

✓
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A Fundamental Tool for Predicting Bankruptcy

**A Master Project (FIN 698) submitted in partial fulfillment of the
requirement for the degree of MBA in Finance**

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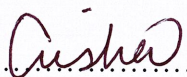
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June / 2015



DECLARATION

I declare that this work is the result of my own investigation and that it has not already been accepted in substance of any degree, nor is it being currently submitted for any degree.

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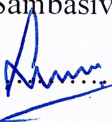
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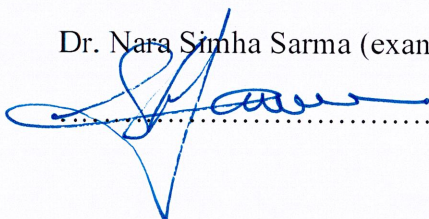
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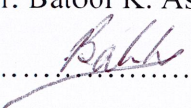
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ABSTRACT

This thesis is partially a replication of a study conducted by Altman (1968) on a different sample size and genre. The main purpose of this thesis is to provide investors with a simple tool that will help them make primary decisions regarding their current or prospective investments. The tool, a mathematical model, predicts companies' failures before their actual occurrence, thus offering investors key information. Knowing that the current literature is filled with models that predict bankruptcy, we attempted to utilize one of the most known models, Altman's Z-score, and investigate the prospect of expanding its applicability to embrace a wider-range of observations. We derived a new model out of the original one, in an attempt to enhance the model's accuracy.

The study was conducted using publicly-available financial statements from 115 US companies across a wide range of sectors—including services, healthcare, and technology—of which 39 filed for Chapter 7 or Chapter 11 bankruptcy in the US courts between 2010 and 2014. Our results ascertain that Altman's model is capable of predicting bankruptcy in companies from a wide range of sectors, exhibiting an accuracy of up to 74.7% one year prior to bankruptcy, 70.2% two years prior to bankruptcy, and 66.3% three years prior to bankruptcy. The developed model, however, exhibits higher accuracy than Altman's in predicting the bankruptcy of companies from the same range of sectors, at 84.1% one year prior to bankruptcy, 79.8% two years prior to bankruptcy, and 73.5% for three years prior to bankruptcy.

In a bid to discover whether the competency of the discriminant models presented can be improved upon when implemented on a homogeneous sample (a sample consisting of bankrupt and non-bankrupt companies from the same sector), the analysis was conducted once again on each sector separately. The results affirm that when using Altman's model on segregated samples, its accuracy in predicting bankruptcy does not significantly improve. In contrast, devising a discriminant model for each sector significantly improves the models' predictive competency.

TABLE OF CONTENTS

DECLARATION.....	ii
ACKNOWLEDGEMENTS.....	iii
ABSTRACT.....	iv
TABLE OF CONTENTS.....	v
LIST OF TABLES.....	viii
LIST OF FIGURES.....	viii
CHAPTER 1: INTRODUCTION.....	1
1.1 Overview	1
1.2 Purpose of the study	2
1.3 Outline of the chapters	3
CHAPTER 2: LITERATURE REVIEW.....	4
2.1 Qualitative Methods	4
2.2 Quantitative Methods	6
2.3 Hybrid Methods	11
2.4 Gap in the Literature	13
CHAPTER 3: METHODOLOGY.....	14
3.1 Sample and data collection procedures.....	14
3.2 Statistical techniques applied	16
3.2.1 Multiple Discriminant Analysis (MDA)	16
3.2.2 Altman's model	17
3.3 Analysis procedures	18
3.4 Hypotheses	20

CHAPTER 4: ANALYSIS AND FINDINGS.....	22
4.1 Characteristics of the sample as a whole	22
4.1.1 Normality of the sample.....	22
4.1.2 Significance of difference between the two groups of the sample..	25
4.2 Characteristics of the sample per sector	27
4.3 Altman's model	29
4.4 Model developed	29
4.5 Segregated sector	32
4.5.1 Using Altman's model	33
4.5.2 By developing a discriminant model for each sector	34
4.5.2.1 Service sector	34
4.5.2.2 Consumer goods	36
4.5.2.3 Technology	37
4.5.2.4 Healthcare	39
4.5.3 Summarized results	41
CHAPTER 5: SUMMARY AND DISCUSSION.....	42
CHAPTER 6: CONCLUSION, LIMITATIONS& FURTHER STUDIES	44
6.1 Conclusion	44
6.2 Limitations	45
6.2.1 Sampling limitations	45
6.2.2 Methodology limitations	45
6.3 Suggestions for further studies	46
BIBLIOGRAPHY.....	47

APPENDIX 1: Characteristics of the sample	50
APPENDIX 2: Group statistics (per sector)	54
Tests of Equality of Group Means (per sector)	57

LIST OF TABLES

1	Sectors of the sample	15
2	Descriptive statistics of the sample	22
3	Group statistics table	26
4	Tests of equality of group means	27
5	Tests of equality of group means (per sector)	28
6	Accuracy of Altman's model in predicting bankruptcy	29
7	Structure Matrix	30
8	Wilks' Lambda	30
9	Accuracy of the developed model in predicting bankruptcy	32
10	The incorporated sectors	33
11	Results for the three periods using Altman's model on each sector	34
12	Structure Matrix (Services)	35
13	Summary of Eigenvalues and Wilks' Lambda tables (services sector) ..	35
14	Structure Matrix (Consumer goods)	36
15	Summary of Eigenvalues and Wilks' Lambda tables(Consumer goods)	37
16	Structure Matrix (Technology)	38
17	Summary of Eigenvalues and Wilks' Lambda tables (Technology)	38
18	Structure Matrix (Healthcare)	39
19	Summary of Eigenvalues and Wilks' Lambda tables (Healthcare)	40
20	Accuracy of the developed models in predicting bankruptcy	41
21	The accuracy of the models when used on the whole sample	42
22	The accuracy of the per-sector models	43

LIST OF FIGURES

1	Distribution of the observations within X_1	23
2	Distribution of the observations within X_2	23
3	Distribution of the observations within X_3	24
4	Distribution of the observations within X_4	24
5	Distribution of the observations within X_5	25

CHAPTER 1

INTRODUCTION

1.1 Overview

When a company files for bankruptcy, there is no good news for investors (equity or debt holders). Even though the company may eventually resume its operations and go back to making profit, those who bear the loss prior to, during and after the bankruptcy proceedings are the investors. In the case of equity holders, the value of their shares decline, resulting in substantial financial loss. This is not the only problem, as the company may cease to pay dividends or get delisted from major exchanges, and hence deprive investors from the stream of income they expect, or reduce the liquidity of their shares. As for debt holders, though given priority during any financial hardship, including bankruptcy and liquidation, their situation is not much better than that of equity holders, as the distressed companies halt their coupon payments, and additionally, their bonds lose liquidity during the bankruptcy process, they lose their prospects, and get downgraded to the status of junk bonds.

The management of the failing company may be well aware of the disaster (bankruptcy) before its actual occurrence, and may take a different stance; some may implement strategies to revive the company and attempt to stop the draining of resources to prevent the company's failure, while others may build their own empires on the wreckage of the company.

Researchers have long proposed means by which investors can predict companies' bankruptcy or failure, and thus help them to make better investment decisions and assume better strategies. Nevertheless, the proposed models varied in their practicality and accuracy, and the increasing creativity and non-standard approaches in

accounting has made it yet even more difficult to predict financial distress and the failure of companies.

Among the pioneering research that has attempted to predict the failure of companies was the work of Altman (1968), in which a multivariate mathematical model capable of predicting bankruptcy was created. However, the model was developed using a stratified sample of companies (matched in asset size) and of the same sector (manufacturing), and therefore enjoys very limited implications.

This thesis comes to build on Altman's model by responding to the suggestions and arguments made by researchers to broaden both the scope and application of Altman model.

1.2 Purpose of the study

The core purpose of this study is to provide investors a practical and easy tool that helps them make initial decisions regarding their investments. The term “initial decisions” refers to simple decisions such as whether a certain stock should be considered for investment or not, and whether the stocks already held by an investor constitute a threat to their wealth or not.

The tool we aim to provide merely predicts bankruptcy of companies, and classifies companies as bankrupt and not-bankrupt, leaving the decisions and investment strategies to the investors.

Though very limited in its implications, the tool is very significant for the following reasons. First, it is easily accessible, as it only requires publicly available information and plain calculations to yield a single score constituting the basis for assessment of a company's fiscal prospects. Second, it could help investors to save time and effort by helping investors screen out bad investments before running analysis, thereby avoiding unnecessary, lengthy evaluation on a vast number of stocks, and allowing investors to focus their analysis exclusively on worthwhile stocks.

CHAPTER 2

LITERATURE REVIEW

How to best predict bankruptcy has been addressed by researchers since the 19th century, yet the topic only began receiving serious attention in the 1930s. Though researchers have largely shared the same objectives, that of accurately predicting companies' failure and/or assessing companies' financial health, they have enriched the literature with a spectrum of models and approaches. In fact, research varies in three core areas, namely the choice of variables or sample characteristics, the choice of methodology, and the application of the model. To gain a meaningful overview of the literature, it is useful to provide a clustered summary of the main research models rather than merely listing them.

At the very broad level of classification, research in this area can be placed into three categories, with the first being qualitative, non-financial based methods to predict bankruptcy, the second being the practice of employing quantitative financial information to predict bankruptcy, and the third being a hybrid form of research that integrates a variety of analytic methods for the purpose of predicting bankruptcy.

2.1 Qualitative Methods

Recent advocates of using non-financial data to predict companies' bankruptcy include Clatworthy & Jones (2006), Kloptchenko, et al. (2004), and Abrahamson & Amir (1996), who have employed various non-financial methods of analysis for the purpose of predicting bankruptcy. Making use of the content of the president's letter, Abrahamson & Amir (1996) devised a numerical measure to calculate the negative impact of the president's letter, and concluded that the content of the letter is associated with performance measures based on financial information, in particular the regression coefficient of earnings levels. Similarly, Kloptchenko, et al. (2004)

combined data mining methods to analyze quantitative and qualitative data from financial reports in order to see whether the textual part of the report contains some indication of future financial performance. The study concluded that the quantitative part of a report only reflects the past performance of the company, while the qualitative part holds a message about the company's future performance. They also highlighted that the tone of a written report tends to change some time before the actual financial changes occur. Likewise, Clatworthy & Jones (2006) pooled quantitative and qualitative data from financial reports in order to see whether the textual part of the report contains some indication of future financial performance. Their findings were similar to those of Kloptchenko, et al. (2004), and affirmed that the quantitative part of a report reflects past performance, while the qualitative part holds a message about the future.

Building upon the work of the non-financial methods mentioned above, Shirata et. al. (2011) analyzed the annual reports of 90 companies that went into bankruptcy between 1999 and 2005 along with the annual reports of 90 companies that did not file for bankruptcy from the Tokyo Stock Exchange market. A Simple Analysis of Failure model (SAF) was used to rank the companies, and the variables for the SAF2002 model were selected using a Classification and Regression Tree (CART). The study considered the fact that certain words appear in specific patterns, and these patterns can be interpreted as clues for predicting bankruptcy; therefore, text data were converted into quantitative indicators. Then, the conditional probabilities were used to extract the expressions specific to the bankrupt group and non-bankrupt group. The expressions included descriptions about the lack of dividends, such as 'to our regret, we decided to close this fiscal year without dividends' or 'the severe economic environment does not allow any dividends this year'. The researchers found that expressions such as 'to our regret' and the indirect phrase 'does not allow', which could be considered as excuses, were found frequently in the annual reports of Japanese companies before their bankruptcy. The study concluded that if these expressions appear together with the word "dividend", the possibility that the company is headed for bankruptcy is high, even if the financial numbers still show a stable position. The study also found that for non-bankrupt companies, words such as "research and development", "capital investment", and "new business" will appear in sentences including "dividend" and "retained earnings". The research thus concluded

that if particular expressions appear together with the words “dividend” or “retained earnings” in the same section of the annual report, they can effectively distinguish between bankrupt companies and non-bankrupt companies.

2.2 Quantitative Methods

As for the second category, which includes research based on quantitative data, or financial information to predict bankruptcy, the studies also varied widely as per the number of factors considered in the models, the methods of analysis employed, and the types and sources of data. Chiefly these research methods made use of indicators value, or absolute value, which is analyzed with reference to the previous years' data, such as financial statements, or against the data of other companies or the industry, as well as methods of rates which eliminate the effect of size and provide a link between indicators of accounts, and most notably methods of scores, which combine a number of indicators to create a representative score. Additionally, the number of factors used in the models ranged widely from one, in univariate models, to 57 factors in multivariate studies, not to mention the vast variety of analysis techniques including logit analysis, probit analysis, neural network, discriminant analysis, and regression, to name a few.

