A comparison of Altman's z-score and the J-model in assessing corporate failure: Evidence from the USA

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ABSTRACT

Over the past decades, researchers developed different models predicting the bankruptcy of companies across the world. However, these models differ greatly in nature, impact and time scale. The rationale of this paper is to discuss a variety of bankruptcy prediction models and its differences. A deeper insight is given to two models using financial ratios. Altman's z-score and the J-model are compared and analyzed using a sample of US companies. In this comparison it was concluded that the J-model is a better predictor of bankruptcy. A new model was established by adding a seventh variable, the debt ratio, to the original J-UK model, which was based on Altman's z-score. The new model, the L-model of bankruptcy, gives a better prediction of companies that fall into the categories of bankrupt and non-bankrupt than Altman's z-score and the J-model.

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Keywords

Bankruptcy, prediction models, Altman's z-score, business failure, Multiple Discriminant Analysis, J-UK model, financial ratios

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1. INTRODUCTION

Bankruptcy is a topic that has been researched for a long time and is still one of the greatest puzzle in corporate finance literature. According to the American Bankruptcy Institute (2018), around 24,000 U.S. businesses filed bankruptcy in each year for the past three years. Since 1980, this number has been decreased with an all-time low of less than 20,000 bankruptcies in 2006 and with a high of almost 83,000 in 1989 (American Bankruptcy Institute, 2018). There are a number of reasons why companies fail, which will be discussed in the following section. In order to better predict upcoming bankruptcies, researchers came up with numerous bankruptcy prediction models in the past. Ohlson (1980) developed a logit model with accounting ratios, Zmijewski (1984) established a probit model using accounting data, Shumway (2001) came up with a hazard model with accounting and market variables and Hillegeist et al. (2004) found a model based on the Black–Scholes–Merton option-pricing model (BSM-Prob model), which uses accounting and market variables as well. One of the most known, but also one of the oldest bankruptcy prediction model is the Altman z-score by NYU Stern Finance Professor Edward Altman (1968). This model uses a multivariate discriminant analysis (MDA) based on accounting variables. Accounting for flaws and limitations on the initial z-model, Almamy, Aston and Ngwa came up with their so-called J-UK model (Almamy, Aston, & Ngwa, 2015). They contributed to Altman's original z-score by adding an additional, sixth variable, cash flow from operations/total liabilities. The J-UK model was established with the aim to test the health of UK companies. In this paper, the term business failure is defined as a company that went out of business and filed for bankruptcy.

Of course, all of the bankruptcy prediction models have their advantages and disadvantages. Depending on the individual purpose, some are better than others in different ways. Many researchers have tested and compared the different models with different countries as evidence, as Shumway (2001) did with the hazard model, Hillegeist et al. (2004) compared Ohlson's O-score, Altman's z-score and the BSM-Prob model, Mossman et al. (1988) who compared four models and Wu et al. (2010) compared five bankruptcy prediction models. To date, however, there has not been a benchmark of Altman's z-score with the J-model providing sufficient evidence across US companies. The purpose of this paper is to investigate a set of selected models of listed companies. The analysis reflects the geographical focus on the US by employing the terminology J-US model instead of the conventional term J-UK model.

The objective of this study is to compare Altman's z-score and the J-US model. This is done by identifying which model has a better predictive power and higher accuracy in assessing corporate failure and whether the difference is statistically significant by performing statistical tests. To investigate the bankruptcy models, the following research question is formulated.

To what degree do the J-US model and Altman's z-score differ in terms of assessing corporate failure?

Eventually, after analyzing the two bankruptcy models, a new model is proposed, which is a better predictor of bankruptcy than Altman's z-score and the J-model

In doing so, this paper adds to the existing knowledge on bankruptcy prediction, particularly to the J-model. By doing so, the difference of the J-model used for the UK and the US will be compared and analyzed.

The following sections reviews literature on bankruptcy prediction, alongside with a discussion on the rational for selecting specific methods in the realm. Results of the two bankruptcy prediction models are subsequently discussed. Based on these insights, the paper then introduces and discusses the new model.

2. LITERATURE REVIEW

2.1 Altman's z-scores

Altman's z-score is a model, developed by Edward I. Altman in 1968, used to test the likelihood of a company to become bankrupt. Altman used a multiple discriminant analysis (MDA) with which he analyzed 66 manufacturing companies. Out of these 66 companies, 33 became bankrupt within the years 1946-1965 and the other half were existing companies in 1966. The original z-score formula applies to manufacturing listed companies and focuses on five financial ratios. Companies with a z-score < 1.81 are likely to face high financial distress. A z-score of 2.99 or higher indicates no danger of bankruptcy. The zone between 1.81 and 2.99 is called zone of ignorance or gray area due to the predisposition of errors. The result of the study was that 94% of the bankrupt firms were correctly classified, while 95% of bankrupt and non-bankrupt were assigned appropriately (Altman, 1968).

$$\mathbf{Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5}$$

With 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/book value of total debt

X_5 = sales/total assets

Z = overall index

These financial ratios have been chosen because they assess the financial health of a company (Atril & Eddie, 2006). The first ratio, working capital to total assets ratio, measures the net liquid assets relative to the total capitalization. The retained earnings / total assets measures the cumulative profitability of a company over time. The third ratio, earnings before interests and taxes (EBIT) / total assets, measures the true productivity of a company's assets. X_4 is the market to book ratio, which measures the amount a company's assets can decline in value before the liabilities exceed the assets and the company becomes bankrupt. The last ratio used by Altman is the total asset turnover emphasizing the sales generating ability of the company's assets (Altman, 1968), (Hillier, Clacher, Ross, Westerfield, & Jordan, 2017, pp. 52-54).

