2017

# A Study comparing financial distress prediction models in Kenya listed non-financial sector

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# A Study Comparing Financial Distress Prediction Models in Kenya Listed Non-Financial Sector

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**A thesis submitted to the School of Management and Commerce in partial fulfillment of the requirements for the Master in Commerce at Strathmore University**

**School of Management and Commerce**

**Strathmore University**

**Nairobi, Kenya**

**June, 2017**

## DECLARATION

I declare that this thesis is my original work and has not been presented to any other university for a ward of a degree. Any work done by other people has been duly acknowledged. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person. It has been examined by a board of Examiners of the Strathmore University



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## APPROVAL

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## ACKNOWLEDGMENTS

To my supervisor Dr. Freshia Waweru, for repeatedly highlighting my work in red for new additions, deletion and corrections, that made me to actually realize what this thesis meant to any person interested in the topic.

## DEDICATION

I dedicate this thesis work to the 21st century person, who would like to know more on predicting company's financial distress or lack of a financial distress, who are keen on 'yesterday' and 'today' financial data to tell about the future.

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| | |
|---|---|
| CMA: | Capital Market Authority |
| EBIT: | Earnings before Interest and Tax |
| FLC: | Financial Life Cycle |
| MDA: | Multivariate Discriminant Analysis |
| NSE: | Nairobi Stocks Exchange |
| UK: | United Kingdom |
| US: | United States |
| USD: | United States Dollar |

## ABSTRACT

Business financial distress for most companies is an absolute affirmation of their inability to endure current operations given their current debt obligations. If the financial distress was expected ahead of time, investors and other stakeholders of the companies would have the ability to take action to reduce risk or avoid loss of business. This research aimed to compare financial distress prediction models and their applicability to predict financial distress of Kenya non-financial sector for period of 2005-2014, the number of Kenyan companies faced with financial distress, be it high debts, declined business operations, lack of cash flow to run its operations or payment of its creditors have increased over time and in some cases have resulted to company's suspension from NSE trading. Data was collected from the company's financial report plus a questionnaire administered to the company's risk officers. Financial profile of thirty-one companies is examined and a model is built using the inferential statistic technique, this is then compared with results of other models used to predict financial distress. The research found that Altman's emerging market model is applicable in Kenya, with adjusted R2 of 71.20%, this however when compared with other models like the O-Score model showed the lowest prediction score, with a combination of four models showing a 86.34% prediction power, this was consistent with findings from the questionnaires where the respondent agreed that their current company models is as a result of different model combined together. The study had some limitations some of which were lack of qualitative aspects such as the company's strategy, age of the firm and quality of management, Altman's model is an accounting based model with historical accounting data that are subject to management manipulations. The model can be used to assist regulators, investors, creditors and scholars to predict financial distress. The incremental information content of different ratios as per different model is examined and a financial distress model is developed.

# CHAPTER ONE: INTRODUCTION

## 1.1 Background to the Study

Achieving the goals of corporate finance requires that any corporate investment be financed appropriately. In company financing, management must identify the "optimal mix" of financing that will result in maximum firm value. The sources of financing are, generically, firms self-generated capital and capital from external funders obtained by issuing of debt and equity. Debt in term of loan still remains the global predominant source of funding for corporate accounting for 63% of the total funding from different financial institutions (Allen and Overy; Corporate funding monitor 2015).

Eight years from the financial crisis and the value of loan made globally to corporate has finally exceeded the pre-crisis peak of USD 3.87 trillion, totaling USD 3.93 trillion in 2014. The total value of finance, across loans, bonds and equity provided to corporate globally also reached a new height of USD 6 trillion (Allen and Overy; Corporate funding monitor 2015). Corporate balance sheets look very different especially on the capital structure (Thomas Reuters, 2015).

Capital structure of a firm is a ratio of debt and equity in the company mode of financing Modigliani and Miller (1958). Capital structure is also referred as financial leverage (Enekwe Chinedu Innocent, Agu Charles Ikechukwu and Eziedo Kenneth 2014). Increases in debt component in company's capital structure either increase the value of the firm or increase the risk of the company, some of which is financial distress.

Korteweg (2007) defined financial distress as the reduction in financial efficiency as a result of cash shortage that includes a condition when promises to creditors of a company are broken or honored with difficulty. Outecheva (2007) further defines financial distress as shortage of cash on the asset side of the balance sheet or as a debt overhanging in liabilities. Andrade and Kaplan, 1997; Asquith et al., 1994; Kaplan and Stein, 1993; Theodossiou et al., 1996; Whitaker, 1999, provides some evidence that financial distress arises in many cases from endogenous risk factors, such as mismanagement, high leverage, and non-efficient operating structure in place.

Corporate financial distress is costly to stakeholders including employees, trade vendors, trade receivables, shareholders, bankers and the government (Warner 1997; Zavgren 1983; Jones 1987; Boritz 1991; Laitinen and Kankaanpaa 1999; Charalambous, Charitou and Kaourou 2000). If the different stakeholders had some probability that a corporation is going to face financial distress in the future, appropriate measures can be in place to avoid such a distress. Persistent financial distress can result into corporate bankruptcy and all its associated costs which include auditor's fees, legal fee, management fee, unemployment, and loss of economic gains for a nation.

A corporation in financial distress can either negotiate privately with its claimants or file under the protection of the legal bankruptcy procedure (CIRPEE, 2010). Chapter 11 of the bankruptcy code presents an alternative to the liquidation of a financial distressed firm by defining a judicial context in which the firm can reorganize its activities in order to emerge as a viable entity. Among the 213 bond defaults recorded by moody's from 1997 to 2005, Davydenko (2010) documents that 54% of them are technical defaults (i.e. missed payment), while 37% are resolved through chapter 11, with only 9% of defaults being solved out of court. These figures highlights need for a better understanding of financial predictive models.

Different papers have served to emphasis the need for a timely prediction model; Campbell, Hilscher and Szilagyi (2008) showed that financial distressed firms had delivered low returns in the US. Beaver (1966) adopted the use of financial ratios in bankruptcy prediction and established that they have predictive powers. Pompe and Bilderbeek (2005) find that liquidity variables from accounting data have predictive power for bankruptcies 4 or 5 years into the future, which is similar for working capital and volatilities as demonstrated by Dambolena and Khoury (1980). Balcean and Ooghe (2004) outlined four statistical models, univariate analysis, risk index models, multi discriminant analysis, and conditional probability models all of which relied solely on financial information, but could not account for changes in internal and external environment of a firm for instance macroeconomic conditions as well as market dynamics. Altman is known for the development of the Z-score formula, a multivariate formula for measuring financial health of company and a is a powerful diagnostic tool

that forecast the probability of a company entering financial distress within two year period, Altman (1968), Taffler (1983, 1984). Taffler (1984) provides a critical review of the outstanding features of Z-score model documented in UK.

In Ghana, Kingsley Appiah (2011) studied 15 listed companies from different sectors and found out that corporate failure cannot be predicted using Altman's model. Samarakoon and Hasan (2003) investigated the ability of Altman's Z-score model to predict corporate distress in emerging market of Sri Lanka the results showed that the model had a remarkable degree of accuracy in predicting distress using financial ratios prior to the year of distress. In Kenya, commercial banks Mamo (2011) found that Altman's financial distress prediction model was accurate predicting eight out of ten failed firms. Hendel (1996) found that Z-score formula is not applicable in recession due to non-liquid assets, such as inventories with low demand which as a result assumes the importance of liquidity. Z-score model is an accounting based model thus lacking much of the theoretical underpinnings. Other financial distress models includes Ohlson's O-score Model (1980), Zmiejewski's Model (1984), Springate Model (Canadian), Blasztk Model, Shumway (2001) Model all of which have explained predictability of financial distress of different companies in different sectors.

### 1.2 Problem Statement

A major concern for stakeholder is to predict the likelihood of financial bankruptcy in order to respond before the events take place. Hence, different bankruptcy prediction models that are able to forecast corporate failure have been developed after Beaver´s pioneering work in 1966. Beaver (1966) came up with a univariate approach to analyse bankruptcy and it was Altman (1968) who based his work (the z- score model) on him. The univariate analysis is the analysis of one single variable and its attributes. However, until now a bankruptcy prediction model with high predictive power still remains a challenge since no model performs with 100% accuracy rate.

The majority of bankruptcy prediction studies have mainly analysed one single method or a combination of two. However, only a few studies have paid attention to multiple models regarding bankruptcy prediction. According to Xiao et al. (2012), the existing

literature showed that a single bankruptcy prediction model faces limitations and multiple bankruptcy prediction models improved the prediction of accuracy in bankruptcy prediction. A limitation of a single model is that due to the fact it is based on some variables will not be able to give a full explanation of bankruptcy prediction. As Sun and Li (2008), for example, analysed different models for bankruptcy prediction, they found out that this mix improves the average prediction accuracy and stability by giving an empirical experiment with listed companies in China. Furthermore, Kim et al. (2002) and Cho et al. (1995) also demonstrated that a combination of multiple bankruptcy models reduces the variance of estimated error and also improves the whole recognition performance.