Studies that predict bankruptcy based on financial data can be dated back to the 1930s, when the Bureau of Business Research (BBR) published a study that analyzed 24 ratios of 29 firms to determine common characteristics of failing firms Bellovary, Gacomino, & Akers(2007). Following the BBR's work, a number of researchers used financial ratios as predictors of companies' failures. Examples of these early studies include FitzPatrick(1932), Smith & Winakor(1935), and Merwin(1942).

A key study in this area was conducted by Beaver (1966), who examined the usefulness of ratios in predicting failure and built an empirical verification of ratio analysis. The study used a univariate model which examined individual ratios' predictive ability, one at a time, to categorize companies as bankrupt and non-bankrupt. In his study, a sample consisting of 158 companies was used, constituting a paired-sample design, wherein for each failed company of the sample, a non-failed company of the same industry and asset size was selected. The time frame of the

study stretched over a ten-year-period, from 1954 to 1964, and the predictive capability of 30 financial ratios considered to be the best indicators of financial security of companies was tested. Beaver found that the best ratios to describe financial failure are Financial Flows/Total Assets, followed by Total Income/Total Liabilities, and then Financial Flows/Total Obligations. For each individual indicator, Beaver calculated a border value, so the firms with an indicator above the value were considered successful, while the firms with values below the border value were considered unsuccessful.

Beaver concluded that ratio analysis can be useful in the prediction of failure for at least five years prior to the actual failure, and that Net Income/Total Debt has the highest predictive ability (92% accuracy one year prior to failure), followed by Net Income/Sales (91%) and Net Income/ Net Worth, Cash Flow/Total Debt, and Cash Flow/Total Assets (each with 90% accuracy).

Correspondingly, Altman presented a paper in 1968 that aimed to assess the quality of ratio analysis as an analytical technique. Unlike Beaver, Altman used a multivariate model, and was actually the first to do so. Altman used 22 financial ratios, but incorporated only five ratios, those found to be significant bankruptcy predictors, in his final model. The ratios are working capital/assets, retained earnings/assets, EBIT/assets, market value of equity/ book value of total debt and sales/assets. Altman tested the accuracy of his model on an initial sample of sixty-six manufacturing corporations. The set of financial ratios was combined in a discriminant analysis approach with coefficients that reflect the contribution of each individual variable to the final score. The "Z-score" categorized companies as bankrupt or non-bankrupt according to a cutoff point, wherein if $Z > 2.99$ the company is classified as healthy, if $Z < 1.81$ the company is classified as bankrupt, and if $1.81 < Z < 2.99$, the company is deemed to exist in a gray area. Altman's model succeeded in predicting bankruptcy with 95% accuracy one year prior to failure. However, the model's capability of accurately predicting bankruptcy diminishes after the second year, where it has an accuracy of 72%, and from there the accuracy drops to 48% for the third year, 29% for the fourth year, and 36% for the fifth year. A limitation to Altman's Z-score model is that it is only applicable when working with public manufacturing companies in the USA; hence, other models were needed to serve different sectors/markets.

Subsequently, Altman, Narayanan, & Haldeman (1977) proposed a more refined model than the original Z-score. The new Zeta Model aimed to keep abreast of the change in financial reporting standards, to include refinements to the discriminant statistical technique, and incorporate a wider range of sectors while attaining higher accuracy rates. A sample comprised of 111 retail and manufacturing companies covering the period 1969-1975 was used. The sample included 53 bankrupt firms and a matched sample of 58 non-bankrupt firms. The research resulted in a seven-variable model which proved highly accurate for predicting bankruptcy up to five years prior to the event, with successful classification of more than 90% one year prior to bankruptcy, and 70% up to five years prior (Altman, Haldeman, & Narayanan 1977). Again, Altman proposed a revised model to his initial Z-score model, namely the Emerging Markets Scoring model, which was applicable to both manufacturing and non-manufacturing companies, and also relevant for both public and private firms (Altman, Hartzell, & Peck, 1995). Though similar to the original model in its variables, the revised model discarded sales to total assets ratios in order to minimize the potential industry effect, and replaced the market value of equity in the equity to book value debt ratio with book value equity to allow for the evaluation of private firms.

Until recently, researchers had found the early models for predicting bankruptcy, such the ones developed by Beaver and the famous "Z-score model" developed by Altman, 1968 to be of great importance, and have used them as the basis for new research with some or no modifications. Li & Rahgozar (2012) for instance, have re-examined the accuracy of the original Z-score model in predicting corporate failures using financial data of US companies spanning the years 2000 and 2010. The results of their study confirmed that the original Z-score model is valuable in predicting corporate financial stress for both manufacturing and non-manufacturing firms. In addition, they investigated whether asset volatility improves the predictive capacity of the Z-score model, and concluded that asset volatility does indeed improve the aptitude of the original model, and thus considered it as a missed variable in the original model developed by Altman. In a similar venture, Kivuvo & Olweny (2014) employed Altman's model to assess the soundness of the financial firms of SACCO located in Kenya. The researchers used the same original model, the same coefficients and the

same cutoff point employed by Altman in his 1968 model to determine the status of companies and thus evaluate the health of the financial sector. The study population was comprised of 215 firms, with 30 selected on a random basis. The researchers assumed a quantitative research design which used longitudinal data for the period 2008 to 2013, and concluded that with 24 companies showing a positive slope and only six companies showing a negative slope and requiring performance improvement, SACCO enjoys a fairly strong financial position.

Alireza, Parviz, & Mina (2012) have recently devised a model that can predict bankruptcy with an accuracy of 94 % one year prior to bankruptcy and more than 80% two years prior to bankruptcy. The researchers used a sample of companies from the textile, pharmaceutical, food, and automotive sectors listed in the Tehran Stock Exchange. Although the researchers used discriminant analysis in a manner similar to Altman, the final model had a different mix of ratios and coefficients than that devised by Altman.

It is astonishing that the very same models that have been proven accurate and reliable over the decades have also been criticized by a cluster of researchers, who have identified many flaws with the models. These include, but are not limited to, Gharghori, Chan, & Faff (2006) and Hillegeist et al. (2004). Both papers questioned the predictive capability of Altman's model, particularly its reliance on accounting information that is ex-poste in nature, highlighting that financial statements are prepared with a going concern assumption, wherein companies are assumed not to be filing for bankruptcy. These characteristics are inconsistent with the forward-looking measure, and thus limit the effectiveness of Altman's model and any other accounting-based models in predicting corporate failure. According to Hillegeist et al. (2004), an added deficiency in Altman's model is its failure to include a measure of asset volatility, which is important because it measures the probability that the value of a firm's assets will decline to the extent that it is unable to pay its debts.

In general, the Multiple Discriminant Analysis (MDA) was sharply criticized, as the validity of its results centers on restrictive assumptions. As argued by Coats & Fant (1993), two assumptions are particularly problematic for ratio analysis. First, MDA requires that the decision set used to distinguish between distressed and viable firms

must be linearly separable. For a single ratio, this means that a value above or below a given threshold point must always signal either distress or good health. Second, MDA does not allow for a ratio's signal to fluctuate depending on its relationship to another ratio or set of ratios. In other words, ratios are treated as completely independent.

From there stemmed other analysis methods, such as the logit and probit models, and more recently the Neural Networks discriminant (NN) or Artificial Neural Network (ANN). Odom and Sharda (1990) and Bell et al. (1990) were probably the first to publish in this area, investigating the ability of neural networks (NNs) to predict bankruptcy. The implementation of NNs in both predicting bankruptcy and in distinguishing bankrupt from non-bankrupt firms, arose from the need to overcome the limitations related to previously-used analysis methods, including the linearity and normality limitations.

At its core, an ANN is a soft-computing technique modelled on the workings of the human brain. The technique of an ANN in bankruptcy prediction involves connected layers of neurons, one layer of input neurons (usually financial ratios), one or more hidden layers of interconnected neurons, and one output layer of neurons (usually just one boolean fail or success neuron). Consequently, a multilayer network is trained by a back propagation learning algorithm, which performs weight-tuning to define whether or not hidden unit representation is most effective at minimizing the error of misclassification. The differences between each predicted output and the corresponding target output are calculated, then the errors are propagated back through the network and the weights between the two layers are adjusted so that if the training example is presented to the network again, the number of errors would decrease. As a result, the algorithm captures properties of the input instances which are most relevant to learning the target function (Haykin, 1999).

As for the logit and probit analysis, they are based on the probability of the firm going bankrupt using non-linear estimations. For instance, in a fundamental study conducted by Ohlson (1980), the researcher used a methodology that maximized the likelihood estimation of the so-called conditional logit model. The data set used in the study was from 1970 to 1976 and relied on observations of 105 bankrupt firms and 2,058 non-bankrupt firms. Ohlson's study was distinctive from prior studies in that the financial

statements for the bankrupt firms were obtained from 10-K financial statements, indicating the point in time the financial statements were released to the public, so one can check whether the company entered bankruptcy prior to or after the date of release. In his study, Ohlson tried to overcome the limitations of the Multivariate Discriminant Analysis (MDA), namely the variance-covariance matrices of the predictors as being the same for both groups (failed and non-failed firms), as well as the requirement of a normally distributed predictors, which mitigates against the use of dummy independent variables. Ohlson's model succeeded in predicting bankruptcy of companies with an accuracy of 85.1% in the first year, and 87.6% and 82.6 % for the second and third years, respectively. The most prominent finding of his study was that it was possible to identify four basic factors as being statistically significant in affecting the probability of failure within one year: the size of the company; the measure(s) of the financial structure; the measure(s) of performance; the measure(s) of current liquidity.

2.3 Hybrid Methods

To enhance the predictive ability of the models used, a third cluster of research emerged, which integrates more than one method of analysis. For instance Chang, Huang, & Tsai (2013) proposed an innovative model that combines financial variables with a system that integrates Case Based Reasoning (CBR) models with a Support Vector Machine (SVM) technique. The study combined the CBR and SVM methods to establish a model for the prediction of enterprise financial crisis. The sample paired healthy and distressed companies of the same industry, similar in capital size, and comparable to product types in a pairing ratio of one to two. The data was drawn from the database of Taiwan Economic Journal (TEJ) on public companies between 1999 and 2009. As many as 41 financial ratio variables were chosen under six classifications, including financial structure, solvency, operating ability, profitability, cash flow and growth. Through Stepwise Regression Analysis, the most effective financial ratios were discovered, and the CBR model was used for grouping. Finally, the SVM method was adopted to determine if the companies were healthy or not. The CBR-SVM model exhibited a prediction accuracy of 93.62%.

Another study in this area was conducted by Jandaghi, Tehrani, Pirani, & Mokhles (2011), who assumed a hybrid approach which combines quantitative with qualitative data to predict bankruptcy and/or assess companies' financial health. The researchers utilized static and trend analysis models to construct and train a back-propagation neural network (BPN) model, which was applied to classify bankrupt and non-bankrupt Iranian firms listed in the Tehran stock exchange (TSE). The data set used for the research consisted of 120 Iranian companies, 60 of which were bankrupt, while the other 60 were "matched" non-bankrupt companies. As many as ten ratio items with influence power were selected and given weights, with the selected ratios falling into four categories: liquidity, operating, profitability and leveraging. Next, the difference between the base previous period and the base period were analyzed, and the variable rate of each of the four categories was calculated. Each category's variable rate was then converted based on the weights; these variable rates were then represented as the variation of the categories. The MATLAB software neural network toolbox is used to construct and train the BPN. Twelve variables served as the input, of which four had category ratios between the base period and previous period, and four were dummy variables used to analyze each category's trend over different periods. Where output number (1) represents a "fine enterprise" and (-1) represents a "risk enterprise", the authors concluded that the proposed hybrid financial analysis model combined with the BPN is capable of providing a very high prediction accuracy rate. The result shows that the proposed system can produce a high rate of risk identification and a low rate of prediction errors. Moreover, effective predictive financial ratios were identified, wherein leveraging and operating trends were identified as highly predictive factors.

By the same token, Martin, Gaythri, Saranya, Gayathri, & Venkatesas (2011) applied a hybrid approach to achieve greater accuracy than that achieved by single models, by constructing a hybrid model which is based on the sequential application of genetic algorithm, fuzzy c-means clustering and Multivariate Adaptive Regression Splines (MARS).