In 2000, Altman came up with a revised z-score, named z'-score, for private companies by changing X_4 from the market value of equity to the book value of equity. In this revised model, the score indicating high financial distress changed from 1.81 to 1.23 (Altman, 2000). The adjusted formula for the z'-score looks as follows:

$$\mathbf{Z' = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.420X_4 + 0.998X_5}$$

Two years later, Altman revised the z-score for non-manufacturers, leaving out the fifth variable, the z''-score. A score below 1.1 indicates a distressed condition (Altman, 2002).

$$\mathbf{Z'' = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4}$$

2.2 The J-UK model

In 2015, Jeehan Almamy, John Aston and Leonard N. Ngwa developed the J-model based on UK companies. With this new model, they tested the health of companies in the UK. They contributed to Altman's first z-score model (1968) and added the sixth variable cash flow from operations/total liabilities.

$$J = 1.484J1 + 0.043J2 + 0.39J3 + 0.004J4 + -0.424J5 + 0.75J6$$

With J1 = working capital/total assets

J2 = retained earnings/total assets

J3 = earnings before interest and taxes/total assets

J4 = market value equity/total liabilities

J5 = sales/total assets

J6 = cash flow from operations/total liabilities

In their study, they tested UK companies before, during and after the financial crisis. They also applied their data on Altman's z-score and then compared their findings of both models. Before the crisis, companies were classified correctly 51,5% using Altman's z-score and 64,1% using the J-model. During the financial crisis, Altman's score classified 67,4% correctly and the J-UK model 79,2%. After the crisis, the classification were the best, with 71,5% for Altman's z-score and 81,2% for the J-UK model. The researchers came to the conclusion that the J-UK model had a higher accuracy of predicting bankruptcy in all cases, before, during and after the financial crisis (Almamy, Aston, & Ngwa, 2015).

The newly added sixth ratio, cash flow from operations / total liabilities, is the cash flow to debt ratio and measures the time it takes a company to repay its debts if the cash flow from operations is used to repay the debt (Hillier, Clacher, Ross, Westerfield, & Jordan, 2017, p. 54).

Via the J4 variable, market value of equity / total liabilities, the researchers used total liabilities instead of the book value of total debt as used by Altman. However, this makes no difference because Altman defined the book value of total debt as current and long-term debt (Altman, 1968).

2.3 Oher bankruptcy prediction models

Besides Altman (1968) and Almamy et al. (2015), other researchers came up with different kinds of models to predict bankruptcy. In the following, a few of the most known models will be introduced.

Beaver (1966) developed an alternative bankruptcy prediction model that is different from Altman's z-score. In his study, a dichotomous classification test was performed to identify the error rates a potential creditor would undergo if companies are classified bankrupt or non-bankrupt on the basis of 14 financial ratios. The sample that was used for this study consists of 79 companies that became bankrupt between 1954 and 1964, and 79 existing companies that were similar to the failed firms in terms of size and industry. The result of his study shows that companies were 78% correctly classified bankrupt five years prior bankruptcy (Beaver, 1966).

In 1972, Deakin took Beaver's study to another level. He analyzed 32 failed companies between 1964 and 1970. Deakin took the same 14 financial ratios that Beaver also used in his study but he used them within a series of multivariate discriminant models. The difference between Beaver's and Deakin's study is that Deakin defined a company as failed which experienced bankruptcy, insolvency or which were liquidated in another form for the benefit of creditors. Whereas Beaver included companies that defaulted on loan obligations or missed preferred dividend payments. He observed that the companies used in this study were mostly financed by debt and preferred stock, which meant that funds were invested in plant and equipment, leading to being unable to generate the sales and net income in order to stimulate the debt. The outcome of Deakin's study is that 90% of the companies were correctly classified bankrupt or non-bankrupt and his model can be used up to three years to predict bankruptcy with adequate certainty (Deakin, 1972).

The Zeta Credit Risk model is another bankruptcy prediction model developed by Altman, with his colleagues Haldeman and Narayanan in 1977. The study included 53 bankrupt and 58 existing manufacturing and retailer companies between 1969 and 1975. The Zeta Credit Risk model can predict insolvency up to five years prior to bankruptcy. Successful classification of the model can be seen of more than 90% one year and 70% five years prior to bankruptcy. The model classifies a company as bankrupt with a negative score, a score larger than zero is classified as non-bankrupt. Altman and his colleagues compared their ZETA model with Altman's z-score with the result that both models show almost the same accuracy of bankruptcy prediction one year prior to bankruptcy but two and more years prior to bankruptcy the ZETA model gives a better prediction. Five years prior to bankruptcy, the ZETA model gives a correct prediction of 70%, whereas the z-score is only 36% accurate (Altman, Haldeman, & Narayanan, 1977).

In 1980, Ohlson developed a probabilistic model of bankruptcy. He used a sample of 105 bankrupt firms and 2,058 existing firms. With his bankruptcy prediction model, he calculated the probability of business failure one and two years prior to bankruptcy using a set of nine variables. His results showed that companies that were bankrupt are more likely to become bankrupt one and two years before they filed bankruptcy compared to existing firms. Hence, one observation would be that not all of the companies in the bankrupt group had a high probability of failure. The mean probabilities of the different groups were 0.39 for firms one year prior to bankruptcy, 0.03 for existing firms and 0.20 for firms two years prior to bankruptcy. One would have expected a higher mean score for the bankrupt companies (Ohlson, 1980).

Zmijewski (1984) investigated methodological issues related to the estimation of financial distress prediction models. In his study, he used companies listed on the American and New York Stock Exchange from 1972 until 1978 and with an industry (SIC) code of less than 6,000 to explore two biases that were generated by data collection from studies determining financial distress. Typically, the two biases may occur when data for financial distressed studies are not collected randomly. The first bias is a choice-based sample bias and occurs when distressed companies are oversampled. The second bias is a sample selection bias and occurs when using a sample selection criterion of "complete data". The result of the first bias illustrated that there was a sample selection bias in most of the financial distress prediction models. The second bias shows similar results: a bias does exist but it is not significant. However, the outcome of both biases was that neither one showed a difference in the financial distress prediction (Zmijewski, 1984).

A more recent study by Liang et al. (2016) discovered that not only financial ratios but also corporate governance indicators are important for predicting failure of companies. However, this might not be suitable for all markets globally. To exemplify, corporate governance indicators might not be suitable for markets with an unclear definition of distressed companies, as well as markets where corporate governance indicators are unclear (Liang, Lu, Tsai, & Shih, 2016).