Kenyan's organizations have in the past been faced with financial distress, this either from high debts, declined business operations, lack of cash flow to run its operations and payment of its creditors in time (CMA statistical Bulletin, 2015). The CMA statistical bulletin has outlined some example of company that were faced with financial distress, they include; Uchumi supermarket Ltd, which reported that the company had a tight cash flow position that made it difficult to maintain its supplier relation (Annual report 2005, pp 10) and a year later it was put under statutory management after losing its customers to competitors and worsened the cash flow position (Annual report 2006). Hutching Biemer Ltd was put under statutory management due to liquidity problems and financial disclosure (NSE Notice, 2010), Mumias Sugar Co (Annual report, 2013), Kenya Airways (Annual report, 2014) both disclosed their cash flow shortages to settle their debts obligations. Other companies that were suspended from trading in the Nairobi security exchange due to financial shortages includes; A Baumann company (Suspended 2008) and Hutching Biemer (again suspended 2015).

Given these observations, a researcher would be interested to find out the best prediction model that can be able to predict any distress before companies goes into bankruptcy.

## 1.3 Research Objective

### 1.3.1 General Objective

The general objective of this research was to compare Financial Distress Prediction Models used in Listed Non-Financial Sector in Kenya

### 1.3.2 Specific Objectives

a. To test the applicability of models used to determine financial distress in public listed non-financial companies in Kenya.
b. To find out other models used to determine financial distress in Kenya non-financial companies.
c. To compare Altman (1968), Ohlson (1980), Zmijewski (1984) and Shumway (2001) financial distress models.

## 1.4 Research Questions

The study attempted to answer the following research questions using the Kenya sample non-financial listed companies:

a. What is the level of applicability of models used to determine financial distress in public listed non-financial companies in Kenya?
b. Which other models did non-financial companies use to determine financial distress in Kenya?
c. What is the relationship among Altman (1968), Ohlson (1980), Zmijewski (1984) and Shumway (2001) financial distress models?

## 1.5 Scope of the Research

This research study used financial data for period 2005 to 2014. In the period 2005 to 2014, Kenya stock market had nine companies being suspended from trading, these includes; Uchumi Supermarket suspended in 2006, A Baumann suspended in 2008, CMC and EAPCC suspended in 2011, BOC and Carbacid suspended in 2005, City trust and Rea Vipingo in 2013 and Hutching Biemer suspended in 2014. In the same period, there were 3 companies delisted, Unilever Tea delisted 2008, Access Kenya 2013 and CMC Holding 2014. These companies were mainly suspended or delisted for various reasons with the major one being financial distress and disclosures.

Eleven out of the twelve companies delisted or suspended were from non-financial sector, thus one of the reasons to cover the non-financial in the period of 2005 to 2014. The research was to compare different financial prediction models and their capability to predict a distress or not of a company one and two years before the distress. For the non-distressed companies, the study used financial report of at least two years to 2014 year 2015 and 2016 were excluded from the study since no company listed in the stock market had either been put under statutory management nor delisted from the stocks market. The research study also excluded the financial sector (namely banks, insurance and Investment firms) from the analysis because they have different asset structure thus likely to affect the Z score.

The same period, 2005 to 2014, the non-financial sector had the most entrants of new entities to be listed in Nairobi Security Exchange with eight out of the nine companies issued IPO between 2005 to 2014 being from non-financial sector and includes Kengen in 2006, Scangroup 2006, Eveready 2006, Access Kenya 2007, Kenya Re 2007, Safaricom 2008, British American 2011, NSE 2014 with only Co-op Bank from financial sector 2008 (CMA statistical Bulletin 2015).

The study aimed to compare different models that have commonly been used to predict financial distress of Kenyan listed (in the main investment market segment) non-financial sector during 2005 to 2014 and that have business operation in Kenya.

One of the common models that has been used over the year and where other models have developed their new formula is the Altman's Z-score model. The Altman Z-Score was found to be 72% accurate in predicting bankruptcy two years before the event, with a Type II error (false negatives) of 6% (Altman, 1968). In a series of subsequent tests covering three periods over the next 31 years (up until 1999), the model was found to be approximately 80%–90% accurate in predicting bankruptcy one year before the event, with a Type II error (classifying the firm as bankrupt when it does not go bankrupt) of approximately 15%–20% (Altman, 2000).

### 1.6 Significance of the Study

The findings of this study will be beneficial to different stakeholders including;

Regulators; this includes Central Bank of Kenya, the Capital market Authority among others, these are tasked with monitoring and ensuring stability in the economy. These regulators can be able to put measures in advance to ensure no adverse effect to the economy in case of financial distress. The regulator will be in a position to put some preventive measures if a distressed actually happened.

Investors; This study can be useful to investors as to recognize the overall level of financial performance affecting their returns on investment. Investors can use the information to determine which stocks to buy, to hold or sell. By applying the Z-score model investors will be able to predict the financial soundness of companies before investing.

Creditors; to assess the credit worthiness of a firm based on financial stability as disclosed by the prediction model on any likelihood of financial distress. This will help creditor decision making to lender more debt to the firms.

Academicians and scholars; the academician will find it useful because they can find areas for further research while also contributing to new knowledge. The research will also show how financial distress affects the different companies and their various stakeholders in the economy.

### 1.7 Organization of the Study

The research comprised five chapters. Chapter two, three, four and five were designed in such a way that they answer the two-research objective already mentioned in chapter one. Chapter two dealt with the literature review on the subject matter discussed by prior authors. Chapter three dealt with the research methodology and methods that the researcher used in the research. Chapter four dealt with data analysis as well as interpretations. Data was obtained from the financial report of the companies for the stated period. Summary and conclusion was in chapter five.

# CHAPTER TWO: LITERATURE REVIEW

## 2.1 Introduction

This chapter reviews the literature on Financial Distress Prediction Models used in Listed No Financial Sector in Kenya different countries and industries. The literature review first outlines the financial distress from theoretical perspective, then a discussion on empirical findings and conclusion.

## 2.2 Theoretical Review

Several theories have been studied to explain predictive of financial distress, they include among others; Financial life cycle (FLC), Financial ratios theory, Fulmer model, Springate model, the Altman's Z-score model, Ohlson's O-score Model and Zmiejewski's Model as some of the traditional methods. Beaver (1967) did a great job on ratio analysis and bankruptcy classification. This was a univariate analysis where each ratio was taken at a time and its effects on the total score checked. He found out that a number of indicators could discriminate between matched samples of failed and non-failed firms, for as long as five years prior to failure.

The Altman's model by Edward I Altman is a multivariate formula for measurements of financial health of a company and a powerful diagnostic tool that forecasts the probability of a company entering into bankruptcy within a period of two or one year. Z-score model is a statistical technique used to classify an observation or make prediction in problems where dependent variables appear in qualitative form. It is therefore unlike in the traditional ratio analysis where each ratio was analyzed at a time, or the other models that were just a buildup of Altman's work. It is able to consider an entire profile of characteristics common to the relevant firms as well as interactions of these properties (Heine 2000)

### 2.2.1 Financial Ratios Theory

Financial ratios are the most commonly used in analyzing, understanding and interpreting corporate financial statement and monitoring corporate performance over time. The ratios

point out changes and identify irregularities, abnormalities and surprises that would require further investigation to ascertain the current and future financial standing of the company (Barry & Elliot, 2006).

Ohlson (1980) established that a widely-used approach in organization failure prediction is the analysis of liquidity ratios. The two most commonly used being current and quick ratios. Current ratio is an indication of a firm's market liquidity, is a ratio of current assets to current liabilities. This ratio shows the company capability to pay its short-term liabilities from short term assets. Acceptable current ratios vary from industry to industry and are generally between 1.5 and 3 for healthy businesses. If a company current ratio is in this range, this indication of good short-term financial strength. If current liabilities exceed current assets (where current ratio is below 1) then the company may have problems meeting its short-term obligations. If the current ratio is too high, then the company may not be efficiently using its current assets or its short-term financing facilities. This may indicate problem in working capital management. The quick ratio is the ratio of current assets excluding stocks to current liabilities. Stock is excluded from this ratio because is not always easy to convert to cash in short period. For quick ratio, a ratio in excess of 1.0 is considered a general indicator of financial safety, though this again depends on different industries or companies.

Ohlson (1980) however also indicated that over time, contrary to expectations, the level of these ratios and trends does not provide a reliable means of predicting financial distress. He therefore suggested additions of other ratios which included debts ratios for instance total debt to total assets, a ratio that measures extent to which company assets are financed by borrowings. A maximum level of 50% is considered appropriate for safety. Earnings before interest and tax (EBIT), this indicates the ability of a company to pay interest charge out of earnings and also used to give a measure of sensitivity to interest rate fluctuations. A ratio in excess of 2.0 is considered necessary for safety.

Reynolds (2002) examined the financial capital structure of major financial companies in Thailand over a period of 1993 to 1998. He used both probit and logistic binomial regression analysis and was able to estimate the probability of a firm surviving to and operating in 1998. The sample studied included 91 major financial companies with the

methodology consisting of postulating a relationship between the probability of a financial company surviving to 1997 and certain key economic determinant; firm size in terms of assets, total assets, net profit, net income, borrowing and lending structures.

The finding of the study was that the firm size (measured in total assets) is inversely related to the probability of survival, indicating that large companies have less of a chance of surviving to 1997 than relatively smaller companies. They also found out that time-variable coefficient is positive; indicating that, as times goes on, the probability of survival increases. Reynolds research concluded that companies with relatively more short-term debt and more non-performing loans appears more likely to survive and by implication, are more cautious about their lending practice. However, Reynolds research cannot be conclusive enough since it fails to consider long-term debts and other determinants such as liquidity.