This is the briefest of literature review, as the topic matter is very wide and has been tackled by a vast number of studies. Yet the significance of its findings keeps making it an area of concern to both researchers and stakeholders seeking a tool to help them

make better decisions. For further reading on the topic, I refer the reader to Belloc, Gacomino, & Akers 2007 publication, *A Review of Bankruptcy Prediction Studies: 1930-Present* and the work of Jackson & Wood (2013).

2.4 Gap in the literature

Reviewing the literature, we noticed that it is rich with bankruptcy prediction models, confirming the privileges brought about with accurate prediction of companies' future standing. Yet, the models are diverse in the type of data and techniques used, the easiness of applying them, their scope and practicality, as well as their accuracy. For instance, the univariate model developed by Beaver (1966) could be considered as simplistic and its competency in providing an inclusive insight to the company's future standing as well as its relevance to the current accounting standards and practices may be questioned. In contrast, a cluster of researchers, including Odom and Sharada (1990), assumed complex and sophisticated models such as Neural Networks (NNs) and other hybrid models, which we think as impractical for broad and mere classification of companies and bankruptcy prediction.

With the available models, we can say that stakeholders or individuals interested in predicting bankruptcy are left between the hammer and the anvil. From there stems the need for a practical tool that integrates the merits of the available models and mitigate their demerits. Hence, we aim to assume a mediating position between simplistic and complex models, in a bid to retain the best of both. The fact that MDA-based models are simpler to apply than NNS yet more comprehensive than univariate models, made it among the best statistical models for the purpose of this thesis. Even though many researchers ventured down this path of developing MDA-based models for predicting bankruptcy, the literature still lacks a broad and general model that could be applied to all companies regardless of their size and sector, which constitute the core of this thesis.

CHAPTER 3

METHODOLOGY

3.1 Sample and data collection procedures

The sample consists of two basic groups, bankrupt and non-bankrupt US public companies. Bankrupt companies have been selected based on the following criteria:

- a. Is a public company listed in any US exchange;
- b. Has filed for bankruptcy in the US courts between 2010 and 2014;
- c. Possesses obtainable financial statements up to 3 years prior to the bankruptcy filing; and
- d. Possesses detailed financial statements (segregating current from non-current assets and liabilities).

From a population of 543 companies that had filed for bankruptcy in the US courts between 2010 and 2014, and were listed on www.bankruptcydata.com, 39 companies were selected, constituting 7.2% of the population.

As for the non-bankrupt group, the following criteria was established:

- a. Is a public company listed in any US exchange;
- b. Has not filed for bankruptcy between 2010 and 2014;
- c. Has obtainable financial statements for 2013, 2012, and 2011; and
- d. Possesses detailed financial statements (segregating current from non-current assets and liabilities).

From an initial list of 1,960 companies obtained from:

http://en.wikipedia.org/wiki/Category:Publicly_traded_companies_of_the_United_States, 76 companies were selected, constituting 3.9% of the population.

It is worth mentioning that unlike many studies in the area, size of companies (measured by total assets) as well as sector were not considered in the sampling

procedure, which has been done on purpose and in response to the suggestions made by a number of researchers, including Ohlson.

Ohlson (1980) commented on the matching procedure used in Multiple Discriminant Analysis models, stating *"there are also certain problems related to the "matching" procedures which have typically been used in MDA. Failed and nonfailed firms are matched according to criteria such as size and industry, and these tend to be somewhat arbitrary. It is by no means obvious what is really gained or lost by different matching procedures, including no matching at all"* (p.112).

In addition to the criteria mentioned, the sample was drawn on a convenience basis, as time was a major limitation. Thus, a larger sample could have been drawn for this study.

The final sample amounted to 115 US public companies listed in the New York Stock Exchange, NASDAQ, and OTC, 39 of which filed for either Chapter 11 or Chapter 7 bankruptcy between 2010 and 2014, while the remaining 76 did not exhibit such financial distress during the selected period. The sample consisted of companies from a variety of sectors, namely Services, with 35 companies; Consumer Goods, with 26 companies; Technology with 22 companies; Healthcare, with 17 companies; Basic Materials with 10 companies; and finally Industrial Goods with 5 companies (See Table 1 below). For the complete list of the companies included in the sample and their characteristics, we refer the readers to Appendix 1.

Table 1: Sectors of the sample

Sectors	Bankrupt	Non-bankrupt	Total companies
Services	17	18	35
Consumer Goods	4	22	26
Technology	8	14	22
Healthcare	5	12	17
Basic Materials	3	7	10
Industrial Goods	2	3	5
Total	39	76	115

After determining the sample, the financial statements and ratios for the whole sample were obtained from the Factset database.

3.2 Statistical techniques applied

Our study makes use of Altman's Z-score model, which is based on Multiple Discriminant Analysis. Thus, it is important to give a brief account of how Multiple Discriminant Analysis works, and to revisit Altman's Z-score model before proceeding to explicate on the methodologies of this study.

3.2.1 Multiple Discriminant Analysis (MDA)

In a nutshell, MDA is a mathematical analysis technique that entails creating a new variable called the discriminant score, which is used to predict to which group an observation belongs.

Similar to regression analysis, MDA devises a discriminant equation, in which the independent variables are multiplied by the coefficients found by analysis, which serve to maximize the distance between the groups, and the sum produces a discriminant score. The discriminant score cannot be used singlehandedly to categorize observations, thus a cut-off point is used to specify a range of scores that will define in which group an observation belongs, bearing in mind that the groups are mutually exclusive, therefore an observation cannot fall into more than one group.

MDA is based on the following key assumptions:

- a. The observations are a random sample;
- b. Each predictor variable is normally distributed; and
- c. The initial classification of the dependent variables is correct.

It is worth noting that the key difference between MDA and regression analysis or analysis of variance (ANOVA) lays in the nature of the dependent variable. In discriminant analysis, the dependent variable must be categorical (name of a group), whereas in regression or ANOVA, the dependent variable must be a continuous variable (numerical).

We find MDA an appropriate statistical technique for the purpose of this study for the following reasons:

- a. The dependent variable is categorical (bankrupt or non-bankrupt);
- b. The dependent variable is a mutually exclusive groups;
- c. The MDA is capable of considering entire independent variables as well as the interaction between variables; and
- d. It provides a single score (the discriminant score), which can be used to classify the object.

3.2.2 Altman's model

It is important to revisit Altman's Z-score discriminant model, as it constitutes the core of this study. Briefly, Edward I. Altman is one of the most renowned figures in bankruptcy prediction studies. He has created a number of discriminant models capable of discriminating between bankrupt and non-bankrupt firms, and thus predicting bankruptcy. His 1968 model consisted of 5 different ratios as independent variables, with assigned weights (coefficients) for each. The ratios were then multiplied with their relevant coefficients, and the sum resulted in a discriminating score named the Z-score.

The Z-score was used to predict whether a company was bankrupt or not based on a certain threshold, or cut-off. According to Altman, a company with a score greater than 2.99 is categorized as healthy, whereas a company with a Z-score below 1.81 is considered bankrupt. Companies with scores greater than 1.81 but less than 2.99 are not classified.

Altman's Z-score discriminating model is as follows:

$$Z = .012X_1 + .014X_2 + .033X_3 + .006X_4 + .999X_5 \quad (1)$$

Wherein Z is the dependent variable and X_1 to X_5 are the independent variables as follows:

$X_1 = \text{Working capital} / \text{Total assets};$

$X_2 = \text{Retained earnings} / \text{Total assets};$

$X_3 = \text{Earnings before interest and taxes} / \text{Total assets};$

$X_4 = \text{Market value equity} / \text{Book value of total debt};$

$X_5 = \text{Sales} / \text{Total assets};$

Bankrupt = value 0;

Non-bankrupt = value 1.

It is noteworthy that each of these variables measure an aspect of the company's profile, and together they are thought to project a comprehensive view of the company's performance, based on which the company will be categorized as healthy or unhealthy. For instance, the first variable, working capital/total assets, is a ratio that evaluates the liquidity of the firm. This ratio basically measures the net liquid assets of the firm relative to its total capitalization. The second variable, retained earnings/total assets, is a profitability ratio that measures the cumulative profitability over time against the total assets. The third variable, earnings before interest and taxes/total assets, is a ratio of productivity, which measures the true productivity of the firm's total assets. The fourth variable, market value of equity/book value of total debt, is a ratio of solvency, which measures how much the firm's assets can decline in value before the liabilities exceed the assets of the firm and become bankrupt. The fifth variable, sales/total assets, is an activity ratio that evaluates the sales generating ability of the firm's assets. It measures the management's capability of dealing with competition.

In his 1968 model, Altman used a sample of bankrupt and non-bankrupt companies from the manufacturing sector. He used an equal number of companies in each group, and matched them according to size, which he measured in total assets.

3.3 Analysis procedures

Having obtained financial data for a three-year period, we are going to arrange the data of the bankrupt and non-bankrupt companies into three categories that we shall refer to as t-1, t-2, and t-3. Wherein t-1 refers to the most recent period, i.e. one year prior to bankruptcy for the bankrupt group and 2013 for the non-bankrupt group; t-2

refers to two years prior to bankruptcy for the bankrupt group and 2012 for the non-bankrupt group; and t-3 refers to three years prior to bankruptcy filing for the bankrupt group and 2011 for the non-bankrupt group.

Next, we are going to obtain descriptive statistics of the variables to identify the distribution of the observations within each variable. Group statistics and tests of equality of group means will also be conducted across the whole sample, as well as on a per-sector basis across the four largest sectors of the sample, with the aim of confirming the difference between the two groups, bankrupt and non-bankrupt, prior to proceeding with the various analyses.

The analysis will be divided in three parts. The first analysis involves employing Altman's original model, without any alterations, on the whole sample, and finding the accuracy of the model in predicting bankruptcy. The second analysis entails building a new model using Altman's independent variables (ratios) with different coefficients as provided by discriminant analysis, with the aim of enhancing the original model's competency in accurately predicting bankruptcy. The third and final analysis aims to determine to what extent running discriminant analysis by sector improves the accuracy of discriminant models, thus Altman's model will be applied to each sector separately, and we will also develop unique discriminant models for each sector. Due to small sample size, this part of the analysis will be conducted on the four largest sectors of the sample, namely the services, consumer goods, technology and healthcare sectors.

With regards to developing a new model, it is worth mentioning that many researchers have ventured down this path, including Alireza, Parviz, & Mina (2012) and Li & Rahgozar (2012), as mentioned in the above literature review.

The steps taken when applying Altman's model are different from those followed when developing a new model. Working with Altman's model, we will simply plug the ratios into the system and calculate the Z-score using the coefficients given by the model. The observations will be categorized as bankrupt or non-bankrupt according to the cut-off point, also provided by Altman's model. Finally, the original group membership will be compared to what was predicted by the model, testing the model's

accuracy. The same procedures are followed for t-1, t-2, and t-3, for the sample as a whole, and for the per-sector analysis.

In contrast, developing our own models entails more steps than using a given model. Initially, we will determine the coefficients for the model, which should maximize the distance between the two groups of the sample, bankrupt and non-bankrupt companies. Then we will identify the importance of the independent variables and their contribution to the model, and finally we will examine the model's capability in explaining the variation in grouping variables prior to actual implementation of the model. Unlike using a given model, developing a new model also requires determining a threshold (cut-off point), which will be calculated as the mean of the two centroids of the groups, and based on which discriminant scores will be assigned to either category, bankrupt or non-bankrupt. Once the model is developed, we will simply plug its coefficients into our data to obtain the discriminant scores, categorize the observations according to the cut-off, and test the model's accuracy in correctly classifying observations by comparing the original group membership to the membership predicted by the model. These same steps will be followed for t-1, t-2, and t-3 to find the accuracy of the model in predicting bankruptcy. We will also develop sector-specific models and test their accuracy in the same manner. It is worth mentioning that Microsoft Excel and SPSS will be used to conduct the analysis.

3.4 Hypotheses

For the purpose of this thesis, 4 pairs of hypotheses tackling different aspects of the study were developed. The first set of hypothesis is concerned with the sample of the study, and can be rephrased as the following question "do the groups of the sample exhibit statistically significant difference?"

The second set of hypothesis concerns the well-known model of Altman, and raises the following question "could the Z-score model developed by Altman predict bankruptcy of heterogeneous observations?"

The third set of hypothesis is related to the worthiness of ratios in predicting bankruptcy and thus the worthiness of developing ratio-based models. It can be rephrased as "do ratios constitute a good measure for predicting bankruptcy?"