2.3.1 Comparative analysis of bankruptcy prediction models

In 2001, Shumway developed a simple hazard model to forecast bankruptcy more accurately. Through this model he determined the risk of business failure at each possible point of time. For this hazard model, three market-driven variables were used to determine failing companies. In the hazard model, the dependent variable is the time that a company is considered healthy. As soon as a company is not considered a healthy company anymore, it is dropped off the list of observations. The risk of a company to become bankrupt varies over time. A company's health is based on the financial data and the age. The hazard model contains ten times more data compared to other bankruptcy prediction models as every year is observed as a single value. The sample Shumway used includes 300 bankrupt companies between 1962 and 1992, retrieved from the American and New York Stock Exchange. He discovered that the hazard model and Altman's coefficients prove that companies are less likely to fail if they have higher earnings compared to assets, if large companies have less liabilities and if companies have high working capital. The hazard model allocates 70% of all bankrupt companies in the highest bankruptcy probability decile, whereas Altman's discriminant analysis gives not an as exact percentage. Comparing the hazard model with Zmijewski's model, both classify companies between 54% and 56% in the highest bankruptcy probability decile. Looking at the model based on market-driven variables, companies are classified 69% in the highest probability decile. Therefore, Shumway came to the conclusion, that forecasting bankruptcy is better when combining market-driven variables with two accounting ratios (Shumway, 2001).

In the research of Hillegeist et al (2004), the probability of bankruptcy is assessed by comparing Altman's z-score (1968) and Ohlson's O-score (1980). This is done by employing a model which uses BSM-Prob market-based variables, based on the Black-Scholes-Merton option-pricing model. The Black-Scholes formula uses current stock prices, expected dividends, the option's strike price, time to expiration, expected volatility and expected interest rates to calculate the value of options (Black & Scholes, 1973).The outcome of the study was that the BSM-Prob model leads to better results compared to accounting-based models. The researchers calculated a pseudo-R^2 for all models and the result was that the BSM-Prob was 71% better than Altman's z-score and there was a 33% difference of Ohlson's O-score and the BSM-Prob model. Their reasoning is that the z-score and O-score have less statistical power in order to give reliable results. It is recommended to use the BSM-Prob model to predict bankruptcy instead of the accounting-based models because it unlocks higher power potential in the overall tests. Although the market-based BSM-Prob model is better than Altman's z-score and Ohlson's O-score, the O-score performs a significantly better prediction of business failure than Altman's z-score (Hillegeist, Keating, Cram, & Lunstedt, 2004). In a study of Bankruptcy Classification Errors in the 1980s researchers found out that Altman's and Ohlson's models performed well in the times they were established but are not applicable in more recent times, even with re-estimated coefficients (Begley, Ming, & Watts, 1996).

In 1988, Mossman et al. compared four bankruptcy prediction models, namely Altman's z-score (1968), the model of cash flows by Aziz, Emanuel and Lawson (1988), a market return model by Clark and Weinstein (1983) and the market return variation model by Aharony, Jones and Swary (1980). However, none of these models were adequate enough to classify companies into bankrupt and non-bankrupt categories (Mossman, Bell, Swartz, & Turtle, 1988).

Wu, Gaunt and Gray (2010) compared five bankruptcy prediction models. They came to the conclusion that Altman's z-score (1968) performed the worst out of the five models. Ohlson's O-Score (1980) and Zmijewski's model (1984) performed well in the 1970's. Shumway's hazard model (2001) performs better than accounting-based models and also outperforms Hillegeist et al. (2004), although Hillegeists' model performs good as well. The researchers concluded that the best and most reliable model would be one that contains key accounting information, market data and firm-characteristics (Wu, Gaunt, & Gray, 2010).

2.4 Reasons for corporate failure

There several factors in the external and internal environment that contribute to failure. Most of the literature only covers the failure of small firms but the failure factors can also apply to large companies. The following section highlights reasons for corporate failure.

Ricketts Gaskill et al. (1993) found four factors contributing to failure of small business apparel and accessory retailers in Iowa. The first factor is poor managerial functions, followed by (2) financial distress, (3) growth and overexpansion, and (4) competition with discount stores and in trade areas (Ricketts Gaskill, Van Auken, & Manning, 1993). Bready III and Moore (2000) confirmed in their study the research of Ricketts Gaskill et al. (1993) that the most common causes for business failure are poor management and lack of capital (Bradley III & Moore, 2000).

In the study of Uhrig-Homburg (2005), she found out that although liquidity problems are often causes of bankruptcy, cash-flow shortage is not an independent factor of bankruptcy (Uhrig-Homburg, 2005)

According to Headd (2003), companies that are larger, have more resources available, better financing and have employees, are more likely to succeed. Furthermore, new established companies are more likely to close, whereby closure does not mean failure. Of all closed firms, one third were successful at closure and two third were unsuccessful. Besides, company size and having employees, a starting capital and having an educated owner are also correlated to the survival of a company. Being young and having no start-up capital are reasons for closure but are not factors for unsuccessful closure (Headd, 2003).

A range of 30% to 50% of business failures are associated with economic factors. Other factors associated with failure rates are lagged employment rates and lagged retail sales. Two fundamental reasons for small business failure are the lack of management skills and insufficient capital. Moreover, interest rates are also positively associated with company failure (Everett & Watson, 1998).

According to Ohlson (1980), he found four factors that are statistically significant in affecting the probability of business failure. The factors are: the size of the company, a measure of the financial structure, a measure of performance, and a measure of current liquidity.

As stated by Ropega (2011), failure can happen to all kinds of businesses but SME's are more likely to fail because they do not have the financial support and resources that big companies have and it is more difficult to get financed by banks. Failure does not have to occur because of poor managerial performance or lack of finance, but can occur as a 'knock-on effect' from steps made by competition, other businesses, suppliers, and customers (Ropega, 2011).

Perry (2001) discovered that failed US companies did less planning than non-failed US companies. Therefore, he concludes that there is a relationship between written business plans and company failure (Perry, 2001).

In similar vein, Hyder and Lussier (2016) discovered that reasons for business failure in Pakistan were poor planning, improper employee staffing and inadequate inflow of capital (Hyder & Lussier, 2016).

As seen above, most researchers discovered that the main reasons for corporate failure is a lack of capital, poor management and competition but also the age of the firm plays a role. Apart from what other researcher stated, Doumpos and Zopounidis (2002) point out that financial ratios are indeed not the source of the problems a firm faces but rather the symptoms of the operating and financial problems (Doumpos & Zopounidis, 2002).

