STATISTICAL APPROACH TO PREDICTION OF FINANCIAL DISTRESS OF LISTED FIRMS IN THE NAIROBI SECURTIES EXCHANGE

BY

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SCHOOL OF MATHEMATICS,STATISTICS AND ACTUARIAL SCIENCE

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DECLARATION

I declare that this research project is my original work and has not been submitted for an award of a degree in any other University for examination or academic purpose.

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This project report has been submitted for examination with my approval as the university supervisor

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DEDICATION

This project is dedicated to my lovely parents Gerphas(deceased) and Hulder Ndiege,brother Iddy Ndiege and the entire Ndiege family for their support in my academic pursuit hitherto. It is also greatly dedicated to my loving wife Naomy and daughter Tirzah, for encouraging and standing with me throughout this study.You are such a beautiful family. May the Almighty God bless you abundantly.

ABSTRACT

This research project examined the phenomenon of bankruptcy prediction from a developing economy perspective using the Altman Z-score models. These models rank among the bankruptcy models, whose main purpose is to detect the impending bankruptcy in good time. Drawing an empirical data from audited financial statements of firms listed in Nairobi Security Exchange in Kenya, the author tested Altman original Z-score (1968)and the Emerging Markets (1993) models using the dataset of the years ending between 2010 and 2015. Since the most frequently used tool so as to predict financial distress and bankruptcy is through financial analysis of financial ratios, this study employed the same ratios and therefore aimed to make an important contribution to the global discourse on corporate failure prediction in an increasingly globalised world.

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LIST OF ABBREVIATIONS

MDA- Multiple Discriminant Analysis

LPM- Linear Probability Model

CUSUM- Cumulative Sum

NSE-Nairobi Securities Exchange

QDA-Quadratic Discriminant Analysis

FDP -Financial Distress Prediction

NM-Non Manufacturing firm

M- Manufacturing firm

KPLC-Kenya Power and Lighting Company

NMG-Nation Media Group

EABL-East African Breweries Limited

EmZ- Emerging markets Z-score

KQ-Kenya Airways

WC-Working Capital

TA-Total Assets

RE-Retained Earnings

EBIT-Earning Before Interest & Taxes

MVE-Market Value of Equity

TL-Total Liabilities

BAT-British American Tobacco

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CHAPTER ONE

INTRODUCTION

0.1 Background Information

Business is any undertaking working towards profit objective. Predicting if a business will do well or go bankrupt, before they actually do has led to propagation of various theories. It is fascinating for researchers to predict in advance if a business will be able to meet its obligation or will dissolve. Business failure has led to many studies of bankruptcy prediction. Business failure as discussed by some leading authors is discussed below. Fitzpatrick (1932) identified five stages leading to business failure. They are (1) incubation (2) financial embarrassment, (3) financial insolvency, (4) total insolvency, and (5) confirmed insolvency. Incubation is when the company‘s financials are just developing. Financial embarrassment is when management becomes aware of the firm’s distressed condition. Financial insolvency occurs when the firm is unable to acquire the necessary funds to meet its obligations. Total insolvency occurs when the liabilities exceed the physical assets. Finally, confirmed insolvency occurs when legal steps are taken to protect the firm’s creditors or liquidation occurs.(Poston, Harmon, Gramlich, 1994)

Kenya has also had her share of corporate failures. The collapse of Webuye Panpaper,Uchumi supermarket Ltd, most recently, the Imperial Bank, Chase bank Ltd and many other corporate failures, in Kenya to some extent, indicate the urgent need for a reliable model which accurately predicts corporate health in Kenya. See the table 1 below for some few selected corporate failures in Kenya.

Source: Nairobi Securities Exchange website (www.nse.co.ke/listed-companies)

Table 1: Sample of some corporate failures in Kenya

Company	Date	Status	Asset base(Ksh)	Creditors base (Ksh)	Staff count
Uchumi supermarket	June 2006	Receivership	6.3 billion	6.3 billion	1,500
Dubai Islamic bank Ltd	August 2015	Receivership	2.92 billion	-	30
Imperial bank Ltd	October 2015	Receivership	49.3 billion	43.3 billion	-
Chase bank Kenya Ltd	April 2016	Receivership	151.8 billion	137.5 billion	1,359
National bank of Kenya Ltd	-	Operational	125.4 billion	114.4 billion	934

0.2 Statement of the problem

The collapse of many corporate institutions in Kenya, with the recent cases of major financial and banking institutions being put under receivership indicate the urgent need to employ a reliable model which may accurately predict corporate health in Kenya.In this study one of the more widely used bankruptcy prediction models,the $Altman's$ Z-score model was used on Kenyan firms.

0.3 Objective of the study

The purpose of this research was to determine whether $Altman's$ Z-score Models used for bankruptcy prediction, could be applied to accurately predict the financial distress of firms listed in NSE, Kenya. The hypothesis of the study therefore was:

H_0 : None of the $Altman's$ Z-score models could be used to predict financial distress of listed Kenyan firms

H_1 : At least one of the $Altman's$ Z-score models could be used to predict financial distress of listed Kenyan firms.

0.4 Significance of the study

The research would be useful to investors in making informed decisions by analyzing the financial ratios of a company before deciding on which shares to buy and which ones to dispose off. Investors who have invested in various companies will have the information to analyze whether their invested companies show any sign of bankruptcy or are still financially sound. Firm managers will pay more attention to managing and controlling their financial stability and the liquidity in their companies. They will also see from this research's evidence whether their firms are falling into the red zone categories or not, thereby making timely responses to financial distress to avoid further losses and avert the situation. The regulators will use the signals from the findings to control the targeted firms and suggest solutions to them while also designing and implementing appropriate policies in ensuring an efficient market system. The government will use the findings in designing strategies to avoid tax losses which are brought about by financial distress. This research will form a basis for further research and scholars will find the information useful in contributing to the pool of knowledge. It will also add to theory by confirming whether the Altman's Z-score models are relevant among the listed firms in the Kenyan context.

CHAPTER TWO

LITERATURE REVIEW

0.5 Introduction

The analysis of corporate distress traces its history back to two centuries ago (Altman E. I. Edith Hotchkiss, 2006). At first, potential corporate distresses were assessed based on some qualitative information, which were very subjective. In particular, four references were mostly used, such as:
(i) The capacity of the manager in charge of the project or company,
(ii) The fact that the manager had an important financial involvement in the company as a financial guarantee,
(iii) The project and the industry in itself, and
(iv) The fact that the firm possessed assets or collateral to back-up in case of a bad situation.
Surprisingly, these recommendations could still be considered in many existing investment decisions.

Later, early in the 20th century, the analysis of companies' financial conditions has moved forward to the analysis of financial statement data, more particularly, to the univariate ratio analysis. It is also interesting to mention that during this period were found some of the most successful contemporary companies in the analysis of the corporate and government financial situations (i.e. Moody's Corporation, Fitch Rating Ltd, and Standard and Poor's a few among others).

0.6 Earlier techniques

As mentioned previously, the early studies concerning ratio analysis for bankruptcy prediction are known as the univariate studies. These studies consisted mostly of analyzing individual ratios, and sometimes, of comparing ratios of failed companies to those of successful firms. However, few studies were published up to the mid 1960. This period is known as a relatively rich in published studies of corporate failures, in which academics advanced further in the field. In particular, Beaver (1966) studied the predictive ability of accounting data as predictors of major events. His work was intended to be a benchmark for future investigations into alternative predictors of failure. Beaver found that a number of indicators could discriminate between matched samples of bankrupt and non-bankrupt firms for as long as five years prior to failure. In a real sense, his univariate analysis of a number of bankruptcy predictors set the stage for the development of multivariate analysis models.

Two years later, the first multivariate study was published by Altman (1968). With the well-known "Z-score", which is a multiple discriminant analysis (MDA) model, Altman demonstrated the advantage of considering the entire profile of characteristics common to the relevant firms, as well as the interactions of these properties. Specifically, the usefulness of a multivariate model taking combinations of ratios that can be analyzed together in order to consider the context or the whole set of information at a time compared to univariate analysis that study variables one at a time and tries to gather most information at once. Consequently to this discriminatory technique, Altman was able to classify data into two distinguished groups: bankrupt and non-bankrupt firms. He also demonstrated a second advantage: if two groups were studied this analysis reduces the analyst's space dimensionality to one dimension.

0.7 Evolution of statistical techniques

$Altman's$ works was then followed by subsequent studies that implemented comparable and complementary models. Meyer and Pifer (1970) employed a linear probability model (LPM). This is a special case of ordinary least square (OLS) regression with dichotomous (0-1) dependent variables for bank bankruptcy prediction. It is interesting to notice that while underlying assumptions of discriminant analysis and LPM are not similar, the results of the methods are identical.

Deakin (1972) compared $Beaver's$ and $Altman's$ methods using the same sample. He first replicated $Beaver's$ study using the same ratios that Beaver had used. Next, he searched for the linear combination of the 14 ratios used by Beaver which best predicts potential failure in each of five years prior to failure. Finally, he devised a decision rule, which was validated over a cross-sectional sample of firms. Deakin's findings were in favor of the discriminant analysis, which compared to the univariate analysis, is a better classifier for potential bankrupt firms. The same year, Edmister (1972) tested a number of methods of analyzing financial ratios to predict small business failures. Even though he found that not all methods and ratios could be used as predictors of failure, he confirmed that some ratios variables could be used to predict failure of small business companies. Finally, Edmister recommended using at least three consecutive year's financial statement to predict small businesses bankruptcies. Altman et al. (1977) constructed a new bankruptcy classification model called the "Zeta model" to update the "Z-score". In particular, they compared linear and quadratic discriminant analyses for the original and holdout samples, introduced prior probabilities of group membership and costs of error estimates into the classification rule, as well as a comparison of the $model's$ results with new bankruptcy classification strategies. Altman et al. obtained good results with a classification accuracy: above 95% one period prior to bankruptcy and above 70% prior to five annual reporting periods.

Altman (1993) adapted his "Z-score" to private firms' application, which he called the "Z'-score". This latest model differs from the original "Z-score" by substituting the book value of equity for the market value, and by re-estimating all the model's coefficients. Altman et al. (1995a) applied a further adaptation of the original "Z-score" to non-manufacturers and emerging markets' firms, called the "Z"-score" model. In this latest model, they decided to drop the asset turnover ratio in order to minimize the potential industry effect compared to the original "Z-score" model. Finally, they also re-estimated the model's coefficients. Few years later, Shumway (2001) developed a dynamic logit or hazard model for forecasting bankruptcy. Compared to the classic logit model that is based on single period data, the hazard model involves the modeling of multiple period data and in complement allows for time-varying covariates. In addition, Shumway considered both classic accounting data and equity market data to form his model.

Recently, Altman, Fargher, and Kalotay (2011) estimated the likelihood of default inferred from equity prices, using accounting-based measures, firm characteristics and industry-level expectations of distress conditions. This approximately enables timely modeling of distress risk in the absence of equity prices or sufficient historical records of default. Model's results are comparable to that of default likelihood inferred from equity prices using the Black-Scholes-Merton structure.
Finally, Altman et al. emphasized the importance of treating equity-implied default probabilities and fundamental variables as complementary rather than competing sources of predictive information.

Finally, for additional readings on the subject of corporate bankruptcy related to this part, readers may refer to E. I. Altman and Edith Hotchkiss (2006), who present in a book several problematic related to the topic; E. I. Altman and Narayanan (1997), who present an international literature review of the topic; Beaver, Correia, and McNichols (2010), who in a monograph discuss the financial distress prediction literature, focusing on (i) the set of dependent and explanatory variables, (ii) the statistical methods of estimation, and (iii) the modeling of financial distress.