The fourth and last set of hypothesis concerns a core matter regarding discriminant models for predicting bankruptcy. It could be rephrased to a question as in "do sector-specific discriminant models surpass general discriminant models in their accuracy to predict bankruptcy?"

The developed hypotheses for this study are listed below.

Hypothesis (1)

H₀: There is no significant difference between bankrupt and non-bankrupt firms.

H₁: There is significant difference between bankrupt and non-bankrupt firms.

Hypothesis (2)

H₀: Altman's model cannot predict bankruptcy of heterogeneous observations

H₁: Altman's model can predict bankruptcy of heterogeneous observations

Hypothesis (3)

H₀: Financial ratios are not good measures for predicting bankruptcy of corporations.

H₁: Financial ratios are a good measure for predicting bankruptcy of corporations.

Hypothesis (4)

H₀: The accuracy of discriminant models in predicting bankruptcy do not improve when used on a sector-specific sample as opposed to a mixed-sector sample.

H₁: The accuracy of discriminant models in predicting bankruptcy improve when used on a sample of one sector as opposed to a mixed-sector sample.

CHAPTER 4

ANALYSIS AND FINDINGS

4.1 Characteristics of the sample as a whole

4.1.1 Normality of the sample

In a bid to gain insight of the characteristics of the sample and its normality, we obtained descriptive statistics for the whole sample, through which we will emphasize on measures of shape such as Skewness and Kurtosis to determine the normality of the distribution of the sample.

As can be seen from Table 2 below, the observations at each variable exhibit positive or negative Skewness. For instance, Variables X_1 , X_2 , and X_3 exhibit negative (left) Skewness with values away from symmetry (approximately 0). On the other hand, variables X_4 and X_5 demonstrate positive (right) Skewness also away from symmetry.

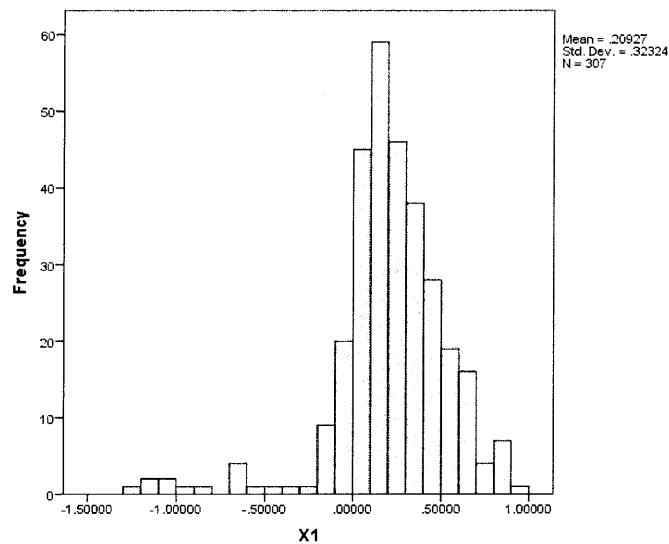
Table 2: Descriptive statistics of the sample

Variable	N	Min	Max	Mean	Std error	Std. Deviation	Skewness	Kurtosis
X1	307	-1.279	.940	.209	.018	.323	-1.342	4.687
X2	307	-8.191	1.446	-.216	.072	1.266	-3.278	12.899
X3	307	-1.330	.527	.0128	.012	.217	-2.734	11.259
X4	307	-.601	16.490	1.1540	.093	1.640	4.668	32.161
X5	307	.000	7.100	.954	.047	.837	2.794	14.323

Another statistical measure by which we can determine the normality of the sample is using Kurtosis. Though the Kurtosis values for each variable are presented in the

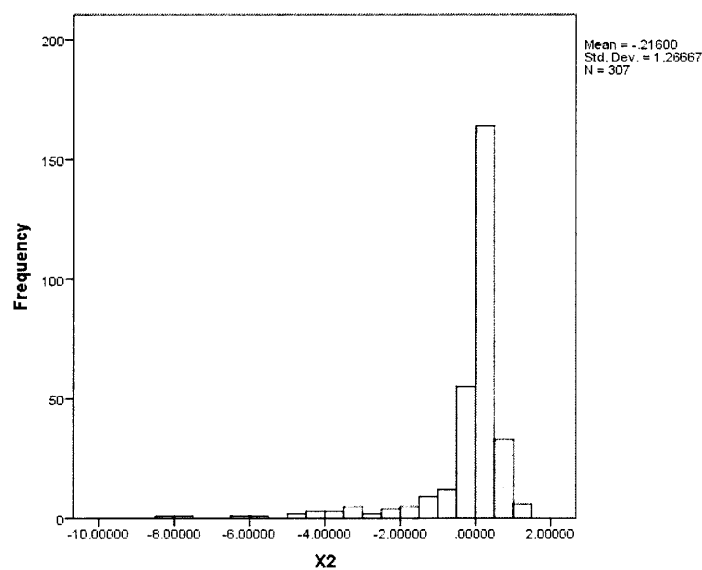
table, examining the histograms as presented in figures 1-5 below provide a more visual representation of the distribution.

Figure 1: Distribution of the observations within X_1



By mere examination of the shape presented in Figure 1, which represents the distribution of the observation for X_1 for the whole sample, we can see that the sample is negatively Skewed with a Leptokurtic shape.

Figure 2: Distribution of the observations within X_2



Similarly, we can infer from Figure 2 above that the observations are far from normality within X_2 . Observations are negatively skewed, with a Leptokurtic shape. Observations also have larger deviations than they exhibited within X_1 .

Figure 3: Distribution of the observations within X_3

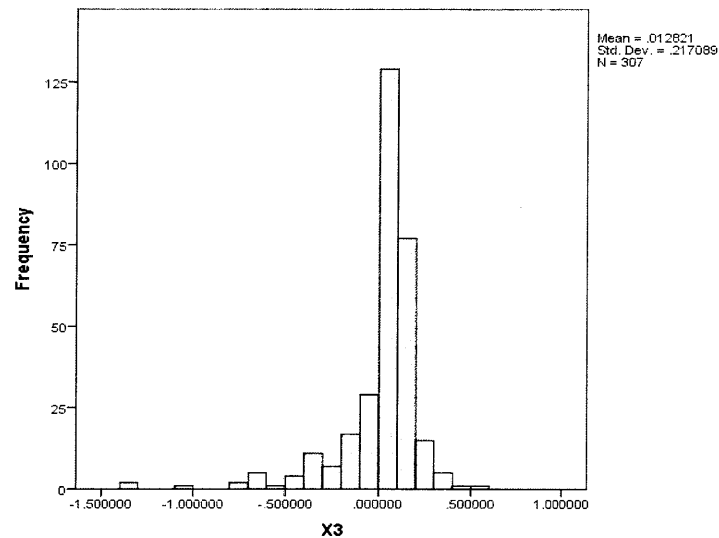
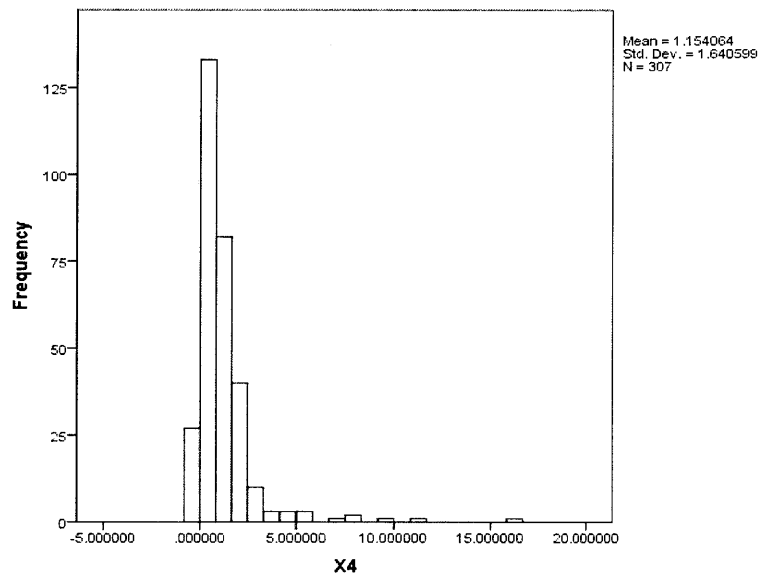


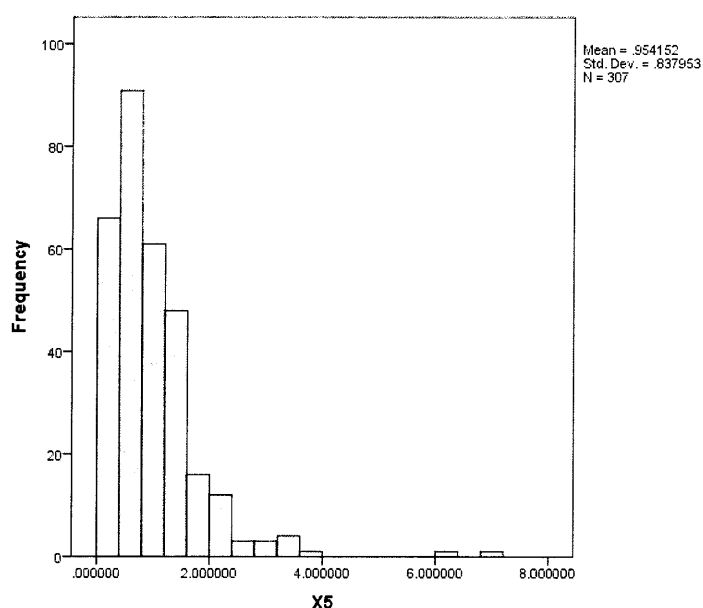
Figure 4: Distribution of the observations within X_4



Observations within X_3 exhibit the least deviation, at .217. Yet, as we can see from Figure 3 above, observations are not normally distributed as the histogram takes a Leptokurtic shape and negative Skewness of -2.734.

In contrast to the distribution of the sample within X_1 , X_2 , and X_3 presented in Figures 1, 2, and 3 earlier. We can see from figures 4 & 5 below that the observations are positively Skewed, at 4.668 and 2.794 for observations within X_4 and X_5 respectively. Again, we can see from the Leptokurtic shapes of the histograms that the sample is far from being normally distributed.

Figure 5: Distribution of the observations within X_5



Overall, Table 3 and Figures 1-5 above affirm that the sample is not normally distributed.

4.1.2 Significance of difference between the two groups of the sample

To ensure that the two groups of the sample are significantly different, we conducted group statistics, which showcases the mean and standard deviation of each variable for the bankrupt and non-bankrupt group, and thus allows for comparison.

Where the bankrupt group is denoted a 0 and the non-bankrupt group denoted a 1, Table 3 above provides strong statistical evidence of significant difference between the means of the bankrupt and non-bankrupt groups at every variable. For instance, the mean of X_1 for the bankrupt group stood at 0.0291, whereas the mean of the same variable for the non-bankrupt group amounted to 0.2674; X_2 for the bankrupt group

amounted to -0.7335 and 0.2192 for the non-bankrupt group and so on affirming that the bankrupt group is significantly different from the non-bankrupt group.

Table 3: Group Statistics Table

Bankrupt / Non-bankrupt		Mean	Std. Deviation	Sample size
0	X ₁	.029	.446	85
	X ₂	-.733	1.538	85
	X ₃	-.095	.242	85
	X ₄	.635	1.664	85
	X ₅	.949	.978	85
1	X ₁	.267	.207	204
	X ₂	.219	.541	204
	X ₃	.090	.107	204
	X ₄	1.350	1.22	204
	X ₅	.931	.548	204
Total	X ₁	.197	.316	289
	X ₂	-.060	1.042	289
	X ₃	.035	.180	289
	X ₄	1.140	1.405	289
	X ₅	.936	.700	289

To further verify the significance of the difference between the two groups (bankrupt and non-bankrupt), we present Tests of Equality of Group Means in Table 4 below.

Table 4 represents a one way ANOVA statistical test of the means. If Wilks' Lambda equals 1, we may infer that the variable is insignificant as a discriminatory function. Examining the table above, we find that each of the variables is significant on its own, as the values remain below 1 except X₅. Additionally, by closely examining the significance level, we find that all variables enjoy a p-value smaller than .05

confirming the significance of the variables as discriminatory functions except X_5 which is found insignificant with a p-value of .842.

Thus, we can assume that it is worthwhile to proceed with the analysis.