3. THEORIES & HYPOTHESIS

The Trade-off theory implies that each company decides on how much it is financed by equity and by debt for balanced costs and benefits. Companies are usually financed through a combination of both, equity and debt, but one may be higher than the other. However there are certain benefits to debt financing. The advantage of debt financing is that debt payments are tax deductible which makes debt financing cheaper than equity financing. However, there is an increase in risk to a company when increasing debt financing (Brealey, Myers, & Allen, 2011, pp. 353-354).

The pecking order theory entails that companies have a set order of priority when it comes to financing. Companies favor internal financing mechanisms over issuing debts. In other words, if issuing debts is not rational anymore, the last option is issuing equity. Whether a company is financing itself internally, through debt or equity gives an insight how the company is performing. If a company uses internal financing, it is considered secure and stable. Debt financing implies a company is capable of paying the debt back, whereas equity financing signifies that a company tries to make money through issuing stocks (Hillier, Clacher, Ross, Westerfield, & Jordan, 2017, pp. 432-433).

Including an additional, sixth variable of cash flow from operations/total liabilities to the Altman's model, is important because cash flow is a major indicator of financial health. The cash flow is a determinant of a business having the ability to generate cash internally. Therefore, including J6 should make the J-model a better predictor of the financial health of the company.

According to Almamy, Aston and Ngwa's research, the J-UK model is a better predictor of the financial health of a UK company than Altman's z-score. But does this only apply to UK companies or is it a model that can be applied universally? In this research, it will be investigated whether the J-model is also a better predictor of corporate failure when using data of bankrupt listed companies in the US. Therefore, the following hypothesis is proposed;

$H1_A$: The J-US model has a better predictive ability of bankruptcy than Altman's z-score.

$H1_0$: The J-US model does not have a better predictive ability of bankruptcy than Altman's z-score.

According to the Trade-off theory, companies using more debt financing are also facing higher risks of not being able to pay back and eventually becoming bankrupt. The pecking-order theory underlines this theory with a company financing itself through debt is more unstable than a company using internal financing.

Therefore, adding an additional variable to the J-model focusing around the debt financing of companies should make the model a better predictor of bankruptcy. The additional variable represents the debt ratio calculated by dividing the total liabilities by the total assets. The debt ratio measures the level of a firms leverage and explains the amount of assets financed by debt. The higher the debt ratio, the more leveraged a firm is, resulting in higher financial risk. This ratio takes all debts into account (Hillier, Clacher, Ross, Westerfield, & Jordan, 2017, p. 50)

With regard to the debt ratio, the study hypothesizes:

$H2_A$: Adding a debt ratio to the J-model is a better predictor of bankruptcy than the original J-model.

$H2_0$: Adding a debt ratio to the J-model is not a better predictor of bankruptcy than the original J-model.

4. METHODOLOGY

For this study, the data was retrieved from Orbis database, provided by Bureau van Dijk – A Moody's Analytics Company. Orbis holds information of about 275 million companies from around the world. The database contains information about finances, directorship, ownership, mergers and acquisitions, and much more. It is possible to customize data by using filters in order to get only the information needed for the analysis (Orbis, 2018).

For the research, the company data was filtered by bankruptcy, listed on the stock market and settled in the USA. Using this selection criteria a random sample of 115 bankrupt companies that filed bankruptcy in 2004 until 2017 has been chosen. Due to data not being available of all companies the sample size was reduced to 27 bankrupt firms. Furthermore, a random sample of 60 existing US companies that are similar to the bankrupt companies in terms of size and industry has been chosen. The companies were still existing in 2017 and data from 2015 has been used for the research.

The customized data of the randomly selected companies consist of the following indicators: the company name, number of employees, year of bankruptcy, working capital, total assets, retained earnings, earnings before interest and taxes (EBIT), market value of equity, sales, cash flow from operations, current assets, and current and non-current liabilities. The market value of equity has been found under the name of market capitalization. For the existing companies, the annual market capitalization was available on ORBIS. For the bankrupt companies, only the monthly market capitalization of each available year was available, with which the annual market capitalization was calculated. By adding the current and non-current liabilities the total liabilities can be calculated. Some companies were missing the data for working capital, hence it was calculated by subtracting the current assets by the current liabilities. All other variables are available on ORBIS and thus, do not require a calculation. The financial information of the companies was used to calculate the financial ratios needed for determining Altman's z-score and the J-model. With the financial ratios the z-score and J-US score of bankrupt US companies were calculated. The calculations were performed through Excel with statistical analysis in SPSS. Results of the two formulas were analyzed through a univariate, bivariate and multivariate analysis, to determine whether companies were correctly classified bankrupt one year prior to bankruptcy according to both models. Moreover, it was tested whether the difference of the percentage of the correctly classified bankrupt companies of both models is statistically significant in order to determine whether there is a difference in the predictive ability of the J-US model and Altman's z-score. Before calculating the financial ratios and the bankruptcy prediction formulas, the raw data was being analyzed. A univariate analysis was performed, describing the variables by providing descriptive statistics of the mean, median, standard deviation, minimum and maximum of each variable. The same was applied to the financial ratios, however these ratios are based on the variables, wherefore the descriptive statistics of the ratios can be explained by the variables. Combined, four tables of descriptive statistics were generated, descriptive statistics of both, bankrupt and existing companies, with each having one table of both, variables and ratios. Besides, a one-way ANOVA was performed to determine whether there is a statistically significant difference between the means of the different financial ratios. Moreover, a bivariate analysis was executed by determining the relationship of the variables. This was done by creating correlation matrices of the variables of the bankrupt and existing companies using Pearson's correlation coefficient. Lastly, a multivariate analysis helped analyzing the effect of the variables. For this a Multiple Discriminant Analysis (MDA) has been conducted. A MDA is a statistical method used if you want to classify data in a set number of groups, in this case, in bankrupt and non-bankrupt (McLaney & Atrill, 2016, p. 275). The purpose of employing an MDA is multifaceted: to investigate differences among groups, to discard variables which are little related to group distinction, to classify cases into groups and to test theory whether cases are classified as predicted. In an MDA, data is usually classified in two or more groups, inter alia, bankrupt and non-bankrupt companies (Klecka, 1980). The MDA was used to find a new formula by adding a new ratio which predicts bankruptcy better than Altman's z-score and the J-model. After performing the MDA, it was possible to test whether there is any statistical variance between the J-model and the new model.