0.8 Evolution and empirical applications in Kenya

Kiragu (1991) carried out a study on the prediction of corporate failure using price adjusted accounting data. He used a sample consisting of 10 failed firms and 10 non failed firms. Financial ratios were calculated from price level adjusted financial statistics. Discriminant model developed showed that 9 ratios had high corporate failure predictive ability. These ratios were times interest coverage, fixed charge coverage, quick ratio, current ratio, equity to total assets, working capital to total debt, return on investments to total assets, change in monetary liabilities, total debt to total assets. The most critical ratios were found to be liquidity and debt service ratios. The results were consistent with the finance theory relating to the firm's risk. The firm has to maintain sufficient liquidity in order to avoid insolvency problems. It also needs to generate sufficient earnings to meet its fixed finance charges. The results however differed from earlier studies done by Altman (1968) and Alareeni and Branson (2012) who had concluded that liquidity ratios were not of any significance in bankruptcy prediction. Both had indicated that efficiency and profitability ratios were the most important. Keige (1991) did a study on business failure prediction using discriminate analysis. He concluded that ratios can be used to predict company failure. However, the types of ratios that will best discriminate between failing companies and successful ones tend to differ from place to place. In Kenya current ratio, fixed charge coverage, return on earning to total assets, and return on net worth can be used successfully in predicting for a period up to 2 years before it occurs. Keige concludes that stakeholders should pay attention to liquidity, leverage and activity ratios. The current study sought to evaluate Altman revised model and determine whether it is necessary to come up with a more up to date model of predicting financial distress in Kenya. The studies preceding the current one have all concentrated on ratios independently and not trying to relate with the rest of the studies that have been carried out earlier. This study will change that approach and take revised Altman model to guide it in a bid to establish its applicability in prediction of financial distress in Kenya.

Itati and Odipo,(2011) carried out a study to assess whether Edward $Altman's$ financial distress prediction model could be useful in predicting business failure in Kenya. The population of this study is composed of all the companies listed in the Nairobi Stock exchange from 1989 to 2008. Twenty firms are selected for the study: 10 firms that continue to be listed and 10 firms that were delisted in Nairobi stock exchange during period 1989 to 2008. The source of Secondary data was obtained from financial reports of these listed and delisted companies at the Nairobi Stock Exchange and the Capital Markets Authority. This research study reveals that Edward Altman's financial distress prediction model is found to be applicable in 8 out of the 10 failed firms that were analyzed, which indicates an 80% successful prediction of the model. On the 10 non-failed firms analyzed, 9 of them proved that Edward Altman's financial distress prediction model was successful, indicating a 90% validity of the model. The study concluded that Edward Altman model of predicting financial failure of companies is a useful tool for investors in the Kenyan market.

The Altman Z score multi discriminant analysis model was used by Mohamed (2013) in his study of bankruptcy prediction of firms listed in the NSE adopted. He used convenient sampling technique and descriptive research design. He established that Altman (1993) Z''-score model was not sufficient to differentiate between failed firms and non-failed firms as compared to that of $Altman's$ Z score of 1968. Altman (1993) Z'' – score was intended for manufacturing and retailing firms. He suggested that investors and stakeholders should pay attention to liquidity and activity ratios. Kipruto (2013) adopted the Multivariant Discriminant Analysis (MDA) statistical technique as used by Altman. He was concerned with testing the validity of Altman's failure prediction model in predicting corporate financial distress in Uchumi supermarkets. He found out that the model was a good predictor. The company recorded declining Z-score values indicating that it was experiencing financial distress and that is why it was delisted from the NSE in 2006.

CHAPTER THREE

METHODOLOGY

0.9 Introduction

The previous and dominant bankruptcy researches usually focus on explaining firm failure by using financial ratios and developing models for bankruptcy prediction. This section is an highlight on the details of MDA, the statistical tool behind Altman Z-score model, adopted for use in predicting companies' financial distress and non-distress status.

0.10 The Multiple Discriminant Analysis (MDA)

The statistical method behind $Altman's$ Z-Score is the MDA which was applied in several contexts since the 1930s (Altman 1968). Although not as popular as regression analysis, MDA has been utilized in a variety of disciplines since its first application in the 1930's. During those earlier years, MDA was used mainly in the biological and behavioral sciences. In recent years, this technique has become increasingly popular in the practical business world as well as in academia. Altman, et.al. (1981) discusses discriminant analysis in-depth and reviews several financial application areas. The purpose of using this method was to overcome the problem of discrepancy in the univariate analysis which was applied by Beaver. Furthermore, the MDA should provide a comprehensive assessment regarding the financial profile of companies (Altman and Sabato 2007).

MDA is a statistical technique used to classify an observation into one of several a priori groupings dependent upon the $observation's$ individual characteristics. It is used primarily to classify and/or make predictions in problems where the dependent variable appears in qualitative form, for example, male or female, bankrupt or non-bankrupt. Therefore, the first step is to establish explicit group classifications. The number of original groups can be two or more. Some analysts refer to discriminant analysis as “multiple” only when the number of groups exceeds two. We prefer that the multiple concepts refer to the multivariate nature of the analysis. After the groups are established, data are collected for the objects in the groups; MDA in its most simple form attempts to derive a linear combination of these characteristics which “best” discriminates between the groups. If a particular object, for instance, a corporation, has characteristics (financial ratios) which can be quantified for all of the companies in the analysis, the MDA determines a set of discriminant coefficients. When these coefficients are applied to the actual ratios, a basis for classification into one of the mutually exclusive groupings exists. The MDA technique has the advantage of considering an entire profile of characteristics common to the relevant firms, as well as the interaction of these properties. A univariate study, on the other hand, can only consider the measurements used for group assignments one at a time.

Another advantage of MDA is the reduction of the analyst’s space dimensionally, that is, from the number of different independent variables to G-1 dimension(s), where G equals the number of original a priori groups. This analysis is concerned with two groups, consisting of bankrupt and non-bankrupt firms. Therefore, the analysis is transformed into its simplest form: one dimension.

In order to do this MDA will take into account various samples from both groups. MDA tries to separate these two groups based on the financial ratios of each sample. Each ratio becomes a variable X and gets its own coefficient V. This leads to the following formula, which calculates a sample’s Z-score:

$$Z = \Sigma_{i=1}^{n} V_i X_i \tag{1}$$

Where there are n different independent variables, of which X_i is an example, and Vi is its coefficient.

As noted before the Z-score of a sample depends on X_i, the value of a financial ratio, and its V_i, the coefficient. MDA then searches for the precise value of Vi that maximizes. The result of the MDA is therefore a formula with the coefficients filled in and a cut-off score for Z. To determine whether or not a business will go bankrupt, you should look to whether its Z-score lies beneath or above the cut-off score. The discriminant equation is thus:

$$Z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \varepsilon \tag{2}$$

which transforms the individual variable values to a single discriminant score, or Z value, which is then used to classify the object. Where;

$$Z \cdots discriminant\ score$$

$$X_i \cdots \cdot independent\ variables$$

$$\beta_i \cdots discriminant\ weight\ for\ independent\ variables$$

$$\beta_0 \cdots constant\ of\ discriminant\ function$$

Suppose you have data for *K* groups, with Nk observations per group. Let *N* represent the total number of observations. Each observation consists of the measurements of *p* variables. The *ith* observation is represented by Xki. Let *M* represent the vector of means of these variables across all groups and Mk the vector of means of observations in the *kth* group.

Define three sums of squares and cross products matrices, S_T,S_W and S_A, as follows:

$$S_T = \Sigma_{k=1}^{K} \Sigma_{i=1}^{N_k} (X_{ki} - M)(X_{ki} - M)' \tag{3}$$

$$S_W = \Sigma_{k=1}^{K} \Sigma_{i=1}^{N_k} (X_{ki} - M_k)(X_{ki} - M_k)' \tag{4}$$

$$S_A = S_T - S_W \tag{5}$$

Next, define two degrees of freedom values, *df1* and *df*2:

$$df1 = K - 1 \tag{6}$$

$$df2 = N - K \tag{7}$$

A discriminant function is a weighted average of the values of the independent variables. The weights are selected so that the resulting weighted average separates the observations into the groups. High values of the average come from one group, low values of the average come from another group. The problem reduces to one of finding the weights which, when applied to the data, best discriminate among groups according to some criterion.The solution reduces to finding the eigenvectors, *V*,of $S_W^{-1} S_A$. The canonical coefficients are the elements of these eigenvectors. Let *M* represent the vector of means of these variables across all groups and *Mk* the vector of means of observations in the *kth* group.

A goodness-of-fit parameter, Wilk's lambda(Λ) , is defined as follows:

$$\Lambda = \frac{|S_W|}{|S_T|} = \Pi_{j=1}^{m} \frac{1}{1+\lambda_j} \tag{8}$$

where λj is the *jth* eigenvalue corresponding to the eigenvector described above and *n* is the minimum of *K-1* and *p* is the variables .

The canonical correlation between the *jth* discriminant function and the independent variables is related to these eigenvalues as follows:

$$r_{cj} = \sqrt{\frac{\lambda_j}{1+\lambda_j}} \tag{9}$$

Various other matrices are often considered during a discriminant analysis. The overall covariance matrix, *T*, is given by:

$$T = (\frac{1}{(N-1)})^{S_T} \tag{10}$$

The within-group covariance matrix, *W*, is given by:

$$W = (\frac{1}{(N-K)})^{S_W} \tag{11}$$

The among-group (or between-group) covariance matrix, *A*, is given by:

$$A = (\frac{1}{(K-1)})^{S_A} \tag{12}$$

The linear discriminant functions are defined as:

$$LDF_k = W^{-1} M_k \tag{13}$$

The standardized canonical coefficients are given by:

$$v_{ij}\sqrt{w_{ij}} \tag{14}$$

where v_{ij} are the elements of V and w_{ij} are the elements of W.
The correlations between the independent variables and the canonical variates are given by:

$$Corr_{jk} = \frac{1}{\sqrt{w_{jj}}}(\Sigma_{i=1}^{p} v_{ik} w_{ji}) \tag{15}$$

0.10.1 Assumptions

1. For purposes of significance testing, the independent variables follow a multivariate normal distribution.
2. The variables $X_1, X_2, \ldots, X_k$ are independent of each other.
3. Groups are mutually exclusive and the group sizes are not grossly different.
4. The number of independent variables is not more than two less than the sample size.
5. The variance-covariance structure of the independent variables are similar within each group of the dependent variable.

When utilizing a comprehensive list of financial ratios in assessing a firm's bankruptcy potential, there is reason to believe that some of the measurements will have a high degree of correlation or collinearity with each other. While this aspect is not serious in Discriminant analysis, it usually motivates careful selection of the predictive variables (ratios). It also has the advantage of potentially yielding a model with a relatively small number of selected measurements which convey a great deal of information. This information might very well indicate differences among groups, but whether or not these differences are significant and meaningful is a more important aspect of the analysis.

Perhaps the primary advantage of MDA in dealing with classification problems is the potential of analyzing the entire variable profile of the object simultaneously rather than sequentially examining its individual characteristics. Just as linear and integer programming have improved upon traditional techniques in capital budgeting, the MDA approach to traditional ratio analysis has the potential to reformulate the problem correctly. Specifically, combinations of ratios can be analyzed together in order to remove possible ambiguities and misclassifications observed in earlier traditional ratio studies.

As we will see, the Z-Score model is a linear analysis in that five measures are objectively weighted and summed up to arrive at an overall score that then becomes the basis for classification of firms into one of the a *priori* groupings (distressed and non-distressed).