Ramanujam (1984) argued that financial performance measures were critical in establishing the level of firm's financial health and as a result would be used to predict financial distress. Ramanujam in his studies stated that the most used variables in univariate measures were return on sale (ROS) and Return on Assets (ROA).

Beaver (1966) focused on financial ratio analysis. The underlining theory or rational for Beavers model was based on the idea that financial ratios exhibit significant differences across failing and non-failing firms, in his pioneering work, Beaver (1966) used 30 financial ratio and 79 pairs of companies (failure/non-failure) and his findings showed that the best distriminant factor was working capital/Debt ratio, which correctly identified 90 percent of the firms one year prior to failure. The second best distriminant factor was the net income/total assets ratio, which had 88 percent accuracy. Beaver 1966, concluded that financial ratios can be used as a predictive variable and later in 1967, Beaver proposed three univariate models of financial ratios that measured profitability, liquidity and solvency.

Emin and Denz (2013), studied 115 firms traded at Istanbul stock exchange-All sector over a period of 2009-2011 and employed a distriminant analysis by using financial ratio of all the 115 firms. To examine the financial success of the firms, Emin and Denz

identified 20 key financial ratios classified under; liquidity, operation, debt management and profitability. As a result of the analysis using these 20 financial ratios, it was identified that there are 5, 3 and 4 important financial ratios in the discrimination of the successful and unsuccessful firms in 2009, 2010 and 2011 respectively. Capital adequacy and net working capital/total assets ratios are seemed to be significant in all three period. According to the formed models, classification success is determined as 88%, 7% 90%, 4% and 92%, 2% in 2009, 2010 and 2011 years respectively. The high accuracy ratio indicates that the developed models for the three years are efficient to determine the financial failure of firms traded in ISE.

Rasheed (1997) noted that most statistically significant results in predicting financial distress were produced by multivariate models, this because they combined financial ratios thus basing their analysis on the entire variable profile of the object simultaneously rather than sequentially examining individual characteristics. Combination of the ratios analyzed together removed possible ambiguities and misclassifications.

Balcean and Ooghe (2004) outlined four statistical models, univariate analysis, risk index models, multi distriminant analysis, and conditional probability models. These models relied solely on financial information but could not account for changes in internal and external environment of a firm for instance macroeconomic conditions as well as market dynamics; these changes were seen as determinant of the firm financial health thus more need to come up with new models. Mensah (1984) warned that in addition to selecting different financial ratios, researcher typically analyze data across several years without considering the underlying economic events in those periods.

### 2.2.2 The Altman's Z-score model

Edward, I Altman was the first one to use ratios in order to determine the bankrupt of a company. This was first done in 1968, and he was there after known as the father of bankruptcy.

E. Altman (1968) spearheaded the use of multivariate distriminant analysis (MDA) in predicting corporate failure. Altman used an initial sample composed of 66 firms with 33 firms in each of the two (failure/non-failure) groups. The bankruptcy group consisted of

companies that filed for bankruptcy petition under chapter 11 of the United States bankruptcy act from 1946 to 1965. All businesses used were manufacturing firms, and small firms with assets of less than $ 1Million were eliminated. An extensive research was done using various variables and those that did not have much influence or significance to the formula when measured independently were dropped.

From the original list of variables, five variables were selected as being the best overall to predict financial distress and to arrive at the final profile of variables the following procedure was utilized starting with observation of statistical significance of various alternative functions including determinant of the relative contributions of each independent variable; evaluation of inter-correlation between relevant variables; observation of the predictive accuracy of the various profile and judgment of the analyst

The five financial ratios used in MDA model were Working Capital to Total Assets, Retained Earnings to Total Assets, Earnings before Interest and Taxes to Total Assets, Market Value of Equity to Book Value of Total Liabilities, and Sales to Total Assets and this was referred as the initial Z score model.

Initial Z score model developed in 1968 had five variables and the Z-score model has been proved to be accurate in predicting bankruptcy especially because it takes into consideration all the firm's key financial aspects like assets, revenue, working capital and earnings.

The original' Z-score model was however found to have some limitations as it only included, publically owned manufacturing companies those that had their shares listed in the stock market. The model does not take into account some exceptional periods like recession where non-liquid assets, such as inventories, is unnecessary since demand is low relative to inventories held.

The model was also based on the market value of the firm and is thus applicable only to publicly traded companies. Altman thus went further to develop two more formulas which would accommodate private and non-manufacturing companies. To be applicable to private firms Altman (2000) developed a re-estimation of the model substituting the market value of the equity for the book value, by using the same data as used in 1968.

This new estimation implies that all the coefficients have to change and that there also will be new values in order to set the areas of safety and risk

If a company stock is not publicly traded, then market value of equity to book value of total liabilities cannot be calculated. To correct this problem, the Z score can be re-estimated using book value of equity. Altman's (2000) revisited Z-Score prediction model proved to be also accurate in predicting bankruptcy correctly. The Type I accuracy is only slightly less impressive than the model utilizing market value of equity but the Type II accuracy is identical.

For Non-manufacturing firms the sales to total assets ratio is believed to vary depending on different industry. It is likely to be higher for service firms than for other manufacturing firms. Since service sector is typically capital intensive. Consequently, non-manufacturing firm are likely to have higher assets turnover and hence Z score. The model is thus likely to under predict certain sorts of bankruptcy. To correct this, Altman suggested the elimination of this ratio in the formula.

The model was extremely accurate in classifying 95% of the total sample correctly one year prior to failure (-1 year), but misclassification of failed firms increased significantly as the prediction time increased (28% at -2 years, 52% at 3 years, 71% at 4 years). In 2000, Altman model was improved for the emerging markets and an emerging market score model was issued.

### 2.2.3 Ohlson's O-score Model (1980)

Another popular financial distress prediction model is the O-score model of Ohlson (1980). Ohlson (1980) was one of the first researcher who criticized Altman and other previous researchers that used the MDA method and came up with his own model based on a statistical method called 'logistic regression'. This method is an alternative to Fisher's (1936) classification method, linear discriminant analysis and is therefore related to Altman's Z-score model (Gareth, 2014). According to Tabachnick & Fidell (1996) "Logistic regression allows one to predict a discrete outcome such as group membership from a set of variables that may be continuous, discrete, dichotomous, or a mix." Therefore the logistic regression may be better suitable for cases when the dependent

variable is dichotomous such as yes/no, pass/fail and bankrupt/non-bankrupt. A study in 2007 from Marquette University asserts a rather spectacular success rate of 96% in both the 1 and 2 year prediction time frames.

When comparing the model of Altman (1968) to Ohlson´s model (1980), Ohlson (1980) critics to the MDA approach in the following points: At first, Ohlson (1980) argues that Altman's model (1968) is based on the assumption that the explanatory variable is normally distributed. Further, a point of critic is that the bankrupt and non-bankrupt firms are matched according to criteria such as size and industry. Therefore, he argues the model is restricted in terms of Comparison of accounting-based bankruptcy prediction models of Altman (1968), Ohlson (1980), and Zmijewski (1984) to German and Belgian listed companies during 2008 - 2013 generalizability. In Ohlson´s point of view variables should not be included for matching reasons but rather for predicting bankruptcy. Ohlson (1980) explained that his model (the logit approach) avoids the aforementioned critics because it is not based on those strict assumptions (Ohlson, 1980).

A study by Wang and Campbell (2005) found out that the Ohlson (1980) model is "an applicable measure for predicting firm delisting in China". The authors studied listed Chinese companies during a period of 2000-2008 and reported that the accuracy rate of Ohlson's model was by 95%. Pongsgat et al. (2004) analysed a matched pair sample of 60 bankrupt and 60 nonbankrupt firms over the years 1998 to 2003. Their study concludes that while each of the two methods has predictive ability when applied to Thai firms. They state that the Ohlson model (1980) has a higher predictive ability in all three years preceding bankruptcy than that of Altman's MDA (1968) model: "The overall difference between Ohlson's model and Altman's model respectively was 69.6 % to 58.9 % for the first year prior to bankruptcy, 69.6 % and 62.5 % for the second year prior to bankruptcy and 69.6 % to 62.5 % for the third year to bankruptcy" (Ponsgat, 2004). Further, Begley et al. (1997) applied Ohlson's model to 1365 industrial firms and reported an overall 98 % classification accuracy.

However some critics are left on Ohlson´s model. The logit approach averages data whereby a healthy firm is given the value of 0 and a non–healthy company the value of 1

(Abdullah et al., 2008). Thereof, the logit approach treats non-healthy companies as if they were bankrupt from the beginning onwards. Studies by Collins and Green (1982) or Ingram and Frazier (1988) came to similar results, saying that generally the logit model (1980) is superior to the multidiscriminant approach by Altman (1968). Chen, Huang and Lin (2009) state: "Logit Regression would have a better theoretical jurisdiction and more diversity and breadth for the independent variables selected".