Table 4: Tests of equality of group means

Variable	Wilks' Lambda	F	Sample size	p-value
X_1	.882	38.316	287	.000
X_2	.826	60.515	287	.000
X_3	.778	81.718	287	.000
X_4	.946	16.354	287	.000
X_5	1.000	.040	287	.842

4.2 Characteristics of the sample per sector

We find that it is important to reexamine the characteristics of the sample once it is segregated by sector, and find whether the observations within each sector exhibit significant difference between the bankrupt and non-bankrupt observations making it worthwhile proceeding with the analysis and developing sound discriminant model for each sector.

Making use of the test of equality of group means, as presented in Table 5 below, we examine the discriminating competency of each variable for each sector separately. The table below only incorporates the sectors to be included in the analysis. However, the tests of equality of group means for all the sectors of the sample are presented in Appendix 2 of this thesis in addition to group statistics per sector.

As Table 5 demonstrates, we find that the selected variables possess discriminating competency between the bankrupt and non-bankrupt groups for each sector. Except X_4 for the consumer goods sector, this appears not to discriminate between both groups, as its Wilks' Lambda figure amounts to 1. Moreover, Table 5 also exhibits the significance of the variables. Knowing that variables are significant when

p-value is less than or equal to 0.05, we infer that most variables are significant with the exception of X_5 for both the services and technology sectors, and X_3 and X_4 for the consumer goods sector.

Table 5: Tests of equality of group means (per sector)

Sector		Wilks' Lambda	F	Sample size	p-value
Consumer goods	X_1	.931	4.967	67	.029
	X_2	.915	6.193	67	.015
	X_3	.965	2.457	67	.122
	X_4	1.000	.008	67	.927
	X_5	.811	15.600	67	.000
Healthcare	X_1	.900	4.214	38	.047
	X_2	.868	5.754	38	.021
	X_3	.800	9.500	38	.004
	X_4	.901	4.169	38	.048
	X_5	.789	10.180	38	.003
Services	X_1	.914	9.326	99	.003
	X_2	.566	75.947	99	.000
	X_3	.695	43.387	99	.000
	X_4	.773	29.155	99	.000
	X_5	.999	.119	99	.731
Technology	X_1	.842	10.137	54	.002
	X_2	.900	6.023	54	.017
	X_3	.784	14.904	54	.000
	X_4	.915	5.043	54	.029
	X_5	.981	1.069	54	.306

The tests we conducted statistically confirm that the bankrupt and non-bankrupt groups of the sample are significantly different. Therefore we reject H_0 of hypothesis 1 stating that no significant difference exists between bankrupt and no-bankrupt firms.

4.3 Altman's Model

In this part, we attempt to apply Altman's original Z-score model on the whole sample of 115 companies from various sectors. We entered the model's coefficients and calculated the Z-score for all companies. Then, using the cut-off as given by the model, we categorized companies as bankrupt and non-bankrupt. This was repeated for the three-years-period. To find the accuracy of the model in predicting bankruptcy, we calculated the number of correct predictions and obtained the percentages of correct predictions as presented in the table below.

Table 6: Accuracy of Altman's model in predicting bankruptcy

Period	Correct classification
t-1	74.7%
t-2	70.2%
t-3	66.3%

Table 6 above exhibits the accuracy of the model in correctly classifying the observations into the appropriate group, and thus predicting bankruptcy. As we can observe, the model exhibits moderate accuracy at 74.7% correct classification for t-1, 70.2% for t-2, and 66.3% for t-3. We can see that the accuracy of the model in predicting bankruptcy subsides the further we get from the bankruptcy incident. Here, we reject H_0 of hypothesis 2 stating that Altman's model cannot predict bankruptcy of heterogeneous observations.

4.4 Model developed

Devising a new model necessitates determining the appropriate coefficients for the model, testing the importance of the variables of the model, examining the model's capability in explaining the variation in grouping variables, and finally testing the accuracy of the model in predicting bankruptcy.

Running the discriminant analysis on the whole sample for the three years period yielded the coefficients as assembled in the discriminant model below

$$Z = .399 X_1 + .428 X_2 + .635 X_3 + .321 X_4 - .135 X_5 \quad (2)$$

Consequently, it is important to verify the relative importance of each variable to the whole model, which is presented in Table 7 below.

Table 7: Structure Matrix

Variable	Function
X ₃	.703
X ₂	.605
X ₁	.481
X ₄	.314
X ₅	-.015

Where .30 constitutes the threshold between important and less important variables, we can see that all variables of the model are important except X₅. The structure matrix above ranks the variables according to their importance to the model, we find that variable X₃ is the most important followed by X₂, X₁, and X₄, while variable X₅ is the least important to the model.

As a final step prior to assessing the competency of the model in predicting bankruptcy, we can examine the model's capability in explaining the variation in grouping variables. To do so, Wilks' Lambda results are presented in Table 8 below.

Table 8: Wilks' Lambda

Wilks' Lambda	Chi-square	df	p-value
.634	129.575	5	.000

Using Wilks' Lambda, we find that the model does not explain 63.4% of the group variation, yet the model enjoys high significance at $p \leq .001$.

After plugging the model in the system and obtaining the discriminant scores, it is important to determine the cut-off point according to which observations are to be assigned to either groups. The cut-off point is the mean of the two centroids of the mean value of the discriminant scores of each group, calculated by the following formula:

$$C = \frac{(n_0 \times \bar{d}_0) + (n_1 \times \bar{d}_1)}{(n_0 + n_1)} \quad (3)$$

Where C is the cut-off point

n_0 = the number of bankrupt observations

n_1 = the number of non-bankrupt observations

$\bar{d}_0$ = average discriminant score of bankrupt observations

$\bar{d}_1$ = average discriminant score of non-bankrupt observations

According to the C-equation above, our C value is -0.114 constituting the threshold between the bankrupt and non-bankrupt group; thus any observation with a discriminant value below the C-value is classified as bankrupt, and any observation above the C-value is classified as non-bankrupt. Running the analysis, we found the following results as presented in Table 9 below.

We can infer from Table 9 that the developed model exhibits moderate accuracy in predicting bankruptcy, at 84.1% for t-1, 79.8% for t-2, and 73.5% for t-3. However, the model's accuracy decreases the further we move from the bankruptcy incident. This fall in the accuracy is expected, as it generally becomes less evident that a

company is encountering distress the farther we move from bankruptcy. Hereby, we can reject the null of hypothesis 3, stating that financial ratios are not a good measures for bankruptcy prediction of corporations, as the model provided exhibits moderate accuracy in predicting bankruptcy.

Table 9: Accuracy of the developed model in predicting bankruptcy

Period	Correct classification
t-1	84.1%
t-2	79.8%
t-3	73.5%

4.5 Segregated sectors

In this part of the study, we will segregate the sample of bankrupt and non-bankrupt companies by sector, then run the analysis on each of the sectors separately. We will first apply Altman's original model to our sectors to determine whether the accuracy of Altman's model in predicting bankruptcy improves in contrast to the model's accuracy when used on the entire sample as a whole.

Following this, we will attempt to devise discriminant models for each of the sectors separately, in order to discover whether doing so improves the results of the discriminant analysis in contrast to running the analysis on the whole sample.

We chose to apply the analysis to the largest four sectors of the sample, the services sector, the consumer goods sector, the technology sector, and the healthcare sector.

Table 10 below exhibits the sectors to be incorporated into this analysis.

Table 10: The incorporated sectors

Sectors	Bankrupt	Non-bankrupt	Total
Services	17	18	35
Consumer goods	4	22	26
Technology	8	14	22
Healthcare	5	12	17

4.5.1 Using Altman's model

As of this part, we used Altman's Z-score model to each sector separately and obtained the Z-scores. Each sector was analyzed separately, and the original group membership was compared to the membership predicted by the Z-model to find the accuracy of the model in predicting bankruptcy.

The results of the per-sector analysis using Altman's Z-score model are presented in Table 11 below. From Table 11, we can see that accuracy of the model varies across the sectors, suggesting that the model is more compatible to certain sectors than others. For instance, the model exhibited superior predictive capability in the technology sector, with accuracy up to 93.8% for t-1. However, the very same model exhibited low predictive capability in the consumer goods sector, with accuracy no more than 52.6% for t-1. Overall, we can conclude that applying Altman's model to each sector separately does not significantly improve the model's accuracy in predicting bankruptcy. We can notice that the accuracy ranges between 52.6% and 93.8% for t-1, 60% and 85.7% for t-2, and 58.8% and 75% for t-3.

Table 11: Results for the three periods using Altman's model on each sector

Sector	Period	Classification		Unclassified	Total	Accuracy
		Correct	Incorrect			
Services	t-1	19	6	10	35	76%
	t-2	20	8	6	34	71.4%
	t-3	18	7	10	34	75%
Consumer goods	t-1	10	9	7	26	52.6%
	t-2	9	6	11	26	60%
	t-3	10	7	9	26	58.8%
Technology	t-1	15	1	6	22	93.8%
	t-2	12	2	8	22	85.7%
	t-3	9	4	9	22	69.2
Healthcare	t-1	10	3	4	17	76.9%
	t-2	10	3	4	17	76.9%
	t-3	10	4	3	17	71.4%

4.5.2 By developing a discriminant model for each sector

For this section, we will run a discriminant analysis on each sector, and create a discriminant model for each sector, then test each model's accuracy. Therefore, this part will be divided in four sections as per the number of sectors we will attempt to analyze.

4.5.2.1 Services sector

Using the ratios of the service companies of the sample, and running discriminant analysis, we obtain the coefficients as assembled in the discriminant equation below. We also determined the cut-off point for this model, using the C-equation presented earlier, which turned to be -0.0181.

$$Z = .034X_1 + .492 X_2 + .484 X_3 + .460 X_4 - .198 X_5 \quad (4)$$

To examine the relative importance of each variable of the model, we can examine the ranking as presented in Table 12 below.

Table 12: Structure Matrix (Services)

Variables	Function
X ₂	.860
X ₃	.650
X ₄	.533
X ₁	.301
X ₅	-.034

We can infer from the table above that all variables to this model are important except X₅. The most important variables are X₂, X₃, X₄, and X₁ in descending order.

As a final step prior to assessing the competency of the model in predicting bankruptcy, we can examine the model's capability in explaining the variation in grouping variables. To do so, we have prepared a summary of Eigenvalue and Wilks' Lambda in the table below.

Table 13: Summary of Eigenvalues and Wilks' Lambda tables (services sector)

Eigenvalues table		Wilks' Lambda table		
Eigenvalue	Canonical correlation	Wilks' Lambda	Chi-square	p-value
1.037	.713	.491	68.654	.000

Using the square of the value presented in the Canonical Correlation column, we find that the model we created is capable of explaining 50.8 % of the variation in group variables. Alternatively, we can examine the variation in the grouping variable that have not been explained by the model using Wilks' Lambda. In doing so, we find that the model does not explain 49.1%, of the variation in grouping variables. However, the model enjoys high significance as $p \leq .001$.

Finally, assessing the accuracy of the model in correctly classifying the observations according to their original group (bankrupt or non-bankrupt), we find that the model has succeeded in correctly classifying the groups at 85%, 82.9%, and 74.3% for the periods t-1, t-2, and t-3, respectively.

4.5.2.2 Consumer goods

Running a discriminant analysis on the consumer goods sector of the sample, we obtained the coefficients assembled in the discriminant equation below, with a cut-off point of 0.474. To find the importance of the variables of the developed model for the consumer goods sector, we have provided the ranking of each variable in Table 14 below

$$Z = .664X_1 + .547X_2 - .509X_3 - .078X_4 + .917 X_5 \quad (5)$$

Table 14: Structure Matrix (Consumer goods)

Variable	Function
X ₅	.698
X ₂	.440
X ₁	.394
X ₃	.277
X ₄	.016

As the table above demonstrates, the most important variables are X_5 , X_2 , and X_1 in descending order. While X_3 and X_4 are seen as less important with values less than the threshold of .30.

As a final step, we examine the model's capability in explaining the variation in grouping variables. To do so, a summary of Eigenvalue and Wilks' Lambda is presented in Table 15 below.

Table 15: Summary of Eigenvalues and Wilks' Lambda tables (Consumer goods)

Eigenvalues table		Wilks' Lambda table		
Eigenvalue	Canonical correlation	Wilks' Lambda	Chi-square	p-value
.478	.569	.677	25.189	.000

Using the square of the value presented in the Canonical Correlation columns, we find our model for the consumer goods sector is capable of explaining 32.4% of the variation in group variables. We can also examine the variation in grouping variables not explained by the model by using Wilks' Lambda. We find that the model does not explain 67.7% of the variation in grouping variables. Yet, the model exhibits superior significance as $p \leq .001$.