0.11 MDA and Least squares estimates in the model

Mathematically $\beta_0, \beta_1, \beta_2 \cdots \beta_k$ can be estimated with the following formula.In general, we can write the equation for a straight line as

$$y = \beta_0 + \beta_1 x \tag{16}$$

where

β_0=y-intercept (value of y when x=0)
β_1= the slope (change in y when x increases by 1 unit)
In many real world situations, the response of interest (e.g profitability, or the variable we want to estimate) cannot be explained perfectly by a deterministic model. When therefore we make adjustment for random variation in the process, y is then broken into a systematic and a random component (error term):

$$y = \beta_0 + \beta_1 x + \varepsilon \tag{17}$$

where:
x=level of predictor variable corresponding to the response
β_0, β_1= unknown parameters
ε= random error component corresponding to the response whose distribution we assume $\approx N(0, \delta)$

Since β_0 can be interpreted as the mean response when x=0, and β_1 as the change in the mean response when x is increased by 1 unit then we can say that y/x $\approx N(\beta_0 + \beta_1, \delta)$

To compute the estimates of the parameters β_0 and β_1, we take a sample of *n* subjects, observing values *y* of the response variable and *x* of the predictor variable. Choosing the values b_0 and b_1 as estimates for β_0 and β_1, we define the fitted equation to be an equation:

$$\widehat{y} = b_0 + b_1 x \tag{18}$$

we can choose the estimates β_0 and β_1 to be the values that minimize the distances of the data points to the fitted line. Now, for each observed response y_i, with a corresponding predictor variable x_i, we obtain a fitted value.

$$\widehat{y}_i = b_0 + b_1 x_i \tag{19}$$

So, minimizing the sum of the squared distances of each observed response to its fitted value i.e minimizing the **error sum of squares**, SSE, where:

$$SSE = \Sigma_{i=1}^{n}(y_i - \widehat{y}_i)^2 = \Sigma_{i=1}^{n}(y_i - (b_0 + b_1 x_i)^2 \tag{20}$$

$$\begin{aligned} b_i &= \frac{\Sigma_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\Sigma_{i=1}^{n}(x_i - \overline{x})^2} \\ &= \frac{SS_{xy}}{SS_{xx}} \end{aligned} \tag{21}$$

and

$$\begin{aligned} b_0 &= \overline{y} - \widehat{\beta}_1 \overline{x} \\ &= \frac{\Sigma_{i=1}^{n} y_i}{n} - b_1 \frac{\Sigma_{i=1}^{n} x_i}{n} \end{aligned} \tag{22}$$

By the method of **least squares** choosing the b_i values that minimize

$$SSE = \Sigma_{i=1}^{n}(y_i - \widehat{y}_i)^2 \tag{23}$$

we obtain the fitted equation as:

$$\widehat{y} = b_0 + b_1 x_1 + b_2 x_2 + \cdots + b_k x_k \tag{24}$$

and the estimate of δ is thus:

$$\delta = \sqrt{\frac{\Sigma_{i=1}^{n}(y_i - \widehat{y}_i)^2}{n-k-1}} = \sqrt{\frac{SSE}{n-k-1}} \tag{25}$$

The Analysis of Variance (ANOVA) table will be very similar to that of a simple linear function, with the only adjustments being in the degrees' of freedom. Table 2 below shows the values for the general case when there are k predictor variables. The researcher relied on computer outputs to obtain the Analysis of Variance and the estimates $b_0, b_1, \cdots, b_k$.

Table 2: Analysis of Variance Table

Source of variation	sum of squares	degree of freedom	mean square	F
MODEL	SSR (model sum of squares)	k	MSR (model mean square)	F
ERROR	SSE (error sum of squares)	n-k-1	MSE (error mean square)	-
TOTAL	SSyy (total sum of squares)	n-1	-	-

Where:

$$SSR = \Sigma_{i=1}^{n}(\widehat{y} - \overline{y})^2 \tag{26}$$

$$MSR = \frac{SSR}{k} \tag{27}$$

$$SSE = \Sigma_{i=1}^{n}(y_i - \widehat{y}_i)^2 \tag{28}$$

$$MSE = \frac{SSE}{n-k-1} \tag{29}$$

$$SSyy = \Sigma_{i=1}^{n}(y_i - \overline{y})^2 \tag{30}$$

0.12 Testing for Association between the Response and the Full Set of Predictor Variables

To see if the set of predictor variables is useful in predicting the response variable, we will test $H_0 : b_1 = b_2 = \cdots = b_k$. Note that if H_0 is true, then the mean response does not depend on the levels of the predictor variables. We interpret this to mean that there is no association between the response variable and the set of predictor variables. The test hypothesis is:

$$H_0 : b_1 = b_2 = \cdots = b_k \text{(z does not depend on any of the } X_i^{\prime}\text{s.)}$$
$$H_1 : \text{Not every } b_i = 0 \text{(z depends on at least one of the } X_i^{\prime}\text{s).}$$

The test statistic is:

$$F_{obs} = \frac{MSR}{MSE}, F_{obs} > F_{\alpha}, k, n - k - 1 \tag{31}$$

We reject the null hypothesis if the p-value is less then α.

Because the Z-score models are in the form of a multiple linear model, we know that a general system of m linear equations with n unknowns can be written as:

$$z_1 = \beta_{11}x_1 + \beta_{12}x_2 + \beta_{13}x_3 + \cdots + \beta_{1n}x_n \tag{32}$$

$$z_2 = \beta_{21}x_1 + \beta_{22}x_2 + \beta_{23}x_3 + \cdots + \beta_{2n}x_n \tag{33}$$

$$z_3 = \beta_{31}x_1 + \beta_{32}x_2 + \beta_{33}x_3 + \cdots + \beta_{3n}x_n \tag{34}$$

.

.

.

$$z_m = \beta_{m1}x_1 + \beta_{m2}x_2 + \beta_{m3}x_3 + \cdots + \beta_{mn}x_n \tag{35}$$

where

x_1,x_2...x_n are the unknown ratios

$\beta_{11}, \beta_{12}...\beta mn$- coefficients of the equation

$z_1, z_2...z_m$ are the constant terms

The above equations can then be expressed as a vector equation.One extremely helpful view is that each unknown is a weight for a column vector in a linear combination.

$$x_1 \left\{ \begin{matrix} \beta_{11} \\ \beta_{21} \\ . \\ . \\ . \\ \beta_{m1} \end{matrix} \right\} + x_2 \left\{ \begin{matrix} \beta_{12} \\ \beta_{22} \\ . \\ . \\ . \\ \beta_{m2} \end{matrix} \right\} + ... + x_n \left\{ \begin{matrix} \beta_{1n} \\ \beta_{2n} \\ . \\ . \\ . \\ \beta_{mn} \end{matrix} \right\} = \left\{ \begin{matrix} z_1 \\ z_2 \\ . \\ . \\ . \\ z_m \end{matrix} \right\} \tag{36}$$

The vector equation above is equivalent to a matrix equation of the form

$$AX = Z \tag{37}$$

where A is an *mxn* matrix,x is a column vector with *n* entries, and z is a column vector with *m* entries:

$$A = \left\{ \begin{array}{ccc} \beta_{11} & \beta_{12} & ...\beta_{1n} \\ \beta_{21} & \beta_{22} & ...\beta_{2n} \\ . & & \\ . & & \\ . & & \\ \beta_{m1} & \beta_{m2} & ...\beta_{mn} \end{array} \right\}, X = \left\{ \begin{array}{c} x_1 \\ x_2 \\ . \\ . \\ . \\ x_n \end{array} \right\}, Z = \left\{ \begin{array}{c} z_1 \\ z_2 \\ . \\ . \\ . \\ z_m \end{array} \right\} \tag{38}$$

0.13 Classification of $Altman's$ Ratios

1.Liquidity ratio

The working capital/total assets ratio, frequently found in studies of corporate problems, is a measure of the net liquid assets of the firm relative to the total capitalization. Working capital is defined as the difference between current assets and current liabilities. Liquidity and size characteristics are explicitly considered.

Ordinarily, a firm experiencing consistent operating losses will have shrinking current assets in relation to total assets. Of the three liquidity ratios evaluated, this one proved to be the most valuable. Two other liquidity ratios tested were the current ratio and the quick ratio. There were found to be less helpful and subject to perverse trends for some failing firms. The ratio is given by:

$$X_1 = \frac{WorkingCapital(WC)}{TotalAssets(TA)}$$

2. Profitability ratio

Retained earnings is the account which reports the total amount of reinvested earnings and/or losses of a firm over its entire life. The account is also referred to as earned surplus. It should be noted that the retained earnings account is subject to ”manipulation” via corporate quasi-reorganizations and stock dividend declarations. While these occurrences are not evident in this study, it is conceivable that a bias would be created by a substantial reorganization or stock dividend and appropriate readjustments should be made to the accounts.

This measure of cumulative profitability over time is what I referred to earlier as a “new” ratio. The age of a firm is implicitly considered in this ratio. For example, a relatively young firm will probably show a low RE/TA ratio because it has not had time to build up its cumulative profits. Therefore, it may be argued that the young firm is somewhat discriminated against in this analysis, and its chance of being classified as bankrupt is relatively higher than that of another older firm, *ceteris paribus*. But, this is precisely the situation in the real world. The incidence of failure is much higher in a firm’s earlier years. In 1993, approximately 50% of all firms that failed did so in the first five years of their existence (Dun and Bradstreet, 1994).

In addition, the RE/TA ratio measures the leverage of a firm. Those firms with high RE, relative to TA, have financed their assets through retention of profits and have not utilized as much debt. The ratio is given by:

$$X_2 = \frac{RetainedEarnings(RE)}{TotalAssets(TA)}$$

3. Solvency ratio

This ratio is a measure of the true productivity of the firm’s assets, independent of any tax or leverage factors. Since a firm’s ultimate existence is based on the earning power of its assets, this ratio appears to be particularly appropriate for studies dealing with corporate failure.

Furthermore, insolvency in a bankrupt sense occurs when the total liabilities exceed a fair valuation of the firm’s assets with value determined by the earning power of the assets. As we will show, this ratio continually outperforms other profitability measures, including cash flow. The ratio is given by:

$$X_3 = \frac{EarningsBeforeInterestandTaxes(EBIT)}{TotalAssets(TA)}$$

4. Leverage ratio

Equity is measured by the combined market value of all shares of stock, preferred and common, while liabilities include both current and long term. The measure shows how much the firm's assets can decline in value (measured by market value of equity plus debt) before the liabilities exceed the assets and the firm becomes insolvent. For example, a company with a market value of its equity of Kenya shillings 100,000 and debt of Kenya shillings 50,000 could experience a two-thirds drop in asset value before insolvency. However, the same firm with Kenya shillings 25,000 equity will be insolvent if assets drop only one-third in value. This ratio adds a market value dimension which most other failure studies did not consider.The reciprocal of X_4 is a slightly modified version of one of the variables used effectively by Fisher (1959) in a study of corporate bond yield-spread differentials. It also appears to be a more effective predictor of bankruptcy than a similar, more commonly used ratio; net worth/total debt (book values). At a later point, we will substitute the book value of net worth for the market value in order to derive a discriminant function for privately held firms (Z') and for non-manufacturers (Z''). The ratio is given by:

$$X_4 = \frac{MarketValueofEquity(MVE)}{BookValueofTotalLiabilities(TL)}$$

5. Capital turnover or Activity ratio

The capital-turnover ratio is a standard financial ratio illustrating the sales generating ability of the firm's assets. It is one measure of management's capacity in dealing with competitive conditions. This final ratio is quite important because it is the least significant ratio on an individual basis. In fact, based on the univariate statistical significance test, it would not have appeared at all. However, because of its unique relationship to other variables in the model, the sales/total assets ratio ranks second in its contribution to the overall discriminating ability of the model. The ratio is given by:

$$X_5 = \frac{Sales(S)}{TotalAssets(TA)}$$

0.14 The Altman Z-Score Model

In this section, the Altman Z-Score will be observed closely by describing how this insolvency prediction model was developed. As mentioned in Section 3.1, the MDA requires at least two groups for doing a classification. Therefore, Altman (1968) initially selected a matched sample of 33 failed and non-failed companies. Regarding the failed group, this consists of U.S. manufacturers which filed for bankruptcy under 'Chapter X' of the 'National Bankruptcy Act' between the years of 1946 and 1965. Furthermore, the asset size ranged between Kenya shillings 70 million and Kenya shillings 2.59 billion which make an average of Kenya shillings 640 million. In order to have a matching sample, the non-failed companies were selected carefully by applying a stratified sample on manufacturers which had an asset size from Kenya shillings 100 million to Kenya shillings 2.5 billion and still operated in 1966. Afterwards, data from balance sheets and income statements were collected.