Further, Hillegeist (2004) adds that there are "two econometric problems with the single period logit model": Firstly, the sample selection bias that arises from only using one and non-randomly selected observation. Secondly, Ohlson´s model (1980) fails by not including time varying changes. Especially, the second point of critics is crucial since Grice and Dugan (2001) emphasizes that the relation between financial ratios, as those mentioned above, and its effect on bankruptcy changes over industries and time. As Hensher and Jones (2007) point it out: "all parameters are fixed and the error structure is treated as white noise, with little behavioural definition". To conclude, the critics suggest that Ohlson´s model (1980) seems to be inefficient and biased although the results of his model suggests a high accuracy rate compared to MDA (1968).

### 2.2.4 Zmiejewski's Model (1984)

The Zmiejewski (1984) model was based partly on Ohlson's (1980) work and is called; 'the probit model'. Similar to logistic regression the probit analysis is a type of regression where the dependent variable can only take two values again bankrupt/non-bankrupt. The name comes from probability + unit. The purpose of the model, similar to those of Altman (1968) and Ohlson (1980), is to estimate the probability that an observation with particular characteristics will fall into a specific one of the categories. The probit model is a type of binary classification model that estimates probabilities greater than 1/2.

Zmiejewski's model takes into account a set of independent variables as well as accounting data. He examines two estimation biases which can result when financial distress models are estimated on non-random samples. According to Zmiejewski (1984), the two biases are choice-based sample biases (i.e. oversampling distressed firms) and sample selection biases (i.e. using a complete data sample selection criterion). Zmijewski

(1984) argues that with the choice-based sample bias the estimated coefficients will be biased, unless one builds a model based on the entire population. The estimation sample Zmijewski's (1984) study contained 40 bankrupt and 800 non-bankrupt firms, and the hold-out sample consisted of 41 bankrupt and 800 non-bankrupt firms. The population of his study consists of all firms listed on the American and New York Stock Exchanges between 1972 and 1978 with SIC-codes below 6000. This means that finance, service and public administration firms were excluded from the research. The accuracy rate of the Zmijewski (1984) model for the estimation sample was 99%, while the accuracy rate of the hold-out sample was not reported. Zmiejewski (1984) came up with three variables that should predict bankruptcy, namely; net income / total assets, total liabilities / total assets and current assets / current liabilities.

Zmiejewski's model (1984) accuracy rate scores pretty high (99%) according to the original (1984) study and high according to several other studies like Oude Avenhuis (2013), Mehrani et al. (2005), Grice and Dugan (2003). Nevertheless there are some critics about the model. Shumway (2001, p. 120) argues that Zmiejewski's model (1984) is in fact only a "one-variable model" because the selected variables are highly correlated to each other. Shumway (2001) even claims that because of this correlation the model has no strong predictive power for bankruptcy. Additionally, Platt and Platt (2002, p. 186) state that "Zmijewski (1984) could not test the individual estimated coefficients for bias against the population parameter" since Zmijewski ran only one regression for each sample size. Another limitation is according to Grice and Dugan (2003) the selection of the ratios. They claim that the ratios were not selected on a theoretical basis, but rather on the basis of their performance in prior studies. However, this will be the case for any bankruptcy prediction study that is based on or helped by prior work such as Beaver (1966).

### 2.2.5 Shumway Model (2001)

One common market-based bankruptcy prediction model is Shumway´s (2001) discrete-time hazard model to predict bankruptcy by using accounting but also market variables. The model is based on a previous study by Shumway (2001) where he found out that many accounting based variables employed in previous studies are not significant in

predicting failures. Shumway (2001) includes market based data, such as firm's market size, firm's previous returns, and the idiosyncratic standard deviation of these returns are better predictors of bankruptcy.

In a study where Abdullah et al. (2008) observed 26 bankrupt and 26 non-bankrupt companies registered on the Malaysian stock exchange compared the MDA, logistic regression and the hazard modes to each other and came to the following results: The MDA model provided an overall accuracy of 80.8 % and 85 %, the logit model predicted 82.7 % and 80 % accurate and the hazard model 94.8 % and 63.9 % (Abdullah, 2008,).To turn it around, one can say the hazard model "provides a higher accuracy rate in the estimation model, but when the estimated equation is applied in the holdout sample, the MDA gives a higher accuracy" (Abdullah, 2008). Consistent with other studies, also Chava and Jarrow (2004) found out that the relative performance of Shumway´s hazard model against accounting models of Altman and Ohlson (1980) is outperforming.

### 2.2.6 Springate Model (Canadian)

The Springate score is a model used to evaluate a firm's probability of bankruptcy. It was created in 1978 by Gordon L.V.S Pringate who continued developing the Altman model. In spite of that, the Springate score is still a less popular model for bankruptcy prediction than Altman's model. Data needed to calculate this ratio is collected from the balance sheet, income statement and cash flow statement. This bankruptcy calculation model is important for the firm's investors and creditors, as it provides information on how close the firm is to a possible bankruptcy. The norms and limitation of this method is that if the value is below 0.862 it means that the possibility of a firm's bankruptcy is high, so the firm is considered unstable and dangerous. In general, if the value of Springate score goes down to 0.9 or below, it would be smart to consider paying serious attention to the firm's condition. If value of $Z < 0.862$, then the firm is classified as "financial distressed"

### 2.2.7 Blasztk Model

Blasztk system model is the only business failure prediction method that was not developed using multiple discriminate analysis. Using this system, the financial ratios for the company to be evaluated are calculated, weighted and then compared with ratios for

average companies in that same industry. One main advantage of this method is that it does compare the company being evaluated with other companies in the same industry (Bilanas, 2004) given by Dunn & Bradstreet.

### 2.3 Empirical Review

Altman (1968), Taffler (1983, 1984) provides a critical review of the outstanding features of Z-score model documented in UK. This approach later followed by Argwal and Tafler (2008a), which provides evidence that momentum, may be a proxy for distress risk. Samarakoon and Hasan (2003) also investigated the ability of Altman's Z-score model to predict corporate distress in emerging market of Sri Lanka. The results showed that the model had a remarkable degree of accuracy in predicting distress using financial ratios prior to the year of distress. In Pakistan, Fawad Hussain, Iqtidar Ali, Shakir Ullah and Madad Ali (2014) found that Altman's Z score model can predict business bankruptcy one, two, three even four years prior to failure with a higher rate of accuracy. The above findings were supported by those of Ijaz (2013) who conducted a study in Pakistan for the period 2009 to 2010. The objective of the study was to test the reliability of the Z-score and current ratio in predicting financial distress among the thirty-five listed companies of the Karachi Stock Exchange. The results indicated that current ratio and Altman's Z-score are reliable tools of assessing financial health of sugar sector listed companies of Karachi Stock Exchange.

Calandro (2007) provided a commentary on the utility of Altman's Z-Score as a strategic assessment and performance management tool. His findings were that while Z-score is both popular and widely used in the filed of credit risk analysis, distressed investing, M&A target analysis, and turnaround management, and it has received relatively little attention as a strategic assessment and performance management tool. Balcean and Ooghe (2004) outlined four statistical models, univariate analysis, risk index models, multi distriminant analysis, and conditional probability models all of which relied solely on financial information, but could not account for changes in internal and external environment of a firm for instance macroeconomic conditions as well as market dynamics. Changes in the macroeconomic and market dynamics were seen as determinant of the firm financial health thus more need to come up with new models.

Shumway (2001) shows that the dynamic Logit model gives better predictive power. Chava and Jarrow (2004) develop this further by adding industry controls and showed that the dynamic Logit model can easily be estimated using standard statistical model in developed countries. Z-score model has some limitations in predicting financial distress, in Argwal and Tafler (2008a) Z-score model, which provided some fascinating evidence that momentum maybe a proxy for distress risk, found out that apparently, markets do not adequately price distress risk using the z-score model.

Hendel (1996) argues that in recession non-liquid assets, such as inventories, is unnecessary since demand is low relative to inventories held. Therefore, during recession firms tend to deviate from one-period profit maximizing behavior by depleting inventories in order to generate cash and improve their chances of survival. This as a result assumes the importance of liquidity and activity ratios that reflect changes in inventory. The Z-score model does not take this into account. Beaver (1966) compared the financial ratios of 79 failed firms with the ratios of 79 matched firms up to five years before the matched firms actually failed.

Using univariate discriminant analysis, he studied large asset size firms that failed between1954-1964 and a stratified sample of successful firms. He tested debt/total assets, earnings after taxes/total assets and cash flow/total debt and concluded that cash flow to total debt had the highest discriminatory power of the ratios examined. Five years before failure, an optimal prediction criterion (i.e., cutoff value) based on the single accounting ratio misclassified only 22% of the validation; one year prior to failure the criterion misclassified only 13% of the validation sample. His study concluded that a single financial ratio can help predict financial distress. Although ratio analysis is important in financial distress detection no single financial ratio can accurately predict financial distress and as Altman (2000) observes a firm with poor profitability and/or solvency record may taken as a potential bankrupt, notwithstanding its above average liquidity situation.

Z-score model is an accounting based model thus lacking much of the theoretical underpinnings. There is an issue of timeliness, accounting data is necessarily out of date and added to this, distressed firms tend to be late reporting (Ohlson 1980: Lennox 1999).

Shaefer (1982) also reported that the Z model also do not take into consideration the one of events like write offs, the model also is not well applicable in newly founded company which will always have a low score due to low or no earning. 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.

