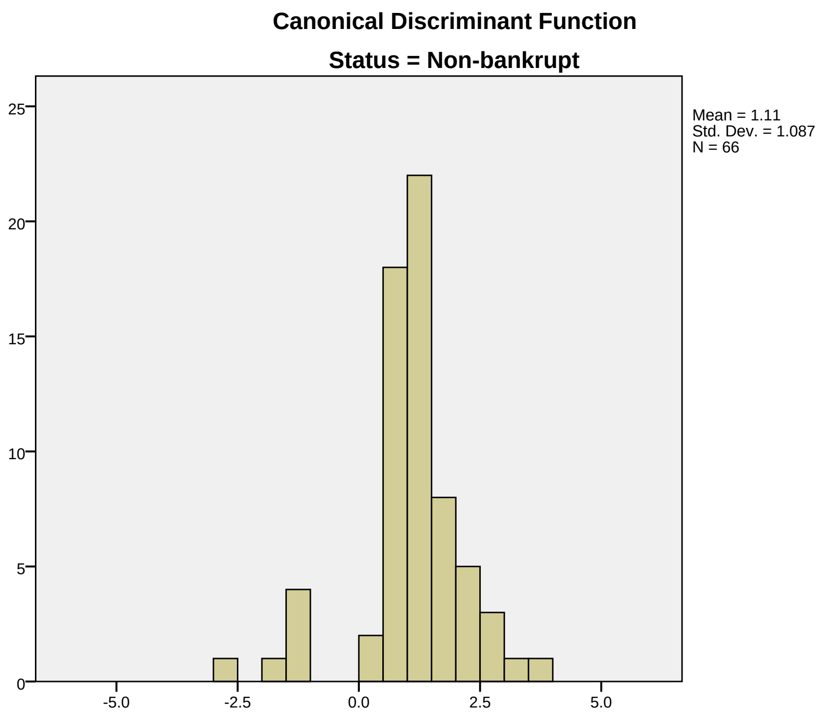
Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
JP Model	.443	103.942	5	.000

Table 13: Model development: canonical discriminant function coefficients

Variables	Coefficients
Working capital/Total assets	1.880
Retained earnings/Total assets	.489
Earnings before interest and taxes/Total assets	.118
Market value of equity/Total liabilities	.081
Sales/Total assets	.125
(Constant)	-.833

Unstandardized coefficients.




Canonical Discriminant Function
Status = Non-bankrupt
Mean = 1.11
Std. Dev. = 1.087
N = 66
25
20
15
10
5
0
-5.0
-2.5
0.0
2.5
5.0