5. RESULTS

This part discusses the results of the previously conducted statistical analysis. The sections starts out with a summary of the statistical findings. Then, the correlation of the different variables is analyzed, followed by synthesis on the regression results.

5.1 Univariate analysis

In this univariate analysis, the mean, median, standard deviation, minimum and maximum of the variables and financial ratios are looked at. These variables are key to calculating the financial ratios used to predict the bankruptcy of companies. The statistical summaries of the variables and ratios can be found in the appendix section at the end of this paper. Table A presents the variables of bankrupt companies, whereas Table B presents the ratios of the bankrupt companies. Table C shows the variables of existing firms and Table D the ratios of existing firms. By comparing the descriptive statistics of both, bankrupt and existing companies, many expected but also unexpected differences can be observed.

The mean, median, standard deviation, minimum and maximum of the total assets, total cash of operating activities, retained earnings and market capitalization are higher for the existing companies than the bankrupt companies. The same applies to the current and non-current liabilities, thus making the total liabilities also higher for existing companies. Looking at the working capital, the mean, standard deviation and maximum are higher for the bankrupt firms. In general, the EBIT of existing companies is higher than the one of bankrupt companies but the minimum score is lower. The mean of the current assets of bankrupt companies is slightly higher than of existing companies. The minimum is lower than existing firms but the maximum is much higher. A surprising difference can be observed in the mean of $-69,952,190.00 sales for existing companies, which is in its negatives. This negative mean can be explained by the very low minimum of $-11,807,000,000. By comparing the ratios of the bankrupt and existing companies it can be seen that the working capital to total assets ratio, as well as the EBIT to total assets ratio are in general higher for existing companies but the standard deviation and maximum are higher for bankrupt companies of this dataset. The existing companies have a better performing retained earnings to total assets ratio and cash flow from operations to total liabilities ratio with a smaller standard deviation than bankrupt firms. The market to book ratio gives higher results for the existing companies. Findings also show that the bankrupt companies perform better than the existing companies in terms of the sales to total assets ratio, which can be explained by the higher sales of bankrupt firms.

Furthermore, a one-way ANOVA (F-test) has been conducted to test the discriminating ability of the ratios. The results demonstrated in Table E of the Appendix show that there is a significant difference between the means of the ratios 2 to 6 but the ratio working capital / total assets shows no significant difference between the means of these ratios at a 5% confidence-interval.

5.2 Bivariate analysis

For the bivariate analysis, the correlation of Pearson's correlation coefficient has been used. Pearson's r has a value between +1 and -1, where +1 indicates a perfect positive linear correlation, 0 indicates no correlation and -1 a perfect negative linear correlation (Dooley, 2009, p. 331). The detailed correlation matrices of the bankrupt and existing companies can be found in the Appendix in Tables F and G.

Table 1
Original * Altman's classification Cross tabulation
Count

		Predicted Group Membership			
		bankrupt	zone of ignorance	non-bankrupt	Total
Original	bankrupt	20	3	4	27
	non-bankrupt	50	9	1	60
Total		70	12	5	87

Table 2
Original * J-model classification Cross tabulation
Count

		Predicted Group Membership		
		non-bankrupt	bankrupt	Total
Original	bankrupt	4	23	27
	non-bankrupt	32	28	60
Total		36	51	87

Looking at the correlation of the variables of bankrupt companies, it has been found that there are almost only positive linear correlations. The variables EBIT and total liabilities, as well as retained earnings and total liabilities however, show no correlation. Overall, a perfectly positive linear relationship can be seen between the variables of working capital and total assets, non-current labilities and total assets, as well as non-current liabilities and working capital. Moreover, current assets and the variables total assets, working capital and non-current liabilities show a perfect positive linear correlation, too. A quite low positive linear correlation can be seen between retained earnings and sales, and market capitalization and EBIT. The correlations of the other variables are medium to high positive linear.

The correlation matrix of existing companies shows only a few negative linear correlations which shape as followed: sales and total assets have a moderate negative linear correlation of -0,339, while sales and total cash from operating activities have a low negative linear correlation of -0,12.

Another moderate negative linear correlation can be seen between sales and retained earnings, as well as sales and total liabilities. Also, sales has no correlation with current and non-current liabilities. The negative linear correlations and lack of correlations with sales can be explained by the sales having a negative mean for existing companies (see Table C in the Appendix).

5.3 Multivariate analysis

After calculating Altman's z-scores and the J-scores, both formulas have been compared. In Table 1, the classification of Altman's formula can be found. Table 2 shows the classification of the J-model. Only 24% of the companies have been correctly classified, however, 74% of bankrupt companies were correctly classified, using Altman's z-score (Table 1). Twelve out of the eighty-seven firms are in the zone of ignorance. This is a completely different finding of what Altman found in 1968 with a correct classification of 95% of all companies. The findings of Shumway (2001) and Wu et al. (2010) also differ from these findings: in Shumway's (2001) study 42.3% of bankrupt companies were correctly classified, whereas in Wu et al.'s (2010) study 28.73% of bankrupt companies were correctly classified. Using the J-model, 63% companies have been correctly classified. These study results are similar to the findings of Almamy et al. (2015) of the classifications before the financial crisis. Findings show that the J-model seems to be a better predictor of bankruptcy. This was confirmed by performing the Chi-square test to determine whether there is enough evidence that the J-US model is indeed a better predictor of bankruptcy than Altman's z-score. Findings of Table H prove that there is enough evidence of a significant difference between the two models.