Taliani (2010) carried out a study on predicting financial distress in commercial banks in Kenya. His study revealed that none of activity and turn-over ratios was found to be critical in predicting financial distress in commercial banks in Kenya. The model attained 70% and 100% correct classification in year 1 and year 3 respectively. The findings are consistent with the studies by Kogi (2003) where he did a study to develop a discriminant model incorporating financial ratio stability that could be used to predict corporate failure. He sought to identify critical financial ratios with significant predictive ability. His finding showed that it was possible to predict corporate failure with up to 70% accuracy three years before actual occurrence using stability discriminant model. Kiege (1991) had earlier formulated a model to predict business failure among Kenyan companies which achieved a prediction accuracy of 90% two years before actual failure.

Bwisa (2007) in his study noted that Altman financial distress prediction model was applicable in Kenya local companies. He found out that model is applicable in the sense that six out of ten failed firms that were analyzed indicated 70% validity of the model. Mamo (2011) studied Kenya commercial bank and found that Altman's financial distress prediction model was accurate predicting eight out of ten failed firm and on sampled non-failed banks, majority of them proved that the Edward Altman's financial distress prediction model was correct with a 90% validity of the model. The findings were also in line with those of Shisia (2014) who conducted a study with the objective of Altman failure prediction model in predicting financial distress in Uchumi Supermarket in Kenya.

They used secondary data for a period of five years from 2001-2006. The study established that Altman failure prediction model was appropriate for Uchumi supermarket as it recorded declining Z-score values indicating that it was suffering financial distress.

In another study in the banking industry Kariuki (2013) sought to establish the impact of financial distress on commercial banks performance. She sought to know whether they are in distress, if so how their performance is affected and how to rectify the situation. A descriptive research design was employed and a sample of 22 banks, 11 listed and 11 unlisted out of the population of 40 banks was selected. Altman's Z-score model was used to measure financial distress while return on assets ratio was used to measure performance. Data was then analyzed using regression model. The findings indicate that most banks under study had financial distress, non-listed banks suffered more. Financial distress had significant impact on financial performance. There is a negative relationship between financial distress and financial performance. The study established the need to reduce financial distress by ensuring financial stability in banks to ensure shareholders confidence.

Most studies done both locally as well as in developed economies agree that the Altman Z-Score model is the most thoroughly tested and broadly accepted distress prediction model. As such it is arguably the most important tool used in turnaround management for diagnosing and evaluating overall financial corporate health, as well as the viability of turnaround or restructuring efforts.

## 2.5 Conceptual Framework

The conceptual framework is presented in figure 2.1 gives us a clear course of action and helps us to understand clearly these variables in relation to the study.

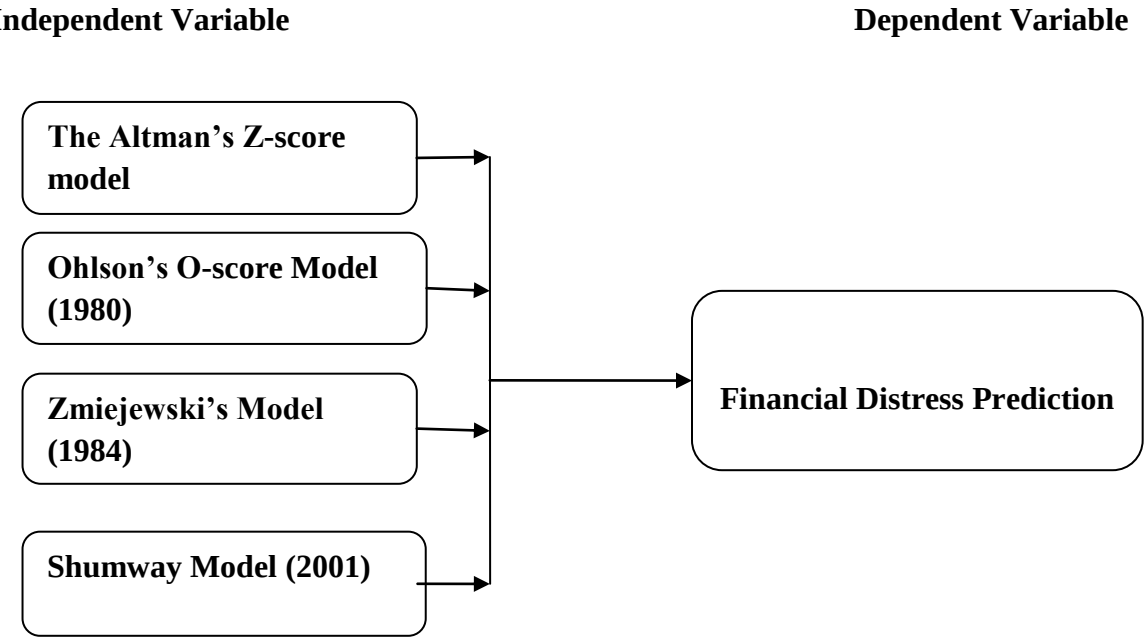


**Figure 2.1: Conceptual Frame Work**

As outlined in the conceptual framework, there are differences between financial distress prediction models. In order to assess the performance of different accounting-based financial distress prediction models, measuring of accuracy rate power of financial distress models is crucial. The higher the accuracy rate of a distress prediction model, the better the forecast of financial distress likelihood. The four predictor models include Altman (1968), Ohlson (1980), Zmijewski (1984) and Shumway (2001) which are in this case the independent variables. The dependent variable is the financial distress prediction.

## 2.4 Chapter Summary

Hofer (1980) Companies in financial distress do not necessary need to go through the legal procedure, they can take remedial action including hiring turnaround managers, disposing of assets or improving working capital management.

Companies in financial distress tend to examine financial restructuring (John, Lang and Netter, 1992; Gilson, John and Lang, 1990; Wruck, 1990; Brown, James and Mooradian, 1992, and Asquith, Gernter and Scharfstein, 1994) or management turnover during the distress (Gilson, 1989).

Thus, need to evaluate whether the emerging market models can be applicable to predict financial distress in advance to avoid such cases as firm's bankruptcy.

# CHAPTER THREE: RESEARCH METHODOLOGY

## 3.1. Introduction

The objective of this study was to compare Financial Distress Prediction Models used in Listed Non-Financial Sector in Kenya. This chapter outlines the procedures and methods used in carrying out the study, including research design, proposed population, sample design, data collection, analysis methods and summary of the findings. A chapter summary is also provided.

## 3.2. Research Design

The study adopted a descriptive and inferential statistics design. With inferential statistics, the research was trying to reach conclusion that extend beyond the immediate data alone. Descriptive research involves gathering data that describe events and then organizes, tabulates, depicts, and describes the data collection (Glass & Hopkins, 1984). Descriptive studies are aimed at finding out "what is," so observational and survey methods are frequently used to collect descriptive data (Borg & Gall, 1989). Descriptive statistics are also very important in reducing the data to manageable form. Thick, rich descriptions of phenomena can also emerge from qualitative studies, case studies, observational studies, interviews, and portfolio assessments and in this study, a research questionnaire was used to obtain information as to what other models non-financial companies in Kenya use to predict financial distress.

Three main purposes of research are to describe, explain, and validate findings. Description research emerges following creative exploration, and serves to organize the findings in order to fit them with explanations, and then test or validate those explanations (Krathwohl, 1993).

Some of the advantages of descriptive research includes; is effective to analyze non-quantified topics and issues, the possibility to observe the phenomenon in a completely natural and unchanged natural environment and the opportunity to integrate the qualitative and quantitative methods of data collection.

### 3.3. Population and Sampling

The population of interest comprised of thirty-eight companies from non-financial sectors listed in the Nairobi security exchange from 2005 to 2014 and those with major business operations in Kenya. This comprised of nine (9) companies that have faced financial distress in the period of consideration and due to the fact, the sample of financial distress companies is very small, these firms will be tested and included in the full sample and will be classified as financially distressed in that particular year when the company reported facing financial distress. For the non-distressed companies, a sample size of 75% of those firms that had not experienced any financial distress was considered for this study from the total 29 companies, only 22 were selected and in total the study sample size was thirty-one companies. The research focused on those companies whose financial statements were available for the period of interest.

### 3.4. Data Collection Methods

The study used both primary and secondary data for non-financial listed firms. The primary data was from the questioner that was accessing what other models are being used to determine financial distress or lack of financial distress in the non-financial listed firms. The questionnaires were distributed to the NSE listed non-financial companies credit or risk officers. The primary data was intended to help the research get first hand information on what other financial prediction model are used in the market.

Secondary data used was as per each model ratio for instance for Altman model; working capital, total assets, retained earnings, earnings before interest tax, book/market value of equity, total liabilities and book value of total liabilities. The secondary data was obtained from the financial statements of the listed non-financial sector, which are archived at the capital market authority library and the company's website.

The research study involved document analysis, this especially analysis of the financial reports by calculating financial ratios as per the different financial distress models. The ratios when weighted in the Z formula gives the overall Z score that were compared to the discrimination sector zones.

### 3.4.1 Validity

Validity is the degree by which the sample of test items represents the content the test is designed to measure. Content validity which was employed by this study is a measure of the degree to which data collected using a particular instrument represented a specific domain or content of a particular concept. Mugenda and Mugenda (1999) contend that the usual procedure in assessing the content validity of a measure is to use a professional or expert in a particular field. Expert opinion was requested from the study supervisor to comment on the representativeness and suitability of questions. The supervisor gave suggestions of corrections to be made to the structure of the questionnaire. This helped to improve the content validity of the data that was collected.