Finally, five ratios were used which had together the highest potential of making a good insolvency prediction. In this context, it was essential that the selected ratios were interrelating as follows:

$$Z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 \tag{39}$$

Where:

Z = discriminant score/overall score

β_0 = the constant

β_j = discriminant coefficient, where j = 1, 2,3, 4,5

X_1 = Working capital/Total assets

X_2 = Retained earnings/Total assets

X_3 = Earnings before interest and taxes/Total assets

X_4 = Market value of equity/Total liabilities

X_5 = Sales/Total assets

Finally, the following discriminant function was established according to the discriminate analysis method:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5 \tag{40}$$

By conducting the study, Altman defined a cutoff point of 2.675 which discriminated failed and nonfailed companies best. The misclassification rate was 5% (17%) one (two) year(s) prior to insolvency (Begley et al., 1996; Bemmann, 2005). Subsequently, the results of the Altman Z-Score will be provided (Altman, 1968,2002): regarding the initial sample of 33 failed and non-failed companies, Altmans model achieved quite good results. The first test was conducted by using financial data from statements one year and the second test two years prior to bankruptcy. Considering the first test, the model could overall classify 95% of the companies correctly.The results can be divided among '$TypeI'$ and '$TypeII'$ errors.

Type I error means that a failed company will be classified as non-failed and Type II error is understood as the misclassification of healthy businesses as failed (Cantor and Mann, 2003).In the Kenyan case,it would mean that rejecting null hypothesis when it is true(type I error) or rejecting the alternative hypothesis when it is equally true(type II error). In this context, the Type I error in the first test was only 6% which means that 31 of the insolvent companies were classified correctly. A better result was achieved in the second group where 32 of the healthy businesses were classified correctly. As a conclusion, outstanding results were achieved for both groups.

Nevertheless, the results of the second test were not as good as in the first one. Overall, the number of companies classified correctly was 54 which constitute 83%. By focusing on the error types, the results are this time quite different. Regarding the first group, only 23 of the failed companies were classified correctly (Type I error: 28%).

On the other hand, the results for the second group were again almost perfect with a Type II error of only 6%. Subsequently, the results are summarized in Table 3 below.

Table 3: Results of the Altman Z-score one and two years prior to bankruptcy

	One year prior to bankruptcy	Two years prior to bankruptcy
Total (correct numbers)	63	54
Total (error rate)	5%	17%
Type I (correct numbers)	31	23
Type I (error rate)	6%	28%
Type II (correct numbers)	32	31
Type II (error rate)	3%	6%

Noteworthy is that Altman tested its model on a holdout sample by selecting companies which were not in the initial sample. Altman (1968) expected good results regarding the initial sample since the calculated discriminant coefficients and the group distributions are based on the 66 companies. In this connection, a holdout sample was required to evaluate the predictability. Therefore, Altman (1968,2002) came up with two secondary samples consisting of failed and non-failed companies. Regarding the former sample, this included 25 insolvent companies with similar asset sizes as in the initial sample. The result (Type I) one year prior to bankruptcy was better than the initial one with 24 companies classified correctly. This means a predictive accuracy of 96%.For the second sample (Type II), 66 companies were selected. An interesting aspect here is that the sample selection concentrated on those businesses which had temporarily problems with the profitability but were not insolvent.

For that reason, the sample included the companies based on their net income (deficits) reported in the financial statements of 1958 and 1961. Additionally, more than 65% reported two or three times negative profits in the last three reporting years. The result in this sample was not as good as the previous one. Here, only 52 of the companies were classified correctly as non-failed (Type II error: 21%). However, ten of the misclassified companies had a Z-Score between 1.81 and 2.67 which classify them as bankrupt but are not as obvious as the majority of the failed companies in the initial sample.

This led to the decision to set up a so called 'zone of ignorance' which is a gray area and where misclassifications can be observed. Consequently, the companies can be categorized into three zones where companies with a Z-Score of more than 2.99 can be seen as healthy and each business having a Z-Score less than 1.81 will be insolvent. The gray area includes all companies which range between 1.81 and 2.99 (Nandi and Choudhary, 2011). The index was interpreted as follows:

$$Z < 2.99 \text{ "Safe" zone,}$$

$$1.81 < Z < 2.99 \text{ "Grey" zone,}$$

$$Z < 1.81 \text{ "Distress" zone}$$

Over the past decades, Altmans Z-Score was applied in many other studies – in the context of different environments – to test its predictability. Especially in the 1980s and 90s, the Z-Score model provided a good predictive accuracy (Xu and Zhang, 2009). Regarding more recent studies, Ahmadi et al. (2012) refers to Gerantonis et al. who applied the Altman Z-Score on Greek companies listed in the Athens Exchange from 2002 until 2008 and where the model provided good results. Another referred study is from Gadiri Mogadam et al. for companies listed in the Tehran Stock Exchange. By considering the first three years prior to bankruptcy, the Altman Z-Score did not perform well.

Furthermore, Pongsatat et al. (2004) compared the model of Altman with that of Ohlson. For that purpose, a matched sample of 60 failed and non-failed companies listed in the Thailand Stock Exchange was selected.

While Ohlsons model had an overall better performance regarding the first three years prior to bankruptcy, the Altman Z-Score performed better in terms of classifying large insolvent companies. Furthermore, the model was often applied on Indian companies where Gowri and Sekar (2014) applied the Altman Z-Score on four listed Indian automotive companies by considering ten years of financial information (2003-2012).

In a further study, they also applied the Springate model to compare it with $Altman's$ Z-Score

(Gowri and Sekar). Additionally, a more comprehensive study on the Indian automobile industry was conducted by Ray (2011) where he applied the model on a sample of 62 companies listed in the Bombay Stock Exchange.

Regarding Sri Lanka, Gunathilaka (2014) tested $Altman's$ model on 82 companies of several industries which are listed in the Colombo Stock Exchange between 2008 and 2012. As a result, the Z-Score model performed well by classifying 86.5% of the companies correctly. By considering Middle East countries, Orabi (2014) selected five failed and non-failed companies listed in the Amman Stock Exchange during the period of 2010/11 for assessing the predictability of $Altman's$ Z-Score regarding the Jordanian economy. The results here were positive. However, the sample size was also quite limited. In Pakistan, Fawad et al. (2014) tested $Altman's$ Z-Score by using financial ratios of 21 companies (between 2000 and 2010) operating in the textile industry. The sample consisted of nine failed and twelve non-failed businesses listed in Karachi Stock Exchange. The model classified 81% of the companies one year and 67% two years prior to bankruptcy correctly. Petrisor and Lupu (2013) applied the Z-Score model on ten companies which were listed in the Bucharest Stock Exchange during the period of 2010/11 to evaluate which companies had the risk of being insolvent.

The application provided results that all considered companies had a Z-Score surpassing 1.81 where four of them surpassed the upper limit (> 2.99). Another study was conducted by Celli (2015). He selected a matched sample of 51 failed and non-failed Italian businesses delisted respectively listed within the period 1995-2013. By considering three years (T) prior to default, both groups provided good results where the overall success rate was 87.3% (T-1), 77.5% (T-2) and 66.6% (T-3).

Maybe in the most interesting related study, Calandro (2007) refers to a case study of GTI Corporation where Altmans Z-Score was successfully used as a tool for strategic assessment and performance management. In this regard, the Z-Scores applicability in the risk management was stated.

There were also studies which modified the original model according to different environmental conditions. Altman and Narayanan (2002) refer to Altman and Izan who developed an insolvency prediction model for Australia by selecting two groups of 50 companies and considering five variables. The model similar to Altmans Z-Score provided quite good results. Besides Altman, other academics also created models based on his work. For instance, Agarwal and Taffler (2005) developed a UK-based Z-Score which was applied on all non-financial companies listed in the London Stock Exchange between 1979 and 2003.

Another example is the study of Bandyopadhyay (2006) where he modified Altmans models and additionally developed a new Z-Score for Indian companies. In this regard, he selected a matched sample of 52 failed and non-failed companies between 1998 and 2003 and further 50 companies as a holdout sample. Furthermore, he finally selected five financial ratios.

The revised and the new Z-Score model performed well where the latter one achieved better results. Again in terms of India, Nandi and Choudhary (2011) applied and modified the Altman Z-Score. However, this study focused on the Indian banking sector where 40 banks are divided equally into two groups. Further five companies were selected as a holdout sample. As a result, a new discriminant function was developed which could classify 92.5% of the initial sample correctly. Additionally, the holdout sample was completely classified correctly.

Regarding Altmans Z-Score on Chinese companies, Wang and Campbell (2010) selected 42 delisted firms during 2000-2008 as failed companies and an equal number of listed companies reflecting the healthy businesses.

In this context, they applied three versions of the Z-Score model. While the first one is the original model, the other two are based on Altman with re-estimated coefficients respectively new variables. While the original and re-estimated model performed well, the revised model provided much better results. Moreover, the two did a further study with the same models by considering a much greater sample and which confirmed the results of the initial study by Wang and Campbell (2010). As described above, the Z-Score model by Altman was applied on Romanian companies. Nevertheless, Miculeac (2011) states that $Altman's$ Z-Score, among other insolvency prediction models, do not provide satisfying results. Because of this, the ‘F’ function was developed as an alternative which considers four indicators being specific to the Romanian economy. However, this model consists of a linear function similar to $Altman's$ Z-Score model.

0.14.1 Versions of the Altman Z-Score

Over time, Altman developed further two versions of his Z-Score which are based on the original model. The two versions are labelled as Z'-Score respectively Z''-Score model. Starting with the former version, the intention was to predict insolvency of firms in the private sector. There were concerns that privately held companies cannot be applied in the original model since it considered only publicly traded firms. Therefore, Altman substituted the market value of equity with the book value in X_4 and re-estimated the entire model were the coefficients, classification criterion and cut-off score changed. Finally, the Z'-Score model looks as follows (Altman, 2002; Altman and Hotchkiss, 2006):

$$Z' = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.420X_4 + 0.998X_5 \tag{41}$$

With this model, companies having Z'-Scores higher than 2.9 are considered as safe while a score under 1.23 means that the company is in the distressed zone. Finally, the grey zone comprises everything in between (Altman and Hotchkiss, 2006).

The Z'-Score model achieved good results with a Type I error of 9.1$\%$ and a Type II error of 3$\%$ (Altman, 2002a). However, this model is barely recognized in literature due to its lack of explanatory content compared to the original model (Reichling et al., 2006).

The Emerging Market Score Model (EM Z- Score Model),which was the relevant model of this study, as Kenya falls under the emerging markets. Proceeding with the Z''-Score model, this version abandoned the variable X_5 (sales/total assets) since this ratio is quite industry-sensitive. Regarding X_4, the book value of equity was considered again. Furthermore, this model should be also applicable on non-manufacturing companies. As a result, the Z''-Score model came up with the following discriminant function (Altman, 2002; Hayes et al., 2010):

$$Z'' = 3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4 \tag{42}$$

With the re-estimation of the model, companies having a Z''-Score below (over) 1.10 (2.60) are considered in the distress (safe) zone (Altman, 2002; Calandro, 2007).

Moreover, the Z''-Score model also served as the fundament for the EMS model which is mentioned above. In this context, however, a constant term of +3.25 was included to standardize scores with a score of zero (Altman, 2002; Altman and Hotchkiss, 2006).