As shown above, Altman's z-score and the J-model do not seem to be good predictors of bankruptcy because the classification results from US companies differ completely from the original findings. Therefore, an additional, seventh variable has been added to the formula: the debt ratio, calculated by dividing the total liabilities by the total assets. This ratio indicates the amount of leverage a company uses. The higher the ratio, the more leverage a firm is using and the weaker the equity position. Moreover, the lower the ratio, the lower the risk (Hillier, Clacher, Ross, Westerfield, & Jordan, 2017, p. 50). In order to determine whether the difference of adding an additional variable is significant, a multiple discriminant analysis has been undertaken for all models. First, an MDA was performed only using the variables for Altman's model (Table 3). Twelve of the original bankrupt companies and 57 of the original existing companies have been correctly classified. Therefore, 79,3% of the original grouped cases have been correctly classified, which is still not close to what Altman found. Using the variables of the J-model, 81,6% of the original grouped cases have been correctly classified (Table 4). This result is similar to the classification result of Almamy et al. (2015) for the J-UK model after the financial crisis in 2008. In Table 5, the results of adding the new seventh variable can be found. It shows that 18 out of 27 original bankrupt companies and 58 out of the 60 original existing companies have been correctly classified. This adds up to only 18.4% being not correctly classified. The MDA shows that there is no significant difference using only the variables Altman used or adding one or two variables to the original five in order to predict bankruptcy. However, this does not mean the new model is not a good predictor of bankruptcy. One explanation for this lies in the fact that the MDAs using Altman's financial ratios and the ratios of the J-model did not results in the same Standardized Canonical Discriminant Function Coefficients, meaning the formulas of the MDA and the ones developed by the other researchers do not align. Comparing the MDA result of the new model with the classification of the J-model shown in Table 2, there is enough evidence of a significant difference between the two models at a 1% confidence interval (Table I, Appendix). Therefore, the new model is a better predictor of business failure than the J-model. The new model gets the name L-model, which determines the L-score of bankruptcy.

The Standardized Canonical Discriminant Function Coefficients (see Table J in the Appendix) of the MDA gave the following formula for the new model:

$$\mathbf{L = -0.113X_1 + 0.238X_2 - 0.052X_3 - 0.051X_4 + 0.011X_5 + 0.729X_6 - 0.639X_7}$$

X_1 to X_6 are the same variables used in the J-model with X_7 being the newly added variable total liabilities / total assets.

A L-score of -1 and less classifies a company has bankrupt, a L-score of -0,8 and higher classifies a company as non-bankrupt. A score between -0,8 and -1 is called the zone of ignorance due to the predisposition of errors.

By further analyzing the three models, Wilks' Lambda displays the model's ability to discriminate. The values range from 0 to 1, where a higher value means a lower ability of the model to discriminate (Klecka, 1980). Tables K-M in the Appendix display Wilks' Lambdas and Chi-squares of the three models. Altman's model has the lowest ability to discriminate with a value of 0,697, followed by the J-model with a value of 0,628 and the L-score with the highest ability to discriminate with a Wilks' Lambda of 0,553. In the context of the Chi-square of the three discriminant models, it can be concluded that all models are highly significant at a 5% significance level of the original variables. Comparing these findings to the results of Almamy et al. (2015) a Wilks' Lambda of 0,995 for Altman's model and 0,983 for the J-UK model were found. Although these results differ from this research, both models are also highly significant at a 5% significance level.

Looking back at the Multiple Discriminant Analysis of the L-model, Table N in the Appendix shows the Test of Equality of Group Means. This test measures the potential of each independent variable before the model is created (Leech, Barrett, & Morgan, 2008, p. 127). For all variables Wilks' lambda is fairly close to 1, which means there is almost no discrimination at the level of how much each independent variable contributes to the model. The p-value indicates that only the working capital to total assets variable does not reject the null hypothesis, all other variables do reject the null hypothesis at a 5% significance level, which means that working capital to total assets does not contribute to the model.

Table 3

Classification Results[a] Altman

			Predicted Group Membership		
		Reality	bankrupt	non-bankrupt	Total
Original	Count	bankrupt	**12**	**15**	**27**
		non-bankrupt	**3**	**57**	**60**
	%	bankrupt	**44,4**	**55,6**	**100,0**
		non-bankrupt	**5,0**	**95,0**	**100,0**

a. 79,3% of original grouped cases correctly classified.

Table 4

Classification Results[a] J-model

			Predicted Group Membership		
		Reality	bankrupt	non-bankrupt	Total
Original	Count	bankrupt	**13**	**14**	**27**
		non-bankrupt	**2**	**58**	**60**
	%	bankrupt	**48,1**	**51,9**	**100,0**
		non-bankrupt	**3,3**	**96,7**	**100,0**

a. 81,6% of original grouped cases correctly classified.

Table 5

Classification Results[a] L- model

			Predicted Group Membership		
		Reality	bankrupt	non-bankrupt	Total
Original	Count	bankrupt	**18**	**9**	**27**
		non-bankrupt	**2**	**58**	**60**
	%	bankrupt	**66,7**	**33,3**	**100,0**
		non-bankrupt	**3,3**	**96,7**	**100,0**

a. 87,4% of original grouped cases correctly classified.

The Eigenvalue (Table O) indicates how much discriminating ability the function possesses. This function has an Eigenvalue of 0,81. The larger the Eigenvalue, the more variance the function explains in the dependent variable. Having an Eigenvalue of 0,81 means that it is considered as not as stable. A good model would have an Eigenvalue more than one (Leech, Barrett, & Morgan, 2008).

6. DISCUSSION & CONCLUSION

6.1 Discussion

The L-model appears to be a good predictor of bankruptcy but it can happen that the model misclassifies companies which is disadvantageous. A company could have a poor profitability and may be considered as bankrupt regarding their solvency record which would lead to classifying the company into bankrupt using the formula but in practice the situation might not be that serious because of its above average liquidity (Altman, 1968, p.591). There are two possible ways of misclassifying a company, by either classifying a failing business as successful or classifying a successful company as failing. This misclassifications could lead to falsely rejecting (Type I error) or falsely accepting (Type II error) the null hypothesis. In this study, the null-hypothesis of both, the hypothesis and sub-hypothesis, have been rejected. Therefore a Type I error could have occurred if companies have been misclassified.

Another rational is that two biases could have occurred as Zmijewski (1984) has found. The first bias, the choice-based sample bias, can be excluded because the sample of distressed companies was not oversampled and the chosen companies were randomly selected. The sample selection bias can also be excluded since all company data necessary for the models was available. Therefore, it can be concluded that none of these biases occurred when conducting the study.

6.2 Limitations and further research

Similar to other studies, this research has limitations that can lead to implications for further research. In the following, seven limitations to this research have been identified.

The first limitation one can observe is that the J-UK model is based on UK companies and thus, does not necessarily apply to companies in all countries of the world. The J-model is quite accurate with US companies but tends to be a better predictor using UK companies. The same applies to the L-model. The L-model is based on US companies and has not been tested with other countries, which represents a critical step for future research by testing whether the L-model only applies to US companies or if other countries could use this model, too, in order to predict business failure successfully.