### 3.4.2 Reliability

Reliability refers to the consistency of measurement and is assessed using the test retest reliability method. Reliability is increased by including many similar items on a measure, by testing a diverse sample of individuals and by using uniform testing procedures. The researcher also computed a Cronbach alpha score of the instrument used to obtain the primary data. Cronbach alpha ranges between 0-1. Scores between 0-0.6 indicate that the instrument has a low reliability while scores of 0.7 and above indicate that the instrument has a high level of internal consistency and reliability (Cooper & Schindler, 2003). The study score was above 0.7 therefore surpassing the required threshold.

## 3.5. Data Analysis

### 3.5.1. Secondary Data Analysis

**Altman Model**

The study applied Altman emerging market model to determine the Z-score value. Companies were first divided into two; Nine financial distressed and twenty-two non-distressed companies. These were further subdivided into different sector as per NSE classifications which includes; agricultural, automobile and accessories, commercial & services, construction & allied, energy and petroleum, manufacturing & allied.

The Z-score value was thereafter calculated using the emerging market model as below;

$$Z = 3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$$

Where;

X1 = Working Capital / Total Assets.

X2 = Retained Earnings / Total Assets.

X3 = Earnings before Interest and Taxes / Total Assets.

X4 = Book Value of Equity / Total Liabilities.

From the research findings, the study further used zone of discrimination to classify the firms in the below zones;

Zone 1; Z > 2.60 -"Safe" Zones

Zone 2; 1.10 < Z < 2.60 -"Grey" Zones

Zone 3; Z < 1.10 -"Distress" Zones

All conclusions were based on the overall Z score and not the value of each individual ratio.

From the zone discrimination and the findings, companies in each sector were then classified as either in Safe Zone (Non-financial distressed), Grey zone (Not-distressed and not safe) and Distress zone (for any distressed company).

For companies classified as financial distress and using the Altman's Z-score the financial distress was not observed for the 2 year period, this was defined as a Type II error. Companies classified as non-distress from the zone of discrimination and there was financial distress observed by the model, this was defined as a Type I error as per below table;

**Table 3.1 Error Matrix**

| **1 & 2 Years prediction** | Classified as non-financial distressed | Classified as financial distressed |
|---|---|---|
| Financial distress Not observed by the model | ✓ | **X** **Type II error** |
| Financial distress was observed by the model | **X** **Type I error** | ✓ |

**Ohlson's O-score Model (1980)**

For Ohlson, the following formula was used;

O-Score = -1.32 – 0.407*AS + 6.03*LM – 1.43*WCM + 0.757*ICR – 2.37*ROA – 1.83*FTDR -1.72*DCLM + 0.285*DCRA – 0.521*CINI

Probability of Failure = P = exp (O-score)/1+exp (O-score)

Where

Adjusted Size: Ohlson measures a company's size as its total assets adjusted for inflation. Smaller companies are deemed to be more at risk of failure.

AS = log (Total assets/GNP price-level index)

Where GNP price-level index = (Nominal GNP/Real GNP)*100

Leverage Measure: Designed to capture the indebtedness of a company, the more leveraged the more at risk the company is to shocks.

LM = Total liabilities/Total assets

Working Capital Measure: Even if a company is endowed with assets and profitability, it must have sufficient liquidity to service short-term debt and upcoming operational expenses to avoid going bust.

WCM = Working capital/Total Assets

Inverse Current Ratio: This is another measure of a company's liquidity.

ICR = Current liabilities/Current assets

Discontinuity Correction for Leverage Measure: Dummy variable equaling one if total liabilities exceed total assets, zero otherwise. Negative book value in a corporation is a very special case and hence Ohlson felt the extreme leverage position needed to be corrected through this additional variable.

Return on Assets: An indicator of how profitable a company is, assumed to be negative for a close to default company.

ROA = Net income/Total Assets

Funds to Debt Ratio: A measure of a company's ability to finance its debt using its operational income alone, a conservative ratio because it does not include other sources of cash. If the ratio of funds from operations to short-term debt is less than one the company may have an immediate problem

FTDR = Funds from operations/Total liabilities

Where Funds from operations = pretax income + depreciation

Discontinuity Correction for Return on Assets: Dummy variable equaling one if income was negative for the last two years, zero otherwise.

Change in Net Income: Designed to take into account any potential progressive losses over the two most recent periods in a company's history.

CINI = (Net income (t) - Net income (t-1)) / (Net income (t) + Net income (t-1))

The O-score is transformed into a probability using a logistic transformation whereby $P>0.5$ indicates an at-risk company and $P<0.5$ a safe one.

A study in 2007 from Marquette University asserts a rather spectacular success rate of 96% in both the 1 and 2-year prediction time frames.

**Zmiejewski (1984) Model**

The following formulae was used for the Zmiejewski model

Zmijewski = - 4.3 - 4.5X1 + 5.7X2 + .004X3

Where;

X1 = Net income / Total assets

X2 = Total liabilities / Total assets

X3 = Current assets / Current liabilities

**Shumway (2001) Model**

Financial Distress $_{it}$ =

$$= \left\{ 1 + \exp\left( - \begin{bmatrix} \alpha + \beta_1 NITL_{it} + \beta_2 TLTA_{it} + \beta_3 \text{RESIZE}_{it} \\ + \beta_4 LEXRETURN_{it-1} \\ + \beta_5 LAGSIGMA_{it-1} + \varepsilon_{it} \end{bmatrix} \right) \right\}^{-1}$$

Where

RESIZE; Log (the number of outstanding shares multiplied by year-end share price then divided by total market value).

LEXRETURN: Cumulative annual return in year t-1 minus the value-weighted NSE index return in year t-1.

LAGSIGMA: Standard deviation of the residual derived from regressing monthly stock return on market return in year t-1.

**Combined Model**

The study further developed a combined model as shown below;

Financial Distress $_{it}$ =

$$= \left\{ 1 + \exp\left( - \left[ \begin{array}{l} \alpha + \beta_1 X2_{it} + \beta_2 X_{3it} \\ + \beta_3 OENEG_{it} + \beta_4 INTWO_{it} \\ + \beta_5 NITL_{it} + \beta_6 CACL_{it} + \varepsilon_{it-1} \end{array} \right] \right) \right\}^{-1}$$

Where, all the variables are defined in the previous models, this model was expected to have more predictive power than any other model.

**3.5.2. Primary Data Analysis**

The main information required from the questionnaires was to answer the second research question on what other models are Kenya's non-financial companies using to predict financial distress. This was the summarized from the questionnaires that had been feedback by different companies.

**3.5.3 Inferential Statistics**

Logistic Regression model was used to establish the relationship between the independent variables and the dependent variable (Financial distress) and the strength upon which the independent variables affect the dependent variable. The study used logistic regression equation. All equations were different based on the different models used.

For the Altman the following model was developed

The linear predictor function $f(i)$ for a particular data point *i* is written as:

$$f(i) = \beta_0 + \beta_1 x_{1,i} + \cdots + \beta_m x_{m,i},$$

Where $\beta_0, \ldots, \beta_m$ are regression coefficients indicating the relative effect of a particular explanatory variable on the outcome.

The model is usually put into a more compact form as follows: The regression coefficients $\beta_0$, $\beta_1$, ..., $\beta_m$ are grouped into a single vector $\boldsymbol{\beta}$ of size $m + 1$. For each data point $i$, an additional explanatory pseudo-variable $x_{0,i}$ is added, with a fixed value of 1, corresponding to the intercept coefficient $\beta_0$.

For Ohlson, the following model was used;

O-score = -1.32 – 0.407*AS + 6.03*LM – 1.43*WCM + 0.757*ICR – 2.37*ROA – 1.83*FTDR -1.72*DCLM + 0.285*DCRA – 0.521*CINI

Zmiejewski (1984) Model used the following model to test the strength of each independent variable. Zmijewski = - 4.3 - 4.5X1 + 5.7X2 + .004X3
Where;
X1 = Net income / Total assets

X2 = Total liabilities / Total assets

X3 = Current assets / Current liabilities

Shumway (2001) Model was as follow

Financial Distress $_{it}$ =

$$= \left\{ 1 + \exp\left( - \begin{bmatrix} \alpha + \beta_1 NITL_{it} + \beta_2 TLTA_{it} + \beta_3 \text{RESIZE}_{it} \\ + \beta_4 LEXRETURN_{it-1} \\ + \beta_5 LAGSIGMA_{it-1} + \varepsilon_{it} \end{bmatrix} \right) \right\}^{-1}$$

Finally the combined predictor model used was;

Financial Distress $_{it}$ =

$$= \left\{ 1 + \exp\left( - \left[ \begin{array}{l} \alpha + \beta_1 X2_{it} + \beta_2 X_{3it} \\ + \beta_3 OENEG_{it} + \beta_4 INTWO_{it} \\ + \beta_5 NITL_{it} + \beta_6 CACL_{it} + \varepsilon_{it-1} \end{array} \right] \right) \right\}^{-1}$$

### 3.6. Ethical Consideration

There were some ethical consideration on this study, some of which included; Reliability of financial reports where companies are thought to have several different books of accounts. This is likely to be a challenge to the research as was not easy to pick this from financial reports. Primary data collection from the questionnaire, where the parties involved might assume that this research is meant to determine their financial health, thus likely to give incorrect information. Confidentiality from most companies which still see some financial details as very confidential and had the fear that this kind of research would bring those particulars to the public.