The Z-score is often used in the z-test in standardized testing. A prediction interval [L,U], consisting of a lower end point designated L and an upper endpoint designated U, is an interval such that a future observation X will lie in the interval with high probability γ, i.e

$$P(L < X < U) = \gamma, \tag{43}$$

For the standard score Z of X it gives

$$P(\frac{L-\mu}{\delta} < Z < \frac{U-\mu}{\delta}) = \gamma \tag{44}$$

By determining the quantile z such that

$$P(-z < Z < z) = \gamma, \tag{45}$$

It follows;

$$L = \mu - z\delta, U = \mu + z\delta \tag{46}$$

For standardization, a random variable x is standardized by subtracting its expected value E[X] and dividing the difference by its standard deviation.

$$\delta(X) = \sqrt{var(X)} \tag{47}$$

$$Z = \frac{X - E[X]}{\delta(X)} \tag{48}$$

If the random variable under consideration is the sample mean of a random sample $X_1, X_2 \ldots, X_n$ of X,then:

$$\overline{X} = \frac{1}{n} \Sigma_{i=1}^{n} X_i \tag{49}$$

and the standardized version is:

$$Z = \frac{\overline{X} - E[X]}{\delta(X)/\sqrt{n}} \tag{50}$$

The Interpretation of Emerging Market Score Model:

EM Z- score > 2.60 means "Safe" Zones

$1.1 <$ EM Z- score < 2.60 means "Grey" Zones

EM Z- score < 1.1 means "Distress" Zones

Below was the SPSS procedure showing how the data from Kenyan firms were used to generate results used in the subsequent sections:

Discriminant Function Analysis Procedure

- Grouping variable: 2015 Profitability
- Predictors: X_1, X_2, X_3, X_4
- Obtain Discriminant function analysis
- Analyze > Classify > Discriminant

CHAPTER FOUR

DATA ANALYSIS AND RESULTS

0.15 Introduction

This section contains data collection, analysis and the final Kenyan model developed from the concept of Altman Z- score model on emerging markets. Since the original Z-score model focused only on manufacturing firms, in Kenyan case, this could not be applied since there were only seven such firms (see appendix II). The author then tested the Emerging markets Z''-score model predictive ability to recent Kenyan businesses, and the results discussed below. Finally, using multiple discriminant analysis and data collected from Kenyan firms during the period 31 December 2010 to 31 December 2015 inclusive as observation, a new Z-score function model was developed to test the accuracy of the Z''-score prediction model.

0.16 Model application

The initial sample consisted of 3 non-profitable and 3 profitable firms for the two years running. In order to have a matching sample, the non-failed companies were selected carefully by applying a stratified sample on firms which had an asset size from Kenya shillings 100 million to Kenya shillings 2.5 billion and still operated as at December 2015.(See appendix III) Afterwards, data from balance sheets and income statements were collected. The Z-score equation generated was then applied on other 16 firms categorized as profitable and 6 firms categorized as non-profitable for purposes of validation, bringing the total number to 22.

To classify the firms into two distinct groups, the author used profitability results for the 2014 and 2015 financial years, with those reporting losses (non-profitable) put against those reporting prof-

its (profitable). 0 means non- profitable firms, 1 means profitable firms where X_1(working capital/total assets), X_2(Retained Earning/ total assets), X_3(EBIT/total assets) and X_4(Market value of equity/total liabilities) were the variables used.
In this context, the practical approach considered three specific characteristics:

0.16.1 Time

When Altman developed his Z-Score in 1968, he used data from companies during the period of 1946 to 1965. This means that the data are at least fifty years old. However, his focus was majorly on the last two years prior to the company being declared bankrupt. The researcher however used the Altman Z-score model developed for emerging markets like Kenya (Altman and Hotchkiss, 2006).For this proposal, the financial ratios of the data used were selected from 2010-2015 annual reports of listed companies at Nairobi Securities Exchange. The choice of using up to 2015 financial year considers that 2014 and 2015 financial years were the most recent years with available data that met the up-to-date motivation of the study.

0.16.2 Accounting Principles

Since the focus was put on companies listed in Nairobi Securities Exchange in Kenya, therefore, the ratios used were those which were seen as indicators for assessing the stability of companies within the scope of balance sheet analysis. The reason of using financial ratios of combining data was because variable in ratios are effective tools for eliminating size effect among different companies. Therefore, when sampling the companies, sizes of them were not considered in this case. The financial ratios were selected under 4 categories – liquidity, profitability, leverage and solvency. Those ratios are the same as Altman's that were used in his study.

0.17 Tests of the assumptions and Fitness

Now that the final model is developed, it is interesting to investigate further the properties of the model. Different analyses and tests were performed in this section. To begin, tests on the major model's assumptions were performed. Then, broader tests of the model good performance were implemented.

0.17.1 Test of Normality

Before using the discriminant analysis technique, it was necessary to test whether distribution of data were normally distributed. In particular, it is reasonable to make this approach because bankruptcy models do often violate the assumption of multivariate normality (Barnes, 1987) (S. Balcaen & Ooghe, 2006). Thus, researchers often neglect tests on assumptions. However, because of the need to understand how well the model can perform, it is necessary to check for this assumption. First was a descriptive test of all predictors on their skewness and kurtosis. The results were as shown in table 4 below:

Table 4: Descriptive Test of all Predictors

	N	Min	Max	Mean	Std dev	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std Error	Statistic	Std Error
X_1	6	0	0	0.09	0.214	-0.728	.845	-.674	1.741
X_2	6	0	1	0.27	0.41	-1.13	.845	1.699	1.741
X_3	6	0	0	0.03	0.155	-0.143	.845	-2.292	1.741
X_4	6	0	1	0.28	0.212	0.415	.845	-1.521	1.741
Valid N	6								

Table 4 illustrated that all of the variables had skewness statistics within [-1, 1], indicating that they were approximately normal. The kurtosis statistics in the table, illustrated the same indication as skewness statistics ranging within [-2, 2].

Unlike the regression, stem-and-leaf plots in discriminant analysis cannot indicate the normality of variables. So, to double check the normality of variables, Kolmogorov-Smirnov test was used rather than stem-and-leaf plots. The null hypothesis of Kolmogorov-Smirnov test is that the data is subject to normal distribution. The result was as follows:

Table 5: Kolmogorov-Smirnov Test of Normality

		X_1	X_2	X_3	X_4
Normal Parameters	N	6	6	6	6
	Mean	.09	.27	.03	.28
	Std deviation	.214	.41	.155	.212
Most extreme differences	Absolute	.246	.21	.196	.223
	Positive	.168	.14	.155	.223
	Negative	-.246	-.21	-.196	-.206
	Kolmogorov-Sminov Z	.603	.513	.481	.546
	Asymp.Sig.(2-tailed)	.86	.955	.975	.927

Table 5 illustrated that all the variables did not reject the null hypothesis that the data was subject to normal distribution at 99% confidence level. So, the data fulfills the assumption of discriminant analysis.

0.17.2 Test of equality of group means

Adhering to the testing sequence of Altman (1968), the first test would be to test for the discriminating ability of the ratios on an individual basis by looking at the equality of group means. The basic principle of tests of equality of group means is to measure if the vectors of the averages of the two opposing groups (non-distressed and distressed firms), are equal. Tests of equality of group means can be performed by the Wilks' Lambda and F tests. More specifically, the statement of hypotheses were:

H_0 : All means are considered equal throughout

H_1 : At least one mean is different from the others

This table contains Wilks' Lambda and mean differences of ANOVA (F) test which were the test of significance of variable's contributions to discriminant function. In the ANOVA table 6 below, the smaller the Wilks's lambda, the more important the independent variable to the discriminant function.

Table 6: Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
X_1	.191	16.928	1	4	.015
X_2	.513	3.795	1	4	.123
X_3	.112	31.587	1	4	.005
X_4	.959	.17	1	4	.702

Table 6 above gives strong statistical evidence of significant differences between the mean of profitable and non-profitable firms for X_3 (EBIT/total asset) and X_1 (working capital/total assets) respectively.

From the table above, it can be seen that all variables have their $Wilks'$ Lambda results inferior or equal to 0.9. In this case, it means that vectors of the averages of the two groups are different. In addition, it can be deduced from the F-tests and their significances that variables X_1 and X_3 present differences in their opposing groups. Therefore, results from both tests demonstrate that variables from opposing groups are different and present signs of discrimination. Thus, these findings strengthen the model developed.

Clearly X_1 (liquidity ratio) and X_3 (Solvency ratio) proved major contributors in predicting financial strength or distress of a firm, with X_2 (Profitability ratio) and X_4 (leverage ratio) being small contributing factors to financial distress or soundness of a firm. The alternative hypothesis therefore could not be rejected.

0.17.3 Test of group Statistics

The idea of this process was to examine the group means and standard deviations to find out any significant group differences. Table 4.4 below showed the differences of the means of independent variables between two groups were -0.0781, 0.26733, 0.3508 and 0.5218 for X_4, X_3, X_1 and X_2 respectively.

The differences of the mean between the two groups from the least to the greatest were X_4(Market value of equity/total liabilities), X_3(EBIT/total asset), X_1(working capital/total assets) and X_2(Retained Earning/ total assets) respectively, proving that the significant contribution to distinguish between the two groups was made by X_2, X_1, X_3 and X_4 respectively. See the table 7 below for the results:

Table 7: Group Statistics

				Valid N(listwise)	
Profitability	Variables	Mean	Std deviation	Unweighted	Weighted
0	X_1	-0.0884	0.1442	3	3.000
	X_2	0.0108	0.4109	3	3.000
	X_3	-0.1085	0.0672	3	3.000
	X_4	0.3154	0.2049	3	3.000
1	X_1	0.2623	0.0319	3	3.000
	X_2	0.5326	0.2154	3	3.000
	X_3	0.1588	0.0476	3	3.000
	X_4	0.2373	0.2566	3	3.000
Total	X_1	0.8695	0.2136	6	6.000
	X_2	0.2717	0.4096	6	6.000
	X_3	0.0252	0.1554	6	6.000
	X_4	0.2763	0.2121	6	6.000

0.17.4 Assessing model fit

Eigenvalues

The Eigenvalues output table computed with SPSS presents information about the efficiency of the discriminatory function. When there are two groups in the analysis, the most meaningful output to look at is the canonical correlation, which is comparable to the $Pearson's$ correlation between the discriminant scores and the groups. The closest the canonical correlation is to 1, the best is the model estimated.

Table 8: Eigenvalues

Function	Eigenvalue	% of variance	Cumulative %	Canonical Correlation
1	66.900	100.0	100.0	0.993

From Table 8 above, it was shown that the canonical correlation was relatively high (0.99), which strengthened the discriminatory power of the model. The canonical correlation value (0.99) indicated the multiple-correlation between the independent variables and the discriminant function. Thus, it indicated that the model could explain 98% (the square of 0.99) of the variance in the discriminant equation.

$Wilks'$ **lambda of the model**

$Wilks'$ lambda is a measure of how well the discriminant function separates groups. According to George H., the smaller $Wilks'$ lambda values, the better the discriminating power of the model. With a $Wilks'$ lambda equal to 0.015, the model appeared to have a good discriminatory ability. Table 9 depicted this situation.

Table 9: Wilks Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig
1	0.015	8.436	4	0.077

Finally, the lower the significance of the model, the better its discriminatory power is. With a chi-square value of 8.436 and a significance of 0.077 (Table 9), the model has a better chance at separating groups. This was also the provision for the proportion of total variability not explained, which was 1.5%.

To conclude this section, the results from the robustness analysis demonstrate that the model developed had very good characteristics. Also, the variables demonstrate signs of good discrimination (tests of equality of group means, Eigenvalues, and $Wilks'$ Lambda).

0.17.5 Test on variance-covariance

Correlation tests of variables are performed in each economic theme (i.e. liquidity, profitability, etc.), in order to distinguish variables that are too much correlated in the same economic theme, and therefore, should not be considered together in the final multivariate model. The within-groups correlation matrix showed the correlations between the predictors. The results were as shown in the table 10 below:

Table 10: Pooled within correlation matrix

		X_1	X_2	X_3	X_4
Correlation	X_1	1.000	-.611	-.769	.451
	X_2	-.611	1.000	.658	-.163
	X_3	-.769	.658	1.000	-.147
	X_4	.451	-.163	-.147	1.000

Table 10 showed the inter-correlation of these two variables X_1(working capital/total assets) and X_3(EBIT/total asset) to be the lowest (-0.769). According to Robert A., inter-correlation denotes the correlation of independent variables among themselves, thereby when inter-correlation was low, it meant that the relationship of these two variables will not have significant impact on their contribution in the formula. In general, $correlations'$ results were relatively low between variables, meaning that data cover different parts of the business without overlapping.