Finally, assessing the accuracy of the discriminant model in correctly classifying the observations to their original group, (bankrupt or non-bankrupt), we find that the model enjoys relatively high accuracy as it succeeded in correctly classifying the observations at 88%, 88.5%, and 84.6% for the periods t-1, t-2, and t-3, respectively.

4.5.2.3 Technology

Running a discriminant analysis for the technology sector of the sample, the following discriminant model is generated, with a cut-off point of -0.339.

$$Z = .275X_1 + .339 X_2 + .605X_3 + .299X_4 - .109 X_5 \quad (6)$$

To assess the importance of the variables for the model of the technology sector, we have provided the ranking of each variable in Table 16 below.

Table 16: Structure Matrix (Technology)

Variable	Function
X ₃	.800
X ₁	.660
X ₂	.509
X ₄	.465
X ₅	-.214

The table above exhibits the ranking of the variables according to their importance. We can see that all variables are important with a value greater than .30, except X₅ which is found less important.

As a final step preceding assessing the competency of the model in predicting bankruptcy, we can examine the model's competence in explaining the variation in grouping variables. A summary of Eigenvalue and Wilks' Lambda is prepared and presented in the table below.

Table 17: Summary of Eigenvalues and Wilks' Lambda tables (Technology)

Eigenvalues table		Wilks' Lambda table		
Eigenvalue	Canonical correlation	Wilks' Lambda	Chi-square	p-value
.431	.549	.699	18.467	.002

We can affirm from the Table 17 above that the model is capable of explaining 30.1% of the variation in the grouping variable, while does not explain 69.9% as indicated by Wilks' Lambda. The table also exhibits that the model for the technology sector is significant with a p-value less than .05 ($p \leq .05$).

Consequently, we can evaluate the model's accuracy in correctly classifying the observations according to their original group (bankrupt or non-bankrupt) by comparing original group membership to membership predicted by the model. We find that the developed model has correctly classified the observations at 80%, 81.8%, and 81.8% for the periods t-1, t-2, and t-3, respectively.

4.5.2.4 Healthcare

Our final analysis entails running the discriminant analysis on our last sector, the healthcare sector. We will assume the same steps as we did in our earlier analysis. Putting together the coefficients for each of the variables, we have constructed the following discriminant model for the healthcare sector with a cut-off point of -1.45.

$$Z = .016X_1 + .469X_2 -.300X_3 -.716X_4 + .852X_5 \quad (7)$$

To rank our variables according to their importance, we can examine the structure matrix provided in Table 18 below.

Table 18: Structure Matrix (Healthcare)

Variables	Function
X ₅	.734
X ₃	.709
X ₂	.552
X ₁	-.472
X ₄	-.470

Knowing that the threshold between highly important and less important variables stands at .3, we can infer that all our variables of this model are important as they are all greater than .3. We can also infer from the table above that the most important variables are X_5 , X_3 , X_2 , X_1 , and X_4 in descending order.

As a final step we examine the model's capability in explaining the variation in grouping variables. To do so, we prepared a summary of Eigenvalue and Wilks' Lambda in Table 19 below.

Table 19: Summary of Eigenvalues and Wilks' Lambda tables (Healthcare)

Eigenvalue table		Wilks' Lambda table		
Eigenvalue	Canonical correlation	Wilk's Lambda	Chi-square	p-value
.497	.576	.668	14.324	.014

The square of the Canonical Correlation value indicates the capability of the model in explaining the variations of the grouping variable, which stood at 33.2%. Alternatively, Wilks' Lambda explains the variation in the grouping variable that could not be explained by the model, which stood at 66.8%. We can also examine the significance of the models from the table above, which demonstrates that the model for the healthcare sector is significant as ($p \leq .05$).

Finally, plugging in the model and comparing the original group membership to that predicted by the model, we find that the model for the healthcare sector correctly classified the observations at 81.3%, 70.6%, and 64.7% for the periods t-1, t-2, and t-3, respectively.

4.5.3 Summarized results

Running discriminant analysis on each sector separately and devising sector-specific models yielded an array of results. To summarize the results of the accuracy of the developed models in predicting bankruptcy for the 3-year period, we present Table 20 below.

Table 20: Accuracy of the developed models in predicting bankruptcy

Sector	Period	Correct classification
Services	t-1	85%
	t-2	82.9%
	t-3	74.3%
Consumer goods	t-1	88%
	t-2	88.5%
	t-3	84.6%
Technology	t-1	80%
	t-2	81.8%
	t-3	81.8%
Healthcare	t-1	81.3%
	t-2	70.6%
	t-3	64.7%

The table demonstrates an overall high accuracy in discriminating between bankrupt and non-bankrupt companies within all sectors and for each period. The models' accuracy in predicting bankruptcy for t-1 stood well above 80%, for t-2 the accuracy remained above 80% for each sector except the healthcare sector with 70.6%, and for t-3 the models' accuracy remained above 64.7%. Hence, we can reject the null of hypothesis 4, stating that the accuracy of discriminant models in predicting bankruptcy do not improve when used on sector-specific sample as opposed to mixed-sector sample.

CHAPTER 5

SUMMARY AND DISCUSSION

Analyzing the sample first as a whole, and again as segregated by sector, yielded a range of results. Therefore, it is useful to summarize the findings in tables, as this will provide the most comprehensive view of the results.

Table 21 below compares the accuracy of Altman's model to that of the developed model when applied on the whole sample, consisting of both bankrupt and non-bankrupt companies across the six sectors. We can infer that the developed model is slightly more accurate than Altman's model in predicting bankruptcy. Yet both models exhibit moderate accuracy in correctly classifying the observations according to their original group, which is attributed to the heterogeneous nature of the sample.

Table 21: The accuracy of the models when used on the whole sample

Period	Altman z-score model	The developed model
t-1	74.7%	84.1%
t-2	70.2%	79.8%
t-3	66.3%	73.5%

The second part entailed applying Altman's model to each sector separately, and also devising a discriminant model for each sector. We have provided a summary comparing the results of each model in the table below.

Table 22: The accuracy of the per-sector models

Sector	Period	Altman z-score model	The developed discriminant models
Services	t-1	76%	85%
	t-2	71.4%	82.9%
	t-3	75%	74.3%
Consumer goods	t-1	52.6%	88%
	t-2	60%	88.5%
	t-3	58.8%	84.6%
Technology	t-1	93.8%	80%
	t-2	85.7%	81.8%
	t-3	69.2%	81.8%
Healthcare	t-1	76.9%	81.3%
	t-2	76.9%	70.6%
	t-3	71.4%	64.7%

We can infer from Table 22 above that overall the accuracy of the developed models surpassed that of Altman's model. Also, the accuracy of Altman's model does not improve significantly when applied to each sector separately. In contrast, we can see that the accuracy of predicting bankruptcy using sector-specific models as the ones developed improve the discriminating accuracy. Therefore, we reject H_0 of hypothesis 4, stating that the accuracy of discriminant models in predicting bankruptcy do not improve when used on a sector-specific sample as opposed to a mixed-sector sample.

CHAPTER 6

CONCLUSION, LIMITATIONS, AND FURTHER STUDIES

6.1 Conclusion

This thesis seeks to provide a fundamental tool capable of predicting the bankruptcy of public companies of various sizes and from diverse sectors to benefit investors who seek to evaluate their current and prospective investments as worthy or unworthy of consideration. In a bid to do so the accuracy and usefulness of an already available model, Altman's Z-score model, was re-examined and the results were compared to those obtained from the newly-developed model. The accuracy of the newly-devised model surpasses that of the original model, particularly when used on a homogeneous sample, and hence we can say that we have succeeded in our endeavor to devise a model capable of predicting bankruptcy.

Four hypotheses constituted the pillars to this thesis, and the analysis proved the following:

- a. With regards to the sample of this study, the two groups of the sample, bankrupt and non-bankrupt, exhibited statistically significant difference, making discriminant analysis a rationale statistical tool to categorize observations or predict group membership.
- b. Though the Z-score model of Altman was specifically developed to predict bankruptcy of manufacturing public companies, we find that it is also capable of predicting bankruptcy of public companies from a mixed sector yet with lower accuracy. Hence, when deciding to use the model to predict bankruptcy

and screen out bad investments, the large potential for misclassification and error should be considered.

- c. Financial ratios are a good measure to predict bankruptcy of companies, and thus it is worthwhile using ratio-based models to predict bankruptcy, or develop new ratio-based models.
- d. The extent to which the accuracy of discriminant models in predicting bankruptcy can be enhanced varies across different models.

6.2 Limitations

The study, though successful in meeting its main objective, is not without flaws and limitations. The key limitations concern two areas of the study, namely the sampling procedures, and the model:

6.2.1 Sampling limitations

Key flaws concerning the sample include the small sample size, the sample selection procedure, and the characteristics of the sample. With regards to the size of the sample, it is considerably small relative to the population (7.1% of the population for the bankrupt group, and 3.9% of the population for the non-bankrupt group). The adverse time factor curbed our ability to draw a larger and more representative sample. Secondly, the selection procedure was largely influenced by convenience also due to the time factor. Thirdly, the sample is not normally distributed, which may have had an impact on the accuracy of the results obtained, particularly that a key assumption to Multiple Discriminant Analysis is the normality of the sample.

6.2.2 Methodology limitations

With regards to the model presented, though broader than the classic Z-score model developed by Altman, as it proved higher accuracy in predicting bankruptcy of companies from a wider range of sectors. Yet, its usage remains limited; as it merely categorizes investments as bankrupt and non-bankrupt, but does not specify the extent

to which a certain investment is valuable or not. This implies that the model should not be used single-handedly for decision-making or strategy formulation. Additionally, the model represents a single cut-off point and thus categorizes observations as either bankrupt or non-bankrupt, resulting in high misclassification of observations with discriminant scores close to the cut-off. What's more, some of the independent variables incorporated in the final developed model(s) were statistically insignificant, in addition to the moderate to low explanatory competency of the model(s) exhibited in the low Canonical Correlation and high Wilks' Lambda figures. Further, the relevance and reliability of ratio-based models for predicting bankruptcy remain questionable according to a vast number of users, who claim that financial statements, and thus any financial statements based models, fail to project the true financial standing of companies, mainly due to the sky-rocketing creativity in accounting. Last but not least, the core of the models developed are based on a model developed more than 40 years ago, raising more questions about the relevance of the models to today's markets and accounting practices.

6.3 Suggestions for further studies

A number of measures can be taken to enhance the validity and reliability of the model and obtain superior accuracy in predicting bankruptcy, opening the door for further studies in the area. These measures include:

- a. Expanding the sample size, and thus enhancing the sample's representation of the population.
- b. Employing longitudinal data, and making use of time series analysis.
- c. Testing and incorporating other ratios into the model and enhancing the model's significance and competency in explaining variations.
- d. Conducting tests of validity and reliability, including the verification of the model's accuracy using a secondary sample.
- e. Incorporating more than one cut-off point, and thus categorizing companies as growing, stable, declining, and failing companies for instance.

BIBLIOGRAPHY

- Abrahamson, E., & Amir, E. (1996). the Information Content of the President's Letter to Shareholders. *Journal of Business Finance & Accounting*, 1157-1182.
- Alireza, F., Parviz, M., & Mina, S. (2012). Evaluation of Financial Ratio Capability to Predict Financial Crisis of Companies. *The IUP Journal of Behavioral Finance*, 57-69.
- Altman, E. I. (1968). Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *The Journal of Finance*, 589-609.
- Altman, E., Hartzell, J., & Peck, M. (1995). *Emerging Markets Corporate Bonds: A Scoring System*. New York: Salomon Brothers Inc.
- Altman, E., Narayanan, P., & Haldeman, R. (1977). ZETA Analysis A New Model to Identify Bankruptcy Risk of Corporations. *Journal of Banking and Finance*, 29-54.
- Beaver, W. H. (1966). Financial Ratios as Predictors of Failure. *Journal of Accounting Research*, 71-111.
- Bell, T., Ribar, G. and Verchio, J., Neural nets vs. logistic regression: a comparison of each model's ability to predict commercial bank failures, *Proceedings of the 1990 Deloitte & Touche/ University of Kansas Symposium on Auditing Problems*, 1990, pp. 29-58
- Bellovary, J., Giaomino, D., & Akers, M. (2007). A Review of Bankruptcy Prediction Studies 1930 to Present. *Journal of Financial Education*, 1-42.
- Chang, P.-C., Huang, C. H., & Tsai, C.-Y. (2013). A Hybrid System by the Iteration of Case-Based Reasoning with Support Vector Machine for Prediction of Financial Crisis. *International Journal of Innovative Computing Information and Control*, 2245-2260.
- Clatworthy, M., & Jones, M. J. (2006). Differential Patterns of Textual Characteristics and Company Performance in the Chairman's Statement. *Accounting, Auditing and Accountability Journal*, 493-511.