# CHAPTER FOUR: DATA ANALYSIS AND INTERPRETATION

## 4.1 Introduction

This chapter presents the research findings compare Financial Distress Prediction Models used in Listed Non-Financial Sector in Kenya. Secondary Data was collected from the Capital Market Authorities, Nairobi security Exchange and company websites. The primary data was from questionnaires that were distributed to NSE non-financial company's risk, credit or finance staff.

## 4.2 Background of Information

The researcher targeted firms listed in the Nairobi Security Exchange from 2005 to 2014 and studied whether the model would predict financial distress (or not) 2 and 1 years before the distress. Firms used were from six (6) Commerce and Service Sector, five (5) Agricultural, four (4) Automobile & Accessories, three (3) constructions & Allied, four (4) energy and petroleum and nine from manufacturing & Allied sector. The study targeted nine firms that had experienced financial distress within this period and twenty-two firms that were operating normally. The distressed firms included Kenya Airways, Uchumi Supermarket, Mumias Sugar Company, Express Group, Sameer Group Africa, A Baumann, CMC, Marshalls East Africa and Eveready East Africa.

For the financial distressed firms, the study picked one (1) year before the distress (this reporting year or the t-1) and 2 years before the distress is disclosed (t-2). Since the study used the CMA 10 Year market survey report for period of 2005 to 2014, for the non-distressed firms, the study used the latest available financial report till end of 2014 exceptional cases, used financial report for period ending March of 2015.

The emerging market Z-score model and its zone of discrimination was then used to classify the firms in the below zones;

a. Zone 1; $Z > 2.60$ -"Safe" Zones

b. Zone 2; $1.10 < Z < 2.60$ -"Gray" Zones

c. Zone 3; $Z < 1.10$ -"Distress" Zones

All conclusions were based on the overall Z score and not the value of each individual ratio.

### 4.3 Applicability of Altman's financial distress model

The first objective of the study was to test the applicability of Altman's financial distress model to Kenyan non-financial sectors. This section is categorised into two sections. The first section analyses the applicability of the model to the distressed firms followed by the non-distressed firms.

### 4.4 Financially Distressed Firms

These are the companies that were facing extreme liquidity problems (Altman, 2000). These companies lacked enough resources to service debts, pay for creditors or maintain their operation costs. The company disclosed this kind of information in their annual financial results.

#### 4.4.1 Commercial and Services Sector

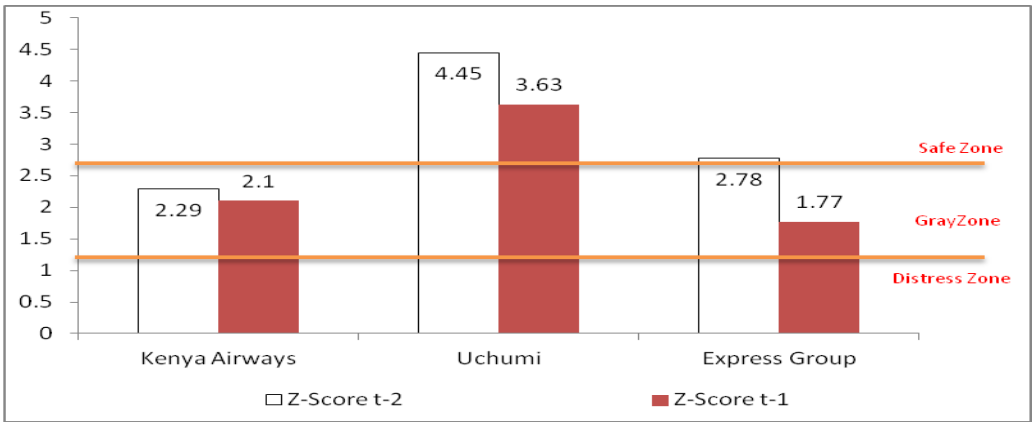


**Figure 4.1 Commercial and Service Sector**

Where;

t-2 is 2 years before company is financial distress

t-1 is 1 year before company is financial distress

From the graph above, a Z-score above 2.6 from the Altman's discrimination zone means the firms are on safe zone, a Z score between 1.1 to 2.6 shows that the firm's was in a 'gray' zone, this mean, there is chance for the company to be either move to distress or

correct the situation and move to the safe zone. From the study, we see Kenya airways and Express Kenya were in some period at the gray zones, this means the Altman' model was able to detect likely financial distresses in those companies.

As at end of 2014 financial year, Kenya Airways disclosed its increased debt to KES 89 billion and the cash flow shortages that had lend to delayed creditor's payment and in the Kenya parliamentary select committee on inquiry of KQ operation, the financial consultant stated that the company did not have enough money to purchase more aircrafts and maintain its operations.

This research study found that the Z scores values for Kenya Airways was 4.7 in 2012, 2.3 in 2013, and 2.1 in 2014. From the Altman's model zone of discrimination above 2.60 was considered as a safe zone for year 2012 while a range between 1.10 and 2.60 was 'Gray' zone. This same period Kenya Airways was experiencing financial distress.

Uchumi supermarket is one of Kenyan's supermarket chain, founded in year 1975 as a public limited liability company. Uchumi supermarket shares were listed in Nairobi stock exchange in 1992. The company was put under receivership in year 2006, due to financial distress that resulted to inability to pay its debts obligations. Uchumi later in 2011 returned to the NSE, but has been facing financial difficulties to settle its due debts and pay supplier including as late as 2014. The Z score value for Uchumi supermarket in 2011 was 5.46, 2012 at 4.48 and 2013 4.45 with 2014 of 3.63, the company's Z scores was above 2.60 meaning that it was in the safe Zones. In 2014, Uchumi financial statements and auditors indicated the company inability to meet its financial obligations including payment of its suppliers and in mid-2015; the company closed all its branches in Tanzania and Uganda citing unprofitability. This shows that the Altman's emerging market model was not able to predict such a financial distress in the company even for three years prior.

For the year ending 2014, Express Group reported a more than 55% decline in revenue, moved from profitability to net loss of KES 77 Million, net cash flow of KES -84Million with retained cash of KES -50 Million. Express Group was a financial distressed firm,

but the Z score from Altman's model shows this company was in 'Gray' zone in year 2012, safe zone in 2013 and again 'Gray' zone in year 2014.

### 4.4.2 Manufacturing and Allied Companies

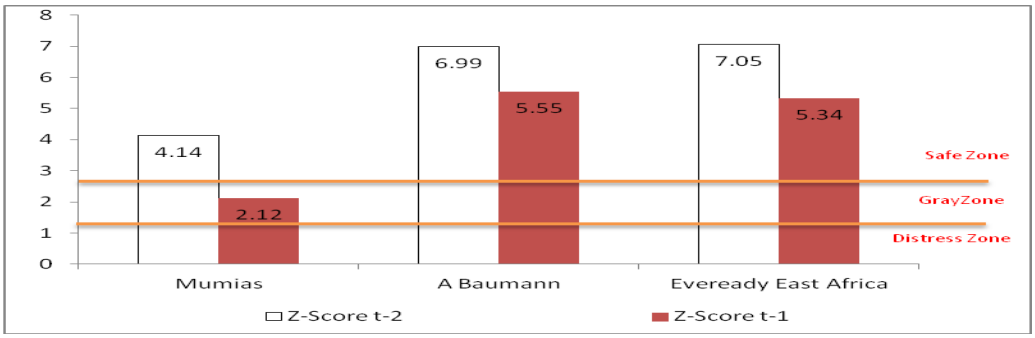


**Figure 4.2 Manufacturing and Allied Companies**

Where;

t-2 is 2 years before company is financial distress

t-1 is 1 year before company is financial distress

Mumias Sugar reported red flag in its cash position at the end 2014. The company closed the year with a loss of KES 2.7 billion and negative cash of KES 1.3 billion. This was mainly from poor business performance ranging from sugar cane poaching, cheap sugar smuggling. The same period, the company issued a statement that it was unable to pay its sugar cane farmers and asked for government financial support to ensure its survival. From the Z score model, we see year 2014, the company is classified in the 'gray" zone, this indication that the model was able to detect a likely financial distress for this company, thus the model was applicable for that period.

In year 2007, A Baumann was facing financial distress to settle its obligations, same year the company disclosed a revenue decline of over 24% and the external auditors issued an opinion "emphasis of matter" on several fixed assets that were sold at a loss. From the calculations done above the, company was found to have a Z score of 6.7 in 2005, 6.99 in 2006 and 5.55 in 2007. According to the Z scores above the company was in the safe zones for three years consecutively. In the year 2007, financial auditors stated cases where the company sold some of its properties like lands at a loose in order to improve its

cash flow positions. This company was later delisted due to poor liquidity positions. On the contrary, Altman's emerging market model classifies A Baumann ltd as a safe company, therefore not applicable in this case.