0.17.6 Regression coefficients

Table 11 below contained the unstandardized discriminant function coefficients. It is an illustration of the test on the assumption that the number of independent variables is not more than two. These would be used like unstandardized b (regression) coefficients in multiple regression – that is, they were used to construct the actual prediction equation which was used to classify new cases. Discriminant function of the Kenyan Z-score model looked like this:

Table 11: Discriminant Function Analysis

	Function
	1
X_1	16.792
X_2	.215
X_3	26.788
X_4	-2.476
(Constant)	-1.508

$$Z = -1.508 + 16.792X_1 + 0.215X_2 + 26.788X_3 - 2.476X_4 \tag{51}$$

Where X_1,X_2,X_3 and X_4 are the liquidity,profitability,solvency and leverage ratios respectively.

Producing a score for Z (discriminant score) for each case using the discriminant function, then the cases with Z values smaller than the cut-off value were classified as belonging to one group while those with values greater were classified into the other group. In this case, the one with smaller Z value belonged to distressed firm while the one with greater Z value belongs to healthy category.

Table 12 below showed the group means on the discriminant analysis where profitability means the status of the firms. 0 means the profitable firms while 1 means the non-profitable firms. Centroids were the mean discriminant scores for each group. This table was used to establish the *cutting point* for classifying cases.

Table 12: Functions at Group centroids

	Function
Profitability	1
0	-6.678
1	6.678

To identify the cut-off point, the group centroids provided information about that. The group centroid is the group means of the predictor variables in distressed group and non-distressed group.

The table 12 showed that distressed firms had a mean of -6.678 while non- distressed firms had a mean of 6.678. Firms that had scores close to a centroid should therefore be predicted as belonging to that group. In this case, the one with Z score near to -6.678 should belong to bankrupt firm while the one with Z score near to 6.678 should belong to non-bankrupt firm. To get the cut off, an average of the two centroids means was calculated and found to be at 0.00. The centroids were calculated based on the function:

$$Z = -1.508 + 16.792X_1 + 0.215X_2 + 26.788X_3 - 2.476X_4 \tag{52}$$

Finally, the classification results table (Table 13) was a table to show the power of the discriminant function in which the rows were the dependent variables and the columns were the predicted status. According to Agresti (1996), the cross validated set of data is a more realistic technique to test the power of the discriminant function than the original classifications since the cross validation successfully classifies all cases that helps one to develop a discriminant function.

The results from table 14 below indicated that the profitable firms were 93.33% classified correctly, with a misclassification of 6.67% (type II error). i.e of the 16 sampled firms that were profitable

Table 13: Classification Results

		Predicted group Membership		
	Profitability	0	1	Total
Original	Count 0	3	0	3
	Count 1	0	3	3
	% 0	100.0	.0	100.0
	1	.0	100.0	100.0
Cross-validated	Count 0	0	3	3
	Count 1	2	1	3
	% 0	.0	100.0	100.0
	1	66.7	33.3	100.0

(non-distressed), only one was misclassified as non-profitable. However, all the distressed firms were correctly classified. (See appendix IV)

Table 14: Type I and II error table

	Distressed firms	Non-distressed firms	Total
Original	6	16	22
Type I (correct numbers)	6	0	6
Type I error	100%	0%	100
Type II (correct numbers)	1	15	16
Type II error	6.6%	93.33%	100

When the emerging markets Z-score model by Altman was used on Kenyan firms, it produced the results as shown:

It was clear that applying Emerging markets Z-score model resulted in a better classification of healthy firms but a misclassification of more distressed firms as depicted by type I error of 50%. (Table 15 above)

Table 15: EmZ-score type I and II errors

	Distressed firms	Non-distressed firms	Total
Original	6	16	22
Type I (correct numbers) Type I error	3	3 50%	6
Type II (correct numbers) Type II error	0 0	16	

Further,applying the model on chase bank Kenya ltd(under receivership),proved that it was reliable as it classified the firm as distressed,confirming the receivership status(see appendix V).

Summary tables of the distressed firms(in Kshs)

Source:Audited financial statements

WORKING CAPITAL							
Firm	2010	2011	2012	2013	2014	2015	Trend
KQ	-2,720	1,408	-1,923	-24,873	-36,543	-42,863	decline
Eveready	274,546	75,281	180,285	245,453	198,041	-48,362	decline
Mumias	3,245,325	3,549,968	1,450,705	-1,360,409	-6,281,845	-11,097,042	decline
Marshalls	-286,456	-307,469	22,636	-73,333	-124,304	-138,682	decline
Transcentury	59,245	298,589	400,618	1,050,342	-773,067	-1,197,919	decline
Express	-175,100,175	-277,562,588	-100,425,831	-60,703,180	-54,15,000	9,637,000	decline

TOTAL ASSETS							
Firm	2010	2011	2012	2013	2014	2015	Trend
KQ	73,263	78,743	77,432	126,278	152,675	187,654	increment
Eveready	1,195,824	1,016,908	1,152,083	942,129	934,832	1,365,155	random
Mumias	18,081,787	30,133,659	27,400,113	27,281,993	23,563,086	20,403,564	decline
Marshalls	1,126,208	1,076,865	515,116	567,095	603,935	551,198	decline
Transcentury	9,432,665	11,295,203	11,543,304	13,288,431	11,633,542	11,157,217	decline
Express	1,139,508,082	769,295,916	503,077,501	487,993,674	480,456,000	444,437,000	decline

EBIT							
Firm	2010	2011	2012	2013	2014	2015	Trend
Kenya Airways	2,671	5,002	2,146	-10,826	-4,861	-29,712	decline
Eveready	14,746	-173,208	68,914	58,239	-232,605	-161,405	decline
Mumias	2,179.9	2,646.6	1,764.03	-2,222.7	-3,405.05	-6,307.3	decline
Transcentury	630,585	869,265	1,226.5	858,590	-2,114.2	-2,956.1	decline
Express	42,190,211	-217,864,257	-13,012,411	-1,490,003	-76,435,000	-75,734,000	decline

RETAINED EARNINGS							
Firm	2010	2011	2012	2013	2014	2015	Trend
KQ	17,662	14,807	0	13,441	10,070	-15,676	decline
Eveready	193,399	69,405	139,495	183,280	20,513	-161,562	decline
Mumias	6,404,00	7,863,551	9,312,806	7,149,058	4,510,363	916,464	decline
Marshalls	-600,475	-409,412	165,575	59,410	60,793	187,260	increment
Transcentury	628,754	577,831	342,436	114,563	163,211	-271,678	decline
Express	104,547,517	-116,175,690	-71,483,108	-69,312,273	-149,752,485	-199,924,000	decline

LIABILITIES							
Firm	2010	2011	2012	2013	2014	2015	Trend
KQ	53,290	55,600	54,409	97,928	127,185	110,161	increment
Eveready	792,425	737,503	801,233	540,088	709,948	1,365,155	increment
Mumias	7,334,258	8,700,509	11,676,427	13,899,503	12,921,281	14,471,520	increment
Marshalls	993,695	490,883	174,966	233,016	324,316	291,972	decline
Transcentury	2,499,786	2,601,926	2,709,180	3,050,654	2,711,002	3,076,745	increment
Express	726,599,896	579,712,712	300,243,146	284,724,421	300,299,000	324,273,000	increment

Altman's EMZ-score model was typically used to analyze the listed firms with assets from 100 million Kenya shillings to 10 trillion Kenya shillings. The study established that there was a general decline in the working capital with a corresponding increase in the liabilities of the financially distressed companies from the year 2010 to 2015 (see summary table of distressed firms above).This indicated that the companies started experiencing reduction in the working capital due to financial difficulties leading to a reduction in the profitability of the company.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

0.18 Introduction

This chapter gives the summary of the study findings, conclusions drawn according to the findings of the study and the recommendations made by the researcher for future improvement. The study also details some recommendations that can be adopted by the relevant authority and stakeholders to enhance effective management of firms. The researcher also enumerated the limitations encountered as well as suggestions for future study.

0.19 Summary

"Although many performance indicators cannot be expected to incur a strong cue that a strategy does not yield the expected results, $Altman's$ Z and Emerging markets Z-score models are argued by some to be broad enough of an indicator for managers to notice" (Ferrier et al., 2002). In other words, $Altman's$ Emerging markets Z-score model may be employed to indicate financial distress especially for emerging markets like Kenya. This study was conducted with the objective of testing the validity of $Altman's$ failure prediction models in predicting corporate financial distress in various companies listed at the NSE, Kenya. Although, the formula has been demonstrated to be fairly predictive in a variety of contexts and cultural settings, it is not designed to be used in every situation. Variations of Altman's Z-score models encompass publicly versus privately held firms and manufacturing versus privately held non-manufacturing firms. There is also the question in extant literature as to whether or not smaller firms require a different formula. Altman's Z-score models have typically been used to analyze firms with assets from 100 million Kenya shillings to 10 trillion Kenya shillings. The study established that there was a general decline in the working capital with a corresponding increase in the liabilities of the financially distressed companies from the year 2010 to 2015 (see summary table of distressed firms).This indicated that the companies started experiencing reduction in the working capital due to financial difficulties leading to a reduction in the profitability of the company.

0.20 Conclusion

This research project analyzed the possibilities of prediction of business bankruptcy by applying the Emerging markets Z- score model. The researcher found out that both the Kenyan developed and emerging market Z-score models can completely predict the sign of a possible bankruptcy that may occur and effective when two years of information were used than one year. It indicated the importance of liquidity ratio, retained earnings, capital efficiency, and operating efficiency. These financial ratios were most significant in bankruptcy prediction for firms listed at the Nairobi Securities Exchange (NSE). Capital efficiency means how a manager manages the assets. The higher the ratio indicates better capital efficiency. The liquidity ratio states a company's capacity to repay short-term creditors out of its total cash. The higher the current ratio, the more capable the company is by paying its obligations. The retained earnings of a company are the percentage of net earnings not paid out as dividends; they are "retained" to be reinvested in the firm or use to pay down debt. The ratio of retained earnings to total assets supports measure to the extent in which a company relies on debt, or leverage. The lower the ratio, the more a company is funding its assets by borrowing instead of through retained earnings, which, again, increases the risk of bankruptcy if the firm cannot meet its debt obligations. The ratio of total liability and value equity includes both common stock and preferred stock. The higher the ratio the better the financial management. So the company should keep all variables high in ratio in order to prevent bankruptcy.

Finally, it can be argued that the model offers perception into measuring the composite financial situation of a firm, a tool for investors that can be used to monitor the safety of their investments and could recommend possibilities for future research among both academicians and practitioners, for developing an improved bankruptcy prediction model for Kenya. The study used secondary data for the stated period 2010 -2015 financial years, sourced from financial reports posted in various listed firms' website, others were from the NSE website on listed firms. There were 67 companies listed at the NSE and this study sought to test the validity of $Altman's$ Emerging markets Z$''$-score model in predicting financial distress among the manufacturing and non- manufacturing companies listed at the NSE as at 31st December 2015. Finally, only data from 22 firms were used as the rest were left out due to missing data or some firms not disclosing vital information necessary for the Z-score calculations. The choice of using up to 2015 financial year considers that 2014 and 2015 financial years were the most recent years with available data that met the up-to-date motivation of the study.

0.21 Recommendations

The researcher was able to confirm according to the evidence that all the variables should be positive in order to have a higher Z-score. Thus, the higher the variables of the Z-score model the higher the Z-Score. As a result, the companies will be saved from the financial distress, based on the analysis via the Z-score model. It should be clear that this model may not be used solely when analyzing a company's financial health, but it should be used rather as an addition to other models. This is because this model, like any other model in its field, is meant as a support in analyses of company financial strength or distress.

0.22 Suggestions for Future Researches

An extension of this study for future study can be developed in several areas. First, interested parties can develop a prediction model for the non-publicly traded firms especially small and medium enterprises (SMSs) firms rather than focusing on publicly traded firms, it will be a valuable and applicable to develop a prediction model for the SME firms because they may have different characteristics. Second, the prediction model could be developed on other sectors in Kenya, such as insurance and banking sectors not only focusing on industrial and service sector. Results from the different models using different predictive variables could be compared to indicate whether the estimated prediction model(s) applied to different sectors could improve classification accuracy. Finally, non-financial information such as disclosure on corporate governance, marketing strategy, human resource management etc can be utilized either alone or in conjunction with financial information to predict the characteristics of distressed and healthy firms.