Furthermore, the models have not been applied to a single, specific industry, nor to a specific size of company. Hence, it would be recommended to analyze the L-model separating companies by industry and also by size, for instance, by dividing the sample of each industry of a specific country into three groups with one being less than 5000 employees, one less than 15000 but more than 5000 employees and the last with more than 15000 employees.

The next limitation represented in, is the small sample size of only 27 bankrupt and 60 existing companies. This was explained due to the lack of financial data on the database OSIRIS. Hence, further researchers should use a larger sample size of both, bankrupt and existing companies, particularly the same amount of companies for both company types. Using a larger sample gives a better accuracy of the model.

Another limitation that was identified is that only financial ratios were used in order to predict bankruptcy of companies. Since also other factors, irrespectively of finances, contribute to business failure, these should be considered when classifying companies into bankrupt and non-bankrupt. The fifth limitation observed is the L-model only classified companies one year prior bankruptcy with an accuracy of 87,4%. In practice, this could be too late for a company in terms of making any financial changes to prevent bankruptcy. Hence, companies should be examined for a longer period of time prior bankruptcy. One idea would be to develop a model that classifies 80% of the companies correctly seven years prior bankruptcy and higher, the closer the company actually gets to becoming bankrupt with, for example, a 98% accuracy one year prior bankruptcy. Through employing this revised approach a company could detect early enough the danger of becoming bankrupt and being able to take action against.

According to Hillegeist et al. (2004) a drawback of this model would be that it is missing a measure of asset volatility. Asset volatility improves bankruptcy forecasting because it determines the tendency of an assets worth declining until a firm being unable to pay its debts back. Therefore, the higher the volatility the larger the probability of bankruptcy (Correia, Kang, & Richardson, 2018), (Hillegeist, Keating, Cram, & Lunstedt, 2004).

The last limitation discovered was the wide range of years taken into consideration. In this study, financial data one year prior bankruptcy was selected ranging from 2004 until 2017. Further research should focus only on a smaller amount of years because the economic situation in 2004 was different from the one in 2017. Future research could categorize years by, for instance, pre- financial crisis, during the financial crisis and post- financial crisis, as done by Almamy et al. (2015).

It is recommended to contribute to this model in future research by extending the formula to obtain a bankruptcy prediction model that operates on high precision and could be used by companies in order to monitor their situation.

6.3 Conclusion

This study explores the statistical deviations of the Altman z-score and the J-model to gain deeper understanding on the predictability of corporate failure. Studies by Shumway (2001) and Hillegeist et al. (2004) found that a bankruptcy prediction model solely based on accounting variables is not as accurate. Analytical findings indicate that the best model to predict business failure contains accounting information, market data and firm-characteristics, according to Wu, Gaunt and Gray (2010). Reason for businesses failing is mainly the lack of capital, poor management and competition, as well as the age of the firm plays a role. Although Doumpos and Zopounidis (2002) said that operating and financial problems are usually the root of the problems resulting in bankruptcy and financial ratios are only the symptoms and first indicators to these problems. Almamy et al. (2015) found a similar model to Altman's z-score that is a better predictor for bankruptcy in the UK. The same model was tested in this study, only difference was that US companies were used. In the analysis both, Altman's z-score and the J-US model, have been compared and analyzed, concluding that the J-US model is a better predictor of bankruptcy than Altman's z-score. Therefore rejecting the null hypothesis and finding that there is indeed a significant difference between the two models. However the J-UK model had a higher accuracy than the J-US model in classifying the companies correctly one year prior bankruptcy. Considering the Trade-off theory and the pecking order theory it seemed suitable to add a ratio to the formula which measures the leverage. A debt ratio was added to the ratios of the J-model and a new model, named L-model of bankruptcy, was established in an MDA. The result yielded a significant difference between the J-US model and the L-model predicting bankruptcy. The L-model classified 87,4% of the bankrupt and existing companies correctly one year prior bankruptcy. Further research on this topic is recommended, by improving the L-model with a higher predictive power.

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9. APPENDIX

Table A
Summary statistics.
This table reports the mean, median, standard deviation, minimum and maximum of the variables used to predict bankruptcy. All numbers are in thousand USD. This data is retrieved from the sample of bankrupt companies.

Variables	Mean	Median	Std. Deviation	Minimum	Maximum
Total assets	1512050,00	125375,00	5084923,05	3753	26147090
Working capital	1014321,41	5445,00	4678773,96	-21811	24383296
Total Cash from Operating Activities	18476,96	-3512,00	129709,40	-169300	549470
Current liabilities	143528,59	50611,00	208769,24	5991	811000
Non-current liabilities	1242775,15	52028,00	4514019,95	15	23529227
Sales	645861,56	164922,00	1298022,31	2738	6286000
Operating P/L [=EBIT]	-72760,44	-2623,00	292058,31	-1154900	443377
Retained Earnings	-184154,33	-68256,00	354482,39	-1050700	828270
Current assets	1136820,78	65098,00	4768137,40	2705	24891459
Market capitalization	242265,15	50237,00	425294,99	1219	1629012
Total liabilities	1386303,74	100451,00	4613472,39	6924	24037390

Table B
Summary statistics.
This table reports the mean, median, standard deviation, minimum and maximum of the ratios used to predict bankruptcy. This data is retrieved from the sample of bankrupt companies.

Ratios	Mean	Median	Std. Deviation	Minimum	Maximum
Working capital / total assets	,075	,05	,50	-1,91	,93
Retained earnings / total assets	-1,90	-1,14	3,72	-19,29	,44
EBIT / total assets	-,26	-,08	,44	-1,68	,46
Market value equity / total liabilities	1,04	,40	1,54	,01	6,62
Sales / total assets	1,55	1,25	1,35	,09	4,95
Cash flow from operations / total liabilities	-,14	-,05	,34	-1,57	,28

Table C
Summary statistics.
This table reports the mean, median, standard deviation, minimum and maximum of the variables used to predict bankruptcy. All numbers are in thousand USD. This data is retrieved from the sample of existing companies.