- Coats, P. K., & Fant, L. F. (1993). Recognizing Financial Distress Patterns Using a Neural Network Tool. *The Journal of Financial Management Association*, 142-155.
- FitzPatrick, P. (1932). A Comparison of Ratios of Successful Industrial Enterprises with those of Failed Companies. *The Certified Public Accountant*, (October, November, December): 598-605, 656-662, 727-731 respectively.
- Gharghori, P., Chan, H., & Faff, R. (2006). Investigating the Performance of Alternative Default-Risk Models: Option-Based Versus Accounting-Based Approaches. *Australian Journal of Management*, 207-234.
- Hillegeist, S., & et., al. (2004). Assessing the Probability of Bankruptcy. *Review of Accounting Studies*, 5-34.
- Haykin, S. (1999). *Neural Networks: A Comprehensive Foundation (2nd e.d.)*. Prentice Hall.
- Jackson, R., & Wood, A. (2013). The Performance of Insolvency Prediction and Credit Risk Models in the UK: A Comparative Study. *The British Accounting Review*, 183-202.
- Jandaghi, G., Tehrani, R., Pirani, P., & Mokhles, A. (2011). Hybrid Financial Analysis Model for Predicting Bankruptcy. *British Journal of Economics, Finance and Management Science*, 37-48.
- Kivuvo, R. M., & Olweny, T. (2014). Financial Performance Analysis of Kenya's SACCO Sector Using Altman z Score Model of Corporate Bankruptcy. *International Journal of Business and Social Sciences*, 34-52.
- Kloptchenko, A., Eklund, T., Back, B., Karlsson, J., Vanharanta, H., & Visa, A. (2004). Combining Data and Text Mining Techniques for Analysing Financial Reports. *International Journal of Intelligent Systems in Accounting, Finance, and Management*, 29-41.
- Li, J., & Rahgozar, R. (2012). Application of the Z -Score Model with Consideration of Total Asset Volatility in Predicting Corporate Financial Failures from 2000-2010. *Journal of Accounting and Finance*, 11-19.

- Martin, A., Gaythri, V., Saranya, G., Gayathri, P., & Venkatesas, P. (2011). A Hybrid Model for Bankruptcy Prediction Using Genetic Algorithm, Fuzzy C-Means and MARS. *International Journal of Soft Computing (IJSC)*, 12-24.
- Merwin, C. (1942). *Financing small corporations in five manufacturing industries, 1926-1936*. New York: National Bureau of Economic Research.
- Odom, M. and Sharada, R. (1990). A neural network model for bankruptcy prediction. *Proceedings of IEEE International Conference on Neural Networks* **2**, 163-168.
- Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*, 109-131.
- Shirata, C. Y., Takeuchi, H., Ogino, S., & Watanate, H. (2011). Extracting Key Phrases as Predictors of Bankruptcy: Empirical Analysis of Annual Reports by Text Mining. *Journal of Emerging Technologies in Accounting*, 31-44.
- Smith, R., & Winakor, A. (1935). *Changes in Financial Structure of Unsuccessful Industrial Corporations*. Urbana: University of Illinois Press.

APPENDIX 1

Characteristics of the Sample

serial	status	company name	symbol	exchange	sector	total assets t-1	total assets t-2	total assets t-3	bankruptcy	date of filing
1	0	ALCO Stores, Inc.	ALCSQ	US OTC	SERVICES	243.9	220.4	212.7	ch 11	10/12/14
2	0	AMARILLO BIOSCIENCES INC	AMAR	US OTC	HEALTHCARE	.115	.115	.259	ch 11	10/31/13
3	0	AMBASSADORS INTERNATIONA L INC	AMIEQ	US OTC	SERVICES	80.263	91.959	211.670	ch11	01/04/11
4	0	AMBIENT CORPORATION	AMBTQ	US OTC	TECHNOLOGY	2.693	18.329	21.874	ch 11	07/28/14
5	0	ATP OIL & GAS CORPORATION	ATPAQ	US OTC	BASIC MATERIALS	3,738	3,617	3,035	ch 11	08/17/12
6	0	BAXANO SURGICAL INC	BAXSQ	US OTC	HEALTHCARE	48.978	32.260	54.032	ch 11	11/12/14
7	0	BEACON POWER CORPORATION	BCONQ	US OTC	CONSUMER GOODS	75.937	50.002	38.595	ch11	10/30/11
8	0	Bionovo, Inc.	BNVIQ	US OTC	HEALTHCARE	18.458	12.982	24.149	ch 7	10/26/11
9	0	CAPITAL GROWTH SYSTEMS INC	CGSYQ	US OTC	TECHNOLOGY	34.379	57.317	30.421	ch11	07/23/10
10	0	CENTRAL EUROPEAN DISTRIBUTION CORPORATION	CEDCQ	US OTC	CONSUMER GOODS	1,767.55	2,072.53	3,396.18	ch 11	07/04/13
11	0	CLEARPOINT BUSINESS RESOURCES INC	CPBRQ	US OTC	SERVICES	2.559	5.081	55.276	ch 11	06/23/10
12	0	CPI Corp.	CPICQ	US OTC	SERVICES	94.53	143.8	166.591	ch 7	05/01/13
13	0	CRUMBS BAKE SHOP INC	CRMBQ	US OTC	SERVICES	20.004	27.886	26.367	ch 11	07/11/14
14	0	dELiA*s Inc	DLIAQ	US OTC	SERVICES	94.492	115.336	139.703	ch 11	12/07/14
15	0	DEX ONE CORPORATION	DEXO	NYSE	SERVICES	2,835	3,460	4,489	ch11	18/03/13
16	0	Digerati Technologies, Inc.	DTGI	US OTC	TECHNOLOGY	.224	.893	.895	ch 11	05/30/13
17	0	DIGITAL DOMAIN MEDIA GROUP INC	DDMGQ	US OTC	SERVICES	197.84	166.72	87.16	ch11	11/09/12
18	0	EAGLE BULK SHIPPING INC	EGLE	NASDAQ	SERVICES	1,723.41	1,789.14	1,867.26	ch 11	08/06/14
19	0	EASTMAN KODAK COMPANY	KODK	NYSE	TECHNOLOGY	4,678	6,239	7,084	ch11	01/01/12
20	0	ENDEAVOUR INTERNATIONA L CORPORATION	ENDRQ	US OTC	BASIC MATERIALS	1,524.8	1,442.5	1,035.2	ch 11	10/10/14
21	0	Environmental Power Corporation	EPGRQ	US OTC	SERVICES	43.385	162.651	200.609	ch 7	07/29/10
22	0	GENCO SHIPPING & TRADING LTD	GSKNF	US OTC	SERVICES	2,957	2,843	3,119	ch 11	21/04/14
23	0	GT Advanced Technologies Inc.	GTATQ	US OTC	TECHNOLOGY	1,187.28	1,002.78	1,126.29	ch 11	10/06/14
24	0	John D. Oil and Gas Company	JDOGQ	US OTC	BASIC MATERIALS	6.979	8.718	10.259	ch 11	01/13/12
25	0	KiOR, Inc.	KIORQ	US OTC	CONSUMER GOODS	86.05	296.037	305.264	ch11	11/09/14

26	0	NII HOLDINGS INC	NIHDQ	US OTC	TECHNOLOGY	8,679.95	9,223.08	9,806.89	ch 11	09/15/14
27	0	PINNACLE AIRLINES CORP	PNCLQ	US OTC	SERVICES	1,475.4	1,498.8	1,289.4	ch 11	04/02/12
28	0	R.R. DONNELLEY & SONS COMPANY	RRD	NASDAQ	SERVICES	7,238	7,263	8,282	ch 11	11/08/14
29	0	RIVERA HOLDINGS CORPORATON	RVHLQ	US OTC	SERVICES	199	205	218.5	ch11	12/07/10
30	0	RoomStore, Inc.	ROOMQ	US OTC	SERVICES	90.217	94.774	105.878	ch 11	12/12/11
31	0	SIGA Technologies, Inc.	SIGA	NASDAQ	HEALTHCARE	193.82	105.84	90.38	ch 11	09/16/14
32	0	THQ INC	THQIQ	US OTC	INDUSTRIAL GOODS	884.86	774.07	598.33	ch11	19/12/12
33	0	TRAILER BRIDGE INC	TRBRQ	US OTC	SERVICES	116.400	118.5	123.3	ch 11	17/11/11
34	0	TranSwitch Corporation	TXCCQ	US OTC	TECHNOLOGY	17.597	27.618	45.818	ch 7	11/21/13
35	0	Unigene Laboratories, Inc.	UGNEQ	US OTC	HEALTHCARE	11.312	17.674	28.470	ch 7	07/02/13
36	0	UniTek Global Services, Inc.	UNTKQ	US OTC	SERVICES	270.550	326.4	348.88	ch 11	11/03/14
37	0	VALENCE TECHNOLOGY INC	VLNCQ	US OTC	INDUSTRIAL GOODS	36.017	21.032	29.636	ch 11	12/07/12
38	0	Vision Industries Corp.	VIICQ	US OTC	CONSUMER GOODS	1.170	.820	.785	ch 11	09/24/14
39	0	Visual Management Systems, Inc.	VMSYQ	US OTC	TECHNOLOGY	1.727	3.631	4.268	ch 11	11/08/10
40	1	3D Systems Corporation	DDD	NYSE	TECHNOLOGY	1,097.86	677.44	462.97	N/A	N/A
41	1	A.SchulmanInc	SHLM	NASDAQ	CONSUMER GOODS	1,238.34	1,193.77	1,239.99	N/A	N/A
42	1	AAR Corp	AIR	NYSE	TECHNOLOGY	2,136.9	2,195.65	1,703.73	N/A	N/A
43	1	Accuride Corporation	ACW	NYSE	CONSUMER GOODS	611.78	677.82	868.86	N/A	N/A
44	1	ACME UNITED CORPORATION	ACU	NYSE MKT	INDUSTRIAL GOODS	68.078	67.827	55.221	N/A	N/A
45	1	Advance Auto Parts	AAP	NYSE	SERVICES	5,564.77	4,613.81	3,655.75	N/A	N/A
46	1	AECOM Technology Corporation	ACM	NYSE	SERVICES	5,665.62	5,664.57	5,789.33	N/A	N/A
47	1	Agilent Technologies Inc	A	NYSE	HEALTHCARE	10,686	10,536	9,057	N/A	N/A
48	1	Amazon.com	AMZN	NASDAQ 100	SERVICES	41,397	32,555	25,278	N/A	N/A
49	1	American Woodmark Corporation	AMWD	NASDAQ	CONSUMER GOODS	293.99	265.12	268.37	N/A	N/A
50	1	AMYRIS INC	AMRS	NASDAQ	CONSUMER GOODS	198.86	242.83	320.11	N/A	N/A
51	1	Avago Technologies	AVGO	NASDAQ	TECHNOLOGY	3,415	2,862	2,446	N/A	N/A
52	1	Babcock & Wilcox Company (BWC)	BWC	NYSE	CONSUMER GOODS	2,609.15	2,840.36	2,689.11	N/A	N/A
53	1	Baidu Inc	BIDU	NASDAQ	TECHNOLOGY	11,725.43	7,330.31	3,708.35	N/A	N/A
54	1	Bill Barrett Corporation	BBG	NYSE	BASIC MATERIALS	2,496.710	2,967.53	2,687.93	N/A	N/A
55	1	BioAmber Inc.	BIOA	NYSE	CONSUMER GOODS	114.08	154.2	68.1	N/A	N/A
56	1	BLUE DOLPHIN ENERGY CORPORATION	BDCO	US OTC	BASIC MATERIALS	57.679	56.381	6.408	N/A	N/A
57	1	CardinalInc	CRDC	NASDAQ	HEALTHCARE	17.761	18.142	11.46	N/A	N/A
58	1	Celgene Corporation	CELG	NASDAQ	HEALTHCARE	13,378.2	11,734.31	10,005.91	N/A	N/A