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APPENDIX

Appendix I : Data Collection Table

Firm	Year	WC	TA	RE	EBIT	MVE	TL
1.B.O.C Kenya Ltd	2010	594,897	2,019,810	1,117,583	114,685	97,627	498,425
	2011	431,292	1,816,803	1,082,817	214,948	97,627	488,068
	2012	564,742	1,989,541	1,147,418	286,692	97,627	534,730
	2013	667,493	2,626,987	1,239,735	308,392	97,627	550,927
	2014	494,298	2,058,476	1,191,444	263,787	97,627	484,394
	2015	561,215	2,108,002	1,243,572	221,489	97,627	548,159
2.Bamburi Cement Ltd	2010	12,460,986	33,502,000	15,931	7,564,000	1,815	11,680,000
	2011	8,259,000	33,502,000	17,983	8,466,000	1,815	9,328,000
	2012	9,451,000	43,038,000	18,875	7,176,000	1,815	12,177,000
	2013	1,180,000	37,035,000	18,874	5,516,000	1,815	11,506,000
	2014	14,785,000	34,082,000	17,220	5,801,000	1,815	43,364,977
	2015	17,014,000	34,337,000	18,348	8,458,000	1,815	48,591,029
3.BAT Kenya Ltd	2010	697,636	7,014,908	1,555,867	2,722,572	1,000,000	6,007,029
	2011	1,639,085	8,409,916	1,648,066	4,484,116	1,000,000	7,338,478
	2012	1,077,148	9,123,815	1,668,918	4,754,302	1,000,000	8,078,578
	2013	1,737,170	10,204,821	1,733,182	5,469,955	1,000,000	10,126,588
	2014	1,789,591	11,070,605	1,780,466	6,371,694	1,000,000	9,862,023
	2015	2,978,502	12,080,481	1,836,936	7,138,902	1,000,000	9,828,006

Firm	Year	WC	TA	RE	EBIT	MVE	TL
4.Carbacid Investments Ltd	2010	318,547	1,512,166	895,794	438,041	169,902	218,409
	2011	358,415	1,739,985	1,041,783	374,210	169,902	272,620
	2012	489,222	2,012,816	1,245,458	535,444	169,902	360,046
	2013	803,650	2,204,399	1,545,035	634,686	169,902	279,970
	2014	824,931	2,533,163	1,784,246	597,262	254,852	376,280
	2015	867,565	2,968,727	2,118,508	580,467	254,852	491,701
5.Crown Paints Kenya Ltd	2010	488,288	1,972,337	783,710	169,480	118,635	991,781
	2011	497,317	2,215,352	933,758	200,539	118,635	1,071,998
	2012	554,535	2,258,263	1,839,651	224,170	118,635	1,034,709
	2013	598,555	2,945,434	1,036,845	333,442	118,635	1,583,720
	2014	723,410	4,292,888	1,522,113	351,363	118,635	2,429,897
	2015	895,410	5,144,409	1,515,959	456,588	355,905	3,064,192
6.E.A.Cables Ltd	2010	396,324	4,518,445	1,087,852	258,645	101,250	2,352,843
	2011	333,192	4,993,032	1,075,665	464,756	126,563	2,214,203
	2012	499,213	6,248,642	1,288,584	753,243	126,563	2,380,631
	2013	686,747	4,857,086	1,230,691	585,400	126,563	2,937,295
	2014	331,176	5,874,140	1,204,942	507,483	126,563	3,980,098
	2015	230,357	5,644,540	1,146,549	38,327	126,563	3,808,890
7.East African Breweries Ltd	2010	5,674,483	38,218,440	10,817,969	12,568,087	1,581,547	14,408,245
	2011	811,271	49,519,364	11,261,368	12,258,989	1,581,547	22,764,436
	2012	-4,426,009	54,584,316	14,985,679	15,253,049	1,581,547	45,868,436
	2013	-8,013,744	57,720,462	20,352,473	11,114,919	1,581,547	50,121,862
	2014	-7,653,496	62,865,943	22,501,939	10,406,619	1,581,547	53,765,095
	2015	560,386	66,639,778	27,105,035	14,151,244	1,581,547	53,586,095

Firm	Year	WC	TA	RE	EBIT	MVE	TL
8.Eveready East Africa Ltd	2010	274,564	1,1954,824	193,399	14,746	210,000	792,425
	2011	75,281	1,016,908	69,405	-173,208	210,000	737,503
	2012	180,285	1,152,083	139,495	68,914	210,000	801,233
	2013	245,453	934,832	183,280	58,239	210,000	540,088
	2014	198,041	942,129	20,513	-232,605	210,000	709,948
	2015	-48,362	1,365,155	-161,562	-161,405	210,000	1,365,155
9.Express Kenya Ltd	2010	-175,100.1	1,139,508.1	104,547.5	42,190.2	177,018.2	726,991.8
	2011	-277,562.5	769,295.6	-116,175.6	-217,864.2	177,018.9	579,712.7
	2012	-100,425.8	503,077.5	-71,483.1	-13,012.4	177,018.9	300,243.1
	2013	-60,703.1	487,993.6	-69,312.2	-1,490.0	177,018.9	284,724.4
	2014	-54,153.0	480,456.0	-149,752.4	-76,435.0	177,018.9	300,299.0
	2015	9,637.0	444,437.0	-199,924.0	-75,734.0	177,018.9	324,273.0
10.Kakuzi Ltd	2010	411,891	3,218,590	1,896,143	558,629	98,000	1,008,086
	2011	823,488	3,817,320	2,401,070	920,093	98,000	1,060,555
	2012	1,091,450	3,571,700	2,703,225	567,806	98,000	770,475
	2013	1,023,474	2,812,785	2,722,542	239,306	98,000	813,515
	2014	3,861,749	4,292,888	2,805,106	232,799	98,000	881,162
	2015	4,559,474	5,144,409	3,234,793	764,445	98,000	1,119,745
11.KenolKobil Ltd	2010	7,134,073	30,372,909	5,342,073	2,836,228	73,588	19,163,705
	2011	7,351,685	45,974,304	7,144,143	4,933,783	73,588	34,323,843
	2012	-800,435	32,684,166	859,568	-8,964,664	73,588	26,238,441
	2013	-1,357,085	28,121,673	1,270,811	563,918	73,588	21,455,379
	2014	-810,903	23,915,166	2,069,743	1,994,716	73,588	16,584,670
	2015	2,044,142	17,377,103	3,567,610	3,364,023	73,588	8,821,464
12.KPLC Ltd	2010	1,736,355	85,025,890	7,856,913	5,632,957	0	56,285,013
	2011	4,780.06	119,878.9	11,751.5	6,254.7	22,042.0	56,285.01

Firm	Year	WC	TA	RE	EBIT	MVE	TL
	2012	-3,223.75	134,131.98	16,739.06	8,506.69	22,021.2	78,258.1
	2013	-3,068.4	177,157.7	20,505.7	6,424.3	22,021.2	113,664.3
	2014	1,564.1	220,109.3	27,305.6	10,198.4	22,021.2	147,223.0
	2015	20,463.2	272,286.0	32,304.1	12,253.5	22,021.2	213,082.0
13.Longhorn Kenya Ltd	2010	179,579	523,000	236,178	21,621	58,500	223,283
	2011	228,686	709,653	346,214	127,746	58,500	307,848
	2012	46,954	661,675	235,999	-22,465	58,500	397,090
	2013	146,172	630,582	293,289	145,007	58,500	273,754
	2014	164,118	718,106	313,728	93,559	58,500	345,866
	2015	155,071	678,213	199,569	119,285	58,500	327,355
14.Marshalls (E.A) Ltd	2010	-286,456	1,126,208	-600,475	-344,722	71,966	993,695
	2011	-307,469	1,076,865	-409,412	181,501	71,966	490,883
	2012	22,636	515,116	165,575	-165,527	71,966	174,966
	2013	-73,333	567,095	59,410	-110,029	71,966	233,016
	2014	-124,304	603,935	60,793	-2,481	71,966	324,316
	2015	-138,682	551,198	187,260	-20,393	71,966	291,972
15.Mumias Sugar Co Ltd	2010	3,245,813	18,081,787	6,404,006	2,179,874	3,060,000	8,700,509
	2011	3,549,968	30,133,659	7,863,551	2,646,575	3,060,000	8,700,509
	2012	1,450,705	27,400,113	9,312,806	1,764,029	3,060,000	11,676,427
	2013	-1,360,409	27,281,993	7,149,058	-2,222,699	3,060,000	13,899,503
	2014	-6,281,845	23,563,086	4,510,363	-3,405,046	3,060,000	12,921,281
	2015	-11,097,042	20,403,564	916,464	-6,307,257	3,060,000	14,471,100

Firm	Year	WC	TA	RE	EBIT	MVE	TL
16.Nation Media Group Ltd	2010	2,523,700	7,975,200	3,916,400	2,146,800	392,800	2,533,100
	2011	3,324,200	8,816,300	4,630,200	2,006,800	392,800	2,693,900
	2012	4,031,500	10,677,400	5,563,100	3,504,600	392,800	3,353,900
	2013	4,449,900	11,444,200	6,176,900	3,587,100	471,000	3,200,800
	2014	4,257,000	11,944,000	6,765,400	3,624,000	471,000	3,176,200
	2015	3,934,000	12,696,700	7,076,000	2,823,200	471,000	3,743,000
17.Safaricom Ltd	2010	-11,249.3	104,120.8	50,691.1	20,966.6	2,000.0	41,825.7
	2011	-12,416.4	113,854.7	56,002.7	18,361.3	2,000.0	46,400.9
	2012	-16,421.7	121,899.6	59,940.5	17,369.0	2,000.0	49,817.9
	2013	-11,235.0	128,866.1	64,015.1	25,450.5	2,000.0	48,591.02
	2014	-9,941.1	134,600.9	68,201.9	34,984.4	2,000.0	43,364.9
	2015	-19,599.7	156,957.6	74,431.3	46,149.5	2,000.0	52,681.09
18.Sasini Ltd	2010	287,997	3,834,665	209,055	689,012	228,055	1,214,970
	2011	125,488	4,090,598	286,544	767,852	228,055	1,087,532
	2012	149,919	3,705,119	381,232	-30,342	228,055	924,771
	2013	92,769	3,936,553	342,820	113,754	228,055	1,227,911
	2014	143,734	8,708,766	348,353	442,723	228,055	1,282,571
	2015	473,019	8,683,167	2,144,228	513,684	228,055	864,866
19.Scangroup Ltd	2010	3,768,948	8,009,431	1,248,761	838,396	234,570	4,431,626
	2011	4,692,339	8,489,938	1,807,599	1,280,100	284,789	4,135,029
	2012	5,257,688	8,361,646	600,955	1,069,566	284,789	3,747,331
	2013	6,200,203	12,744,583	1,128,343	963,093	378,865	4,618,133
	2014	6,483,150	13,284,104	975,468	912,277	378,865	4,741,473
	2015	6,458,441	12,468,479	1,833,541	875,271	378,865	3,864,219

Firm	Year	WC	TA	RE	EBIT	MVE	TL
20.Trans-Century Ltd	2010	59,245	9,432,665	628,754	630,585	136,975	2,499,786
	2011	298,589	11,295,203	577,831	869,265	136,975	2,601,926
	2012	400,618	11,543,304	342,436	1,226,473	136,975	2,709,180
	2013	1,050,342	13,288,431	114,563	858,590	136,975	3,050,654
	2014	-773,067	11,633,542	163,211	-2,114,202	136,975	2,711,002
	2015	-1,197,919	11,157,217	-271,678	-2,956,073	136,975	3,076,745
21.Total Kenya Ltd	2010	3,023,678	30,375,677	2,837,562	1,388,425	4,774,771	20,795,824
	2011	2,356,187	35,198,166	2,452,527	57,850	4,774,771	26,003,348
	2012	5,415,296	32,980,604	2,250,385	-64,301	9,974,771	18,787,928
	2013	6,516,519	39,984,165	3,436,769	2,084,517	9,974,771	24,605,105
	2014	7,315,927	32,541,800	4,483,132	2,276,005	9,974,771	16,116,377
	2015	8,077,529	34,225,035	5,657,455	2,618,697	9,974,771	16,625,289
22.Unga Group Ltd	2010	2,075,474	5,064,420	1,117,583	335,101	378,535	1,699,717
	2011	2,467,821	5,708,897	1,082,817	631,070	378,535	1,963,946
	2012	2,676,938	6,410,259	1,544,540	348,195	378,535	2,421,041
	2013	2,653,341	8,108,379	1,595,723	389,458	378,535	3,817,078
	2014	2,761,816	8,026,578	1,840,932	567,735	378,535	3,339,335
	2015	3,150,554	8,635,129	2,209,594	635,695	378,535	3,316,509