Variables	Mean	Median	Std. Deviation	Minimum	Maximum
Total assets	2812854,22	1008545,50	4849261,21	65037,00	25500000,00
Working capital	427963,67	134781,00	730422,66	-86535,00	3435243,00
Total Cash from Operating Activities	290212,22	83455,50	625875,07	-13447,00	3919400,00
Current liabilities	571308,05	212101,50	1026310,01	9433,00	6056152,00
Non-current liabilities	2330035,17	971221,00	3651074,52	77762,00	23282020,00
Sales	-69952,19	47747,50	1835061,30	-11807000,00	4984400,00
Operating P/L [=EBIT]	812107,70	147206,50	2833988,95	-5683000,00	13967000,00
Retained Earnings	1208917,32	358591,00	2514187,97	6727,00	15771000,00
Current assets	1085470,05	438570,00	1888943,28	39225,00	9261000,00
Market capitalization	3455986,92	914349,33	9329379,81	22659,51	68286368,80
Total liabilities	1780225,37	588310,50	3164812,77	18533,00	17612000,00

Table D
Summary statistics.
This table reports the mean, median, standard deviation, minimum and maximum of the ratios used to predict bankruptcy. This data is retrieved from the sample of existing companies.

Ratios	Mean	Median	Std. Deviation	Minimum	Maximum
Working capital / total assets	,19	,18	,14	-,20	,57
Retained earnings / total assets	,11	,20	,57	-2,43	,97
EBIT / total assets	,04	,07	,16	-,75	,31
Market value equity / total liabilities	2,79	1,52	3,22	,11	15,74
Sales / total assets	1,11	,86	,71	,19	3,87
Cash flow from operations / total liabilities	,19	,16	,18	-,29	,75

Table E
ANOVA

	F	Sig.
Working capital / total assets	2,621	,109
retained earnings / total assets	16,986	,000
EBIT / total assets	21,546	,000
market value equity / total liabilities	7,241	,009
sales / total assets	4,075	,047
cash flow from operations / total liabilities	35,890	,000

Table F
This table shows the Pearson's correlation coefficient of the variables used to predict bankruptcy using data from bankrupt companies.

		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]
Total assets	[1]	1										
Working capital	[2]	,977**	1									
Total Cash from Operating Activities	[3]	,854**	,833**	1								
Current liabilities	[4]	,530**	,381*	,400*	1							
Non-current liabilities	[5]	,993**	,993**	,849**	,458**	1						
Sales	[6]	,498**	,309	,393*	,832**	,404*	1					
Operating P/L [=EBIT]	[7]	,331*	,313	,267	,026	,288	,083	1				
Retained Earnings	[8]	,555**	,547**	,585**	,041	,528**	,147	,802**	1			
Current assets	[9]	,984**	,999**	,838**	,411*	,997**	,346*	,307	,542**	1		
Market capitalization	[10]	,801**	,683**	,679**	,713**	,752**	,779**	,126	,271	,709**	1	
Total liabilities	[11]	,995**	,989**	,849**	,494**	,999**	,432*	,283	,518**	,994**	,768**	1

**. Correlation is significant at the 0.01 level (1-tailed).
*. Correlation is significant at the 0.05 level (1-tailed).

Table G
This table shows the Pearson's correlation coefficient of the variables used to predict bankruptcy using data from existing companies.

		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]
Total assets	[1]	1										
Working capital	[2]	,713**	1									
Total Cash from Operating Activities	[3]	,884**	,610**	1								
Current liabilities	[4]	,761**	,905**	,565**	1							
Non-current liabilities	[5]	,691**	,882**	,554**	,921**	1						
Sales	[6]	-,339**	,146	-,120	,058	,073	1					
Operating P/L [=EBIT]	[7]	,547**	,766**	,580**	,678**	,559**	,509**	1				
Retained Earnings	[8]	,915**	,470**	,801**	,512**	,459**	-,611**	,243*	1			
Current assets	[9]	,789**	,942**	,672**	,943**	,900**	,114	,785**	,520**	1		
Market capitalization	[10]	,701**	,549**	,916**	,481**	,469**	,217*	,695**	,546**	,632**	1	
Total liabilities	[11]	,974**	,666**	,820**	,731**	,663**	-,466**	,413**	,960**	,719**	,590**	1

**. Correlation is significant at the 0.01 level (1-tailed).
*. Correlation is significant at the 0.05 level (1-tailed).

Table H

Chi-Square Tests between Altman's z-score and the J-model

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	17,653[a]	1	,000		
Continuity Correction[b]	15,546	1	,000		
Likelihood Ratio	21,231	1	,000		
Fisher's Exact Test				,000	,000
Linear-by-Linear Association	17,421	1	,000		
N of Valid Cases	**76**				

a. 0 cells (0,0%) have expected count less than 5. The minimum expected count is 9,12.

b. Computed only for a 2x2 table

Table I

Chi-Square Tests between the new model and the J-model

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	4,880[a]	1	,027		
Continuity Correction[b]	4,073	1	,044		
Likelihood Ratio	4,850	1	,028		
Fisher's Exact Test				,036	,022
Linear-by-Linear Association	4,843	1	,028		
N of Valid Cases	131				

a. 0 cells (0,0%) have expected count less than 5. The minimum expected count is 17,21.

b. Computed only for a 2x2 table

Table J

Standardized Canonical Discriminant Function Coefficients

	Function 1
Working capital / total assets	-,113
retained earnings / total assets	,238
EBIT / total assets	-,052
market value equity / total liabilities	-,051
sales / total assets	,011
cash flow from operations / total liabilities	,729
Total liabilities / total assets	-,639

Table K

Wilks' Lambda for Altman US model

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	,697	29,747	5	,000

Table L

Wilks' Lambda for J-US model

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	,628	38,160	6	,000

Table M

Wilks' Lambda for L-US model

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	,553	48,353	7	,000

Table N

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
Working capital / total assets	,970	2,621	1	85	,109
retained earnings / total assets	,833	16,986	1	85	,000
EBIT / total assets	,798	21,546	1	85	,000
market value equity / total liabilities	,921	7,241	1	85	,009
sales / total assets	,954	4,075	1	85	,047
cash flow from operations / total liabilities	,703	35,890	1	85	,000
Total liabilities / total assets	,735	30,601	1	85	,000

Table O

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	,810[a]	100,0	100,0	,669

a. First 1 canonical discriminant functions were used in the analysis.