59	1	Consol Energy Inc	CNX	NYSE	BASIC MATERIALS	11,393.67	12,670.91	12,525.7	N/A	N/A
60	1	cooper companies Inc	COO	NYSE	HEALTHCARE	3,137.26	2,941.38	2,624.52	N/A	N/A
61	1	Crown Holdings	CCK	NYSE	CONSUMER GOODS	8,030	7,490	6,868	N/A	N/A
62	1	Dish Network	DISH	NASDAQ	SERVICES	20,375.63	17,440.74	11,540.93	N/A	N/A
63	1	DOLLAR TREE INC	DLTR	NASDAQ	SERVICES	2,752	2,328.6	2,380.5	N/A	N/A
64	1	EBay	EBAY	NASDAQ	SERVICES	41,488	37,074	27,320.22	N/A	N/A
65	1	EOG Resources Inc	EOG	NYSE	BASIC MATERIALS	30,574.24	27,336.58	24,838.8	N/A	N/A
66	1	Expedia, Inc.	EXPE	NASDAQ	SERVICES	7,739.48	7,085.2	6,505.26	N/A	N/A
67	1	FedEx Corporation	FDX	NYSE	SERVICES	33,567	29,903	27,385	N/A	N/A
68	1	fleetcor technology incorporation	FLT	NYSE	SERVICES	3,952.97	2,721.87	2,334.89	N/A	N/A
69	1	freesealesemiconductor	FSL	NYSE	TECHNOLOGY	3,047	3,171	3,415	N/A	N/A
70	1	General Cable	BGC	NYSE	CONSUMER GOODS	4,578.9	4,919.9	4,370.4	N/A	N/A
71	1	Gibraltar Industries Inc	ROCK	NASDAQ	CONSUMER GOODS	914.720	899.120	872.06	N/A	N/A
72	1	Gilead Sciences Inc	GILD	NASDAQ	HEALTHCARE	22,496.79	21,239.840	17,303.13	N/A	N/A
73	1	Globe Specialty Metals Inc	GSM	NASDAQ	CONSUMER GOODS	871.62	936.75	678.27	N/A	N/A
74	1	Gorman-Rupp Company	GRC	NYSE MKT	CONSUMER GOODS	355.64	335.18	298.7	N/A	N/A
75	1	Guidewire Software	GWRE	NYSE	TECHNOLOGY	312.27	284.25	207.78	N/A	N/A
76	1	Haemonetics Corporation	HAE	NYSE	HEALTHCARE	1,461.92	911.14	833.26	N/A	N/A
77	1	Haynes International Inc	HAYN	NASDAQ	BASIC MATERIALS	597.85	626.93	596.570	N/A	N/A
78	1	Hexcel Corporation	HXL	NYSE	TECHNOLOGY	1,836.1	1,603.1	1,376.1	N/A	N/A
79	1	Horsehead holding Corp	ZINC	NASDAQ	BASIC MATERIALS	1,005.31	811.83	631.49	N/A	N/A
80	1	Ilex Corporation	IEX	NYSE	CONSUMER GOODS	2,887.58	2,785.390	2,836.11	N/A	N/A
81	1	Intelligent Systems Corporation	INS	NYSE MKT	INDUSTRIAL GOODS	10.627	9.936	10.105	N/A	N/A
82	1	International Paper Company	IP	NYSE	CONSUMER GOODS	31,528	32,153	26,993	N/A	N/A
83	1	KapStone Paper and Packaging Corporation	KS	NYSE	CONSUMER GOODS	2,651.86	1,131.17	1,124.35	N/A	N/A
84	1	Layne Christensen Company	LAYN	NASDAQ	SERVICES	812.23	832.47	834.38	N/A	N/A
85	1	Lennar Corporatopn	LEN	NYSE	INDUSTRIAL GOODS	11,273.25	10,362.21	9,154.67	N/A	N/A
86	1	Level 3 Communications Inc	LVL	NYSE	TECHNOLOGY	12,874	13,307	13,188	N/A	N/A
87	1	MarroneBioinnovationsInc	MBII	NASDAQ	CONSUMER GOODS	68.879	78.282	9.818	N/A	N/A
88	1	Martin Marietta Materials Inc	MLM	NYSE	BASIC MATERIALS	3,259.83	3,160.93	3,147.82	N/A	N/A
89	1	MetaboliX Inc	MBLX	NASDAQ	CONSUMER GOODS	26.738	53.51	82.912	N/A	N/A
90	1	Monster Beverage Corporation	MNST	NASDAQ	CONSUMER GOODS	1,420.51	1,043.33	1,362.4	N/A	N/A
91	1	Moog Inc.	MOG.A	NYSE	TECHNOLOGY	3,327.1	3,105.91	2,842.97	N/A	N/A
92	1	Natus Medical Incorporated	BABY	NASDAQ	HEALTHCARE	426.44	391.85	314.32	N/A	N/A
93	1	Nike, Inc.	NIKE	NYSE	CONSUMER GOODS	17,941	15,770	15,307	N/A	N/A
94	1	Oil States International Inc	OIS	NYSE	SERVICES	4,131.26	4,439.96	3,703.64	N/A	N/A

95	1	OM Group Inc	OMG	NYSE	CONSUMER GOODS	1,783.1	2,499.43	2,869.72	N/A	N/A
96	1	OrexigenThrapeuti csInc	OREX	NASDAQ	HEALTHCARE	180.12	139.15	149.7	N/A	N/A
97	1	ProtalixBioTherap eutics	PLX	NYSE MKT	HEALTHCARE	113.33	78.73	51.81	N/A	N/A
98	1	Raytheon company	RTN	NYSE	TECHNOLOGY	25,967	26,686	25,854	N/A	N/A
99	1	Royal Caribbean Cruises Ltd.	RCL	NYSE	SERVICES	20,072.95	19,827.93	19,804.41 0	N/A	N/A
100	1	SanDisk	SNDK	NASDAQ	TECHNOLOGY	10,488.72	10,339.13	10,174.65	N/A	N/A
101	1	SIFCO Industries	SIF	NYSE MKT	TECHNOLOGY	105.77	106.55	80.01	N/A	N/A
102	1	Signet Jewelers limited	SIG	NYSE	SERVICES	3,715.8	3,611.4	3,089.8	N/A	N/A
103	1	Sonoco products company	SON	NYSE	CONSUMER GOODS	3,979.29	4,176.07	3,986.17	N/A	N/A
104	1	Starbucks corporation	SBUX	NASDAQ	SERVICES	11,516.7	8,219.2	7,370.4	N/A	N/A
105	1	trina solar ltd	TSL	NYSE	CONSUMER GOODS	2,567.19	2,864.93	2,877.42	N/A	N/A
106	1	TripAdvisor Inc	TRIP	NASDAQ	SERVICES	1,473.01	1,299.19	835.89	N/A	N/A
107	1	Triumph Group Inc	TGI	NYSE	TECHNOLOGY	5,183.51	4,554.76	4,470.24	N/A	N/A
108	1	TRW Automotive Holdings Corp	TRW	NYSE	CONSUMER GOODS	12,252	10,857	10,262	N/A	N/A
109	1	Varian Medical Systems Inc	VAR	NYSE	HEALTHCARE	3,468.47	2,878.73	2,498.76	N/A	N/A
110	1	VersarInc	VSR	NYSE MKT	SERVICES	57.377	53.377	53.376	N/A	N/A
111	1	Wal-mart stores Inc	WMT	NYSE	SERVICES	203,110	193,410	185,300	N/A	N/A
112	1	Waters Corporation	WAT	NYSE	HEALTHCARE	3,582.63	3,168.15	2,723.23	N/A	N/A
113	1	Whole Foods Market Inc	WFM	NASDAQ	SERVICES	5,538	5,294.22	4,292.08	N/A	N/A
114	1	Yelp Inc	YELP	NYSE	TECHNOLOGY	515.98	187.7	43.82	N/A	N/A
115	1	Zimmer Holdings	ZMH	NYSE	HEALTHCARE	9,580.6	9,012.4	8,515.3	N/A	N/A

Total assets in million US dollars

APPENDIX 2

Group Statistics and Tests of Equality of Group Means (per sector)

Group Statistics					
Sector	Bankrupt / Non-bankrupt	Mean	Std. Deviation	Sample size	
Basic materials	0	X1	-.292	.489	8
		X2	-.986	1.502	8
		X3	-.012	.073	8
		X4	.063	.190	8
		X5	.189	.108	8
	1	X1	.156	.213	21
		X2	-.052	1.099	21
		X3	.020	.096	21
		X4	.854	.354	21
		X5	1.091	1.868	21
	Total	X1	.032	.366	29
		X2	-.310	1.268	29
		X3	.011	.090	29
		X4	.636	.477	29
		X5	.842	1.632	29
Consumer goods	0	X1	.038	.333	6
		X2	-1.123	1.852	6
		X3	-.168	.264	6
		X4	1.170	1.158	6
		X5	.182	.217	6
	1	X1	.280	.246	63
		X2	.010	.976	63
		X3	.006	.262	63
		X4	1.221	1.324	63
		X5	1.006	.503	63
	Total	X1	.259	.261	69
		X2	-.088	1.106	69
		X3	-.008	.265	69
		X4	1.217	1.303	69
		X5	.934	.537	69
Healthcare	0	X1	.589	.189	6
		X2	-2.249	1.918	6
		X3	-.334	.188	6
		X4	3.575	5.287	6
		X5	.169	.166	6

Industrial goods	1	X1	.391	.221	34
		X2	-.341	1.777	34
		X3	.0168	.266	34
		X4	1.543	1.256	34
		X5	.526	.263	34
	Total	X1	.421	.226	40
		X2	-.627	1.903	40
		X3	-.035	.283	40
		X4	1.848	2.336	40
		X5	.473	.280	40
	0	X1	.348	.118	3
		X2	-.313	.061	3
		X3	-.195	.215	3
		X4	.701	.386	3
		X5	1.095	.320	3
Services	1	X1	.561	.111	9
		X2	-.268	.848	9
		X3	.044	.034	9
		X4	1.308	.781	9
		X5	1.104	.534	9
	Total	X1	.508	.144	12
		X2	-.279	.724	12
		X3	-.015	.145	12
		X4	1.156	.739	12
		X5	1.102	.475	12
	0	X1	-.038	.463	48
		X2	-.277	.414	48
		X3	-.039	.147	48
		X4	.382	.540	48
		X5	1.256	1.110	48
Technology	1	X1	.172	.184	53
		X2	.286	.213	53
		X3	.116	.084	53
		X4	1.014	.625	53
		X5	1.192	.753	53
	Total	X1	.072	.360	101
		X2	.018	.429	101
		X3	.042	.141	101
		X4	.714	.664	101
		X5	1.222	.935	101
	0	X1	.131	.253	14
		X2	-1.425	2.866	14
		X3	-.183	.443	14

	X4	.325	.934	14
	X5	.963	.644	14
	X1	.316	.163	42
	X2	-.111	1.164	42
1	X3	.096	.101	42
	X4	2.080	2.857	42
	X5	.8291	.316	42
	X1	.270	.204	56
	X2	-.440	1.812	56
Total	X3	.026	.262	56
	X4	1.641	2.623	56
	X5	.862	.420	56

Tests of Equality of Group Means

Sector		Wilks' Lambda	F	Sample size	p-value
Basic materials	X1	.689	12.173	27	.002
	X2	.888	3.415	27	.076
	X3	.973	.753	27	.393
	X4	.433	35.376	27	.000
	X5	.937	1.822	27	.188
Consumer goods	X1	.931	4.967	67	.029
	X2	.915	6.193	67	.015
	X3	.965	2.457	67	.122
	X4	1.000	.008	67	.927
	X5	.811	15.600	67	.000
Healthcare	X1	.900	4.214	38	.047
	X2	.868	5.754	38	.021
	X3	.800	9.500	38	.004
	X4	.901	4.169	38	.048
	X5	.789	10.180	38	.003
Industrial goods	X1	.556	7.997	10	.018
	X2	.999	.008	10	.930
	X3	.441	12.691	10	.005
	X4	.862	1.600	10	.235
	X5	1.000	.001	10	.979
Services	X1	.914	9.326	99	.003
	X2	.566	75.947	99	.000
	X3	.695	43.387	99	.000
	X4	.773	29.155	99	.000
	X5	.999	.119	99	.731
Technology	X1	.842	10.137	54	.002
	X2	.900	6.023	54	.017
	X3	.784	14.904	54	.000
	X4	.915	5.043	54	.029
	X5	.981	1.069	54	.306