Appendix II : Emerging Z-Score results Table

No	Firm	Sector	Year	Z-score	Status
1	B.O.C Kenya Ltd	Manufacturing & Allied	2010	2.0044	Grey
			2011	2.2925	Grey
			2012	2.3831	Grey
			2013	1.9167	Grey
			2014	2.2362	Grey
			2015	2.1133	Grey
2	Bamburi cement ltd	Construction	2010	2.9440	Safe
			2011	3.8000	Safe
			2012	3.2419	Safe
			2013	3.3644	Safe
			2014	2.9376	Grey
			2015	3.3861	Safe
3	British America Tobacco	Manufacturing & Allied	2010	2.3950	Grey
			2011	2.9318	Grey
			2012	2.6248	Grey
			2013	2.3690	Grey
			2014	2.6165	Grey
			2015	2.8413	grey
4	Carbacid Investments ltd	Manufacturing & Allied	2010	2.9359	Grey
			2011	2.4998	Grey
			2012	2.7764	Grey
			2013	3.1648	Safe
			2014	2.8872	Grey
			2015	2.5784	Grey

No	Firm	Sector	Year	Z-score	Status
5	Crown paints Kenya ltd	Construction	2010	3.2370	Safe
			2011	3.485	Safe
			2012	3.9209	Safe
			2013	3.6756	Safe
			2014	2.1515	Grey
			2015	2.2239	Grey
6	E.A.Cables ltd	Construction	2010	2.1593	Grey
			2011	2.1343	Grey
			2012	1.8892	Grey
			2013	2.1356	Grey
			2014	2.8921	Grey
			2015	0.6657	Distress
7	East African Breweries ltd	Manufacturing & Allied	2010	2.7366	Grey
			2011	2.1024	Grey
			2012	2.2461	Grey
			2013	2.0037	Grey
			2014	1.8929	Grey
			2015	2.2537	Grey
8	Eveready East Africa ltd	Manufacturing & Allied	2010	2.2141	Grey
			2011	1.2003	Grey
			2012	1.9061	Grey
			2013	0.9277	Distress
			2014	2.5410	Grey
			2015	0.3902	Distress

No	Firm	Sector	Year	Z-score	Status
9	Express Kenya ltd	Commercial& Services	2010	0.5268	Distress
			2011	-0.6529	Distress
			2012	0.6004	Distress
			2013	1.2716	Distress
			2014	0.4841	Distress
			2015	0.3902	Distress
10	Kakuzi	Agricultural	2010	2.883	Grey
			2011	3.1450	Safe
			2012	3.1654	Safe
			2013	3.2242	Safe
			2014	2.6332	Grey
			2015	2.9687	Grey
11	KenolKobil Ltd	Energy & Petroleum	2010	4.5306	Safe
			2011	5.8008	Safe
			2012	5.1344	Safe
			2013	4.5425	Safe
			2014	4.1266	safe
			2015	6.1636	safe
12	Kenya Power & Lighting Co.Ltd	Energy & Petroleum	2010	1.4102	Distress
			2011	1.2069	Distress
			2012	1.4754	Distress
			2013	0.8403	Distress
			2014	0.8729	Distress
			2015	0.8386	Distress

No	Firm	Sector	Year	Z-score	Status
13	Longhorn Kenya Ltd	Commercial & Services	2010	3.0289	Safe
			2011	4.3935	Safe
			2012	2.0264	Grey
			2013	3.3654	Safe
			2014	3.0451	Safe
			2015	2.4986	Grey
14	Marshalls E.A Ltd	Automobiles & Accessories	2010	-0.7354	Distress
			2011	-0.2273	Distress
			2012	0.1530	Distress
			2013	-0.1835	Distress
			2014	0.3768	Distress
			2015	0.3903	Distress
15	Mumias sugar Co.Ltd	Manufacturing & Allied	2010	2.2222	Grey
			2011	1.9462	Grey
			2012	1.4757	Distress
			2013	0.6081	Distress
			2014	0.1613	Distress
			2015	-1.2121	Distress
16	Nation Media Group Ltd	Commercial & Services	2010	3.2506	Safe
			2011	3.3007	Safe
			2012	3.4911	Safe
			2013	2.3529	Grey
			2014	3.4276	Safe
			2015	2.9323	Grey

No	Firm	Sector	Year	Z-score	Status
17	Safaricom Ltd	Telecommunication	2010	2.0507	Grey
			2011	1.9479	Grey
			2012	1.8979	Grey
			2013	2.3078	Grey
			2014	2.5799	Grey
			2015	2.5273	Grey
18	Sasini Ltd	Agricultural	2010	0.2342	Distress
			2011	0.2192	Distress
			2012	0.4050	Distress
			2013	0.4805	Distress
			2014	0.6218	Distress
			2015	0.8721	Distress
19	Scangroup Ltd	Commercial& Services	2010	1.3206	Distress
			2011	1.8258	Grey
			2012	1.9934	Grey
			2013	1.6224	Distress
			2014	1.5875	Distress
			2015	1.3735	Distress
20	Trans-Century	Investment	2010	1.5873	Distress
			2011	1.0597	Distress
			2012	1.3190	Distress
			2013	1.2348	Distress
			2014	0.2514	Distress
			2015	-0.1843	Distress

No	Firm	Sector	Year	Z-score	Status
21	Total Kenya Ltd	Energy & Petroleum	2010	3.1438	Safe
			2011	3.2904	Safe
			2012	4.2331	Safe
			2013	4.5954	Safe
			2014	6.1082	Safe
			2015	4.8653	Grey
22	Unga Group Ltd	Manufacturing & Allied	2010	4.0284	Safe
			2011	4.0974	Safe
			2012	3.6907	Safe
			2013	2.7518	Grey
			2014	3.1516	Safe
			2015	3.2736	Grey

Appendix III:Sample Stratification table

Firm	X1	X2	X3	X4	EMZ-Score	Status	2014 Prof-itability	2015 Prof-itability	2015 TA(in billions)	2014 TA(in billions)	Kenyan Firms Z-score	Status	Error
1.Express	0.021	-0.449	-0.170	0.545	1.354	grey	0	0	444,437	480,456	-7.156	distress	
2.Marshalls	-0.251	0.339	-0.036	0.246	2.717	safe	0	0	551,198	603,935	-7.258	distress	
3.Longhorn	0.286	0.294	0.175	0.015	6.907	safe	1	1	678,213	718,106	7.067	safe	
4.Eveready EA	-0.035	0.142	-0.118	0.158	2.849	safe	0	0	1,365,155	942,129	-5.618	distress	
5.BOC Kenya	0.266	0.589	0.105	0.178	7.812	safe	1	1	2,108,002	2,0584,476	5.463	safe	
6.Carbacid Investment	0.292	0.713	0.195	0.518	9.351	safe	1	1	2,968,727	2,533,163	7.505	safe	

Appendix IV:Kenyan firms Z-score table

Firm	X1	X2	X3	X4	EMZ-Score	Status	2014 Prof-itability	2015 Prof-itability	2015 TA(in billions)	2014 TA(in billions)	Kenyan Firms Z-score	Status	Error
1.Express	0.021	-0.449	-0.170	0.545	1.354	grey	0	0	444,437	480,456	-7.156	distress	
2.Marshalls	-0.251	0.339	-0.036	0.246	2.717	safe	0	0	551,198	603,935	-7.258	distress	
3.Longhorn	0.286	0.294	0.175	0.015	6.907	safe	1	1	678,213	718,106	7.067	safe	
4.Eveready EA	-0.035	0.142	-0.118	0.158	2.849	safe	0	0	1,365,155	942,129	-5.618	distress	
5.BOC Kenya	0.266	0.589	0.105	0.178	7.812	safe	1	1	2,108,002	2,0584,476	5.463	safe	
6.Carbacid Investment	0.292	0.713	0.195	0.518	9.351	safe	1	1	2,968,727	2,533,163	7.505	safe	
7.Kakuzi	0.886	0.628	0.148	0.087	12.20	safe	1	1	5,144,409	4,292,888	17.27	safe	
8.EA Cable	0.040	0.203	0.006	0.033	4.26	safe	1	1	5,644,540	7,889,496	-0.679	distress	type2
9.Unga Group	0.364	0.255	0.073	0.114	7.092	safe	1	1	8,635,129	8,026,578	6.363	safe	
10.BAT Kenya	0.159	0.098	0.382	0.101	7.29	safe	1	1	12,080,481	11,070,605	11.17	safe	

Firm	X1	X2	X3	X4	EMZ-Score	Status	2014 Prof-itability	2015 Prof-itability	2015 TA(in billions)	2014 TA(in billions)	Kenyan Firms Z-score	Status	Error
11.KQ	-0.228	-0.099	-0.158	0.375	0.757	distress	0	0	187,654	152,675	-10.53	distress	
12.NMG	0.309	0.557	0.222	0.125	8.725	safe	1	1	12,697,000	11,944,000	9.459	safe	
13.Sasini	0.054	0.246	0.059	0.263	5.087	safe	1	1	16,044,527	14,929,577	0.393	safe	
14.Kenol Kobil	0.117	0.205	0.193	0.008	6.000	safe	1	1	17,377,103	23,915,166	5.676	safe	
15.Mumias sugar	-0.543	0.044	-0.309	0.211	-2.026	distress	0	0	20,403,564	23,563,086	-19.43	distress	
16.Trans century	-0.107	-0.024	-0.269	0.045	0.703	distress	0	0	21,817,981	19,463,658	-10.64	distress	
17.Total Kenya	0.236	0.165	-0.011	0.599	5.889	safe	1	1	34,225,035	32,541,800	0.694	safe	
18.Bamburi	0.495	0.534	0.246	0.15	10.05	safe	1	1	34,377,000	34,082,000	13.15	safe	
19.EA BL	0.008	0.404	0.211	0.029	6.076	safe	1	1	40,263,838	33,362,861	4.310	safe	
20.Safaricom	-0.124	0.474	0.294	0.080	6.037	safe	1	1	156,960.0	220,109.3	4.175	safe	
21.KP LC	0.075	0.118	0.045	0.103	4.540	safe	1	1	275,493.1	220,926.5	0.729	safe	
22.Crown paints	0.174	0.294	0.088	0.116	6.071	safe	1	1	5,144,409	4,292,888	3.569	safe	

Appendix V:Testing the applicability of the model on Chase bank Kenya (under receivership)

Firm	Year	WC	TA	RE	EBIT	MVE	TL
1.Chase bank Kenya Ltd	2010	-933,932	21,858,591	185,545	535,083	1,400,000	20,143,814
	2011	-1,169,998	36,449,609	315,077	830,171	2,500,000	33,454,171
	2012	-1,992,560	49,672,063	258,282	1,331,252	4,500,000	44,534,631
	2013	-1,134,909	78,768,838	110,115	2,287,074	7,000,000	71,141,419
	2014	3,348,641	109,158,624	413,426	3,353,941	10,000,000	97,783,719
	2015	2,862,786	145,795,560	-1,758,529	-1,007,646	10,960,000	134,444,564

Firm	X1	X2	X3	X4	EMZ-Score	Status	2014 Prof-itability	2015 Prof-itability	2014 TA(in billions)	2015 TA(in billions)	Z-score	Status
1.Chase bank Kenya	0.019	-0.013	-0.069	0.081	2.958	safe	1	0	109,158,624	145,795,560	-3.234	distress