In the 2014 Financial report, Eveready East Africa had never paid shareholders divided since listing in 2006 due to poor financial results, the company has had declined revenue over the period as they claim stiff competition from cheap product and in year 2014, the firm closed with net loss of KES 177 Million, Negative operating cash of KES -146 Million with retained cash of KES -285 Million. This eventually led to company closure of its core business (Battery manufacture-accoutered for 60% of its revenue). Using Altman's Z score model, the score was above 2.60 meaning that the company was in a safe zone for the 3-year period before company closure.

### 4.4.3 Automobiles and Accessories

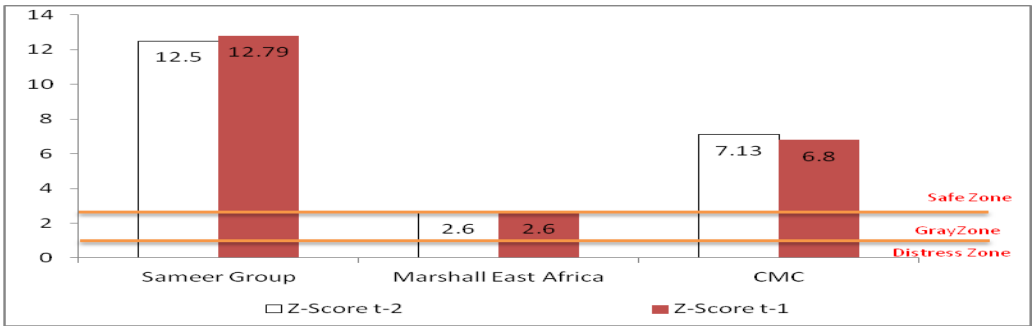


**Figure 4.3 Automobiles and Accessories**

Where;

t-2 is 2 years before company is financial distress

t-1 is 1 year before company is financial distress

Sameer group Africa Z scores fall between 12.50 and 12.79. According to Altman's model if a Z score falls within this range the firm is considered to be in a safe zone. Sameer Group is therefore considered to be operating in the safe zones. Thus, Altman's model was inappropriate to predict the financial distress of Sameer Group.

Marshalls East Africa was one of the financial distressed firm as at year ended 2014, with company declined revenue, closing the year at a KES 2Million loss and Net cash from operations of KES -26 Million. Using Altman's model, the results shows that the firm was in gray zone for the three years to 2014.This shows that the Altman's model showed a likely distress being experienced in the company, thus the model was applicable to predict financial ditress.

CMC financial distress was brought to the limelight from the year 2010 when it reported decline in profit and negative retained cash of KES 1.3 Billion, with negative operating cash of KES 302 Million in 2010, while 2009 was negative KES 1.25 Billion. In the following year (2011), CMC disclosed huge amount of funds that had not been recorded including KES 255 Million believed to be banked in offshore accounts by the former chairman. The financial distress went on for the year that followed till the company was deregistered in the NSE. CMC Motor had a Z score of 7.13 in 2009 and 6.80 in 2010. According to the Altmans model a Z score greater than 2.6 was considered to be in safe zone. CMC was one of the distressed companies in Nairobi Security exchange in 2010. From the results Altman's model was not applicable to predict financial distress. This shows that this model was in appropriate to predict company financial distress.

**Table 4.1: Findings Summary (financial distressed classification)**

| | | **TRUE** | **FALSE** |
|---|---|---|---|
| **Decision** | **1 & 2 Year prediction** | Classified as non-financial distressed | Classified as financially distressed |
| Fail to Reject | Financial distress Not observed by the model | | **54% Type II error** |
| Reject | Financial distress was observed by the model | **Type I error** | 44% |

From the study, Altman's model was able to correctly classify four out of the nine companies classified as financial distress (44%), these were the firms classified in the

"gray" zone, an indication that they were experiencing some financial distress and were likely to move to safe zone or distress zone. There was a Type II error I the study, an indication that 54% of the companies were misclassified in the safe zone while they were experiencing financial distress.

### 4.5 Non-financially Distressed Firms

These were companies that did not have any liquidity problem in the period of 2005 to 2014. The financial reports did not disclose anything that was alarming to indicate any liquidity problems or business losses.

#### 4.5.1 Commercial and Services

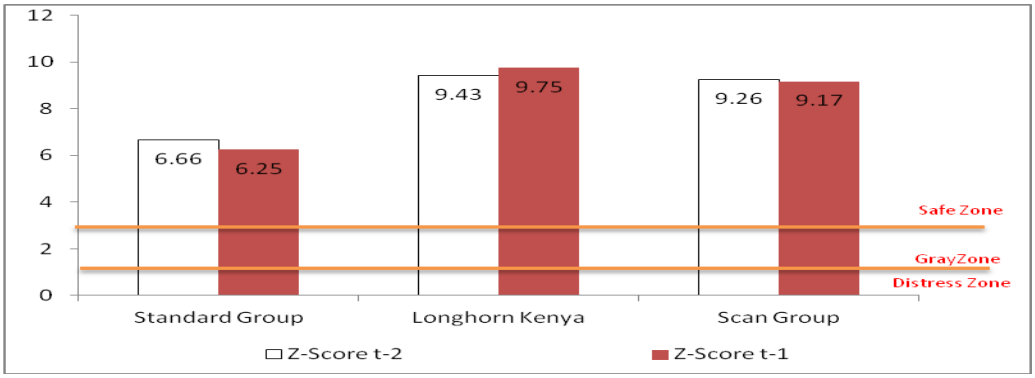


**Figure 4.4 Commercial and Services**

The study found that standard group Z score falls within a range of between 5.72 and 6.65 from year 2010 to year 2014. According to Altman's model if a Z score falls within this range the firm is considered to be in a safe zone. This shows that the Altman's emerging market model was able to predict the non-distress of this company as at end 2014. Longhorn Kenya also was in the safe zones for year 2013 and 2014 with Z scores of 9.43 and 9.74. These results prove the applicability of Altman's business failure prediction model since Longhorn Kenya was classified as a non-distressed firm.

Scan group Z score values were in year 2008 9.26 and in 2009 the Z score value was 9.17. From the Altman's model, any firm with a Z score value above 2.60 is classified as being in a safe zone. This clearly indicates that in the two years analyzed, Scan Group had been in a safe zone. The findings show that the EACL Z scores values for year 2012

was 7.79, 6.14 in 2013 and 5.20 in 2014. This proves the applicability of Altman's financial distress prediction model.

### 4.5.2 Automobiles and Accessories

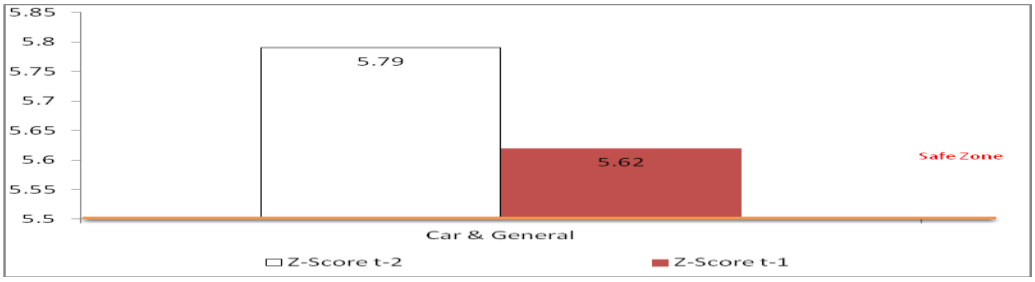


**Figure 4.5 Automobiles and Accessories**

From the findings, Car and General Z score values were varying from 5.61 to 6.65. This indicates that Car and General was in a safe zone in the years 2010 to 2013.This proves the applicability of Altman's prediction model.

### 4.5.3 Agricultural

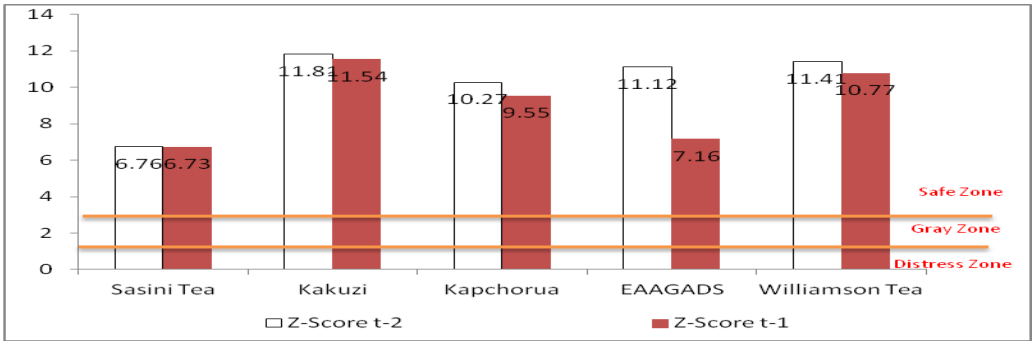


**Figure 4.6 Agricultural**

Where;

t-2 is 2 years before company is financial distress

t-1 is 1 year before company is financial distress

This study revealed that Sasini Tea Limited was in safe zone in the years 2012, 2013 and 2014. These results prove the applicability of Altman's prediction model since Sasini Tea was classified as a non-distressed firm in the same period. Kakuzi Z score values were year 2012 12.60, in 2013 11.81 and in 2014 the Z score was 11.54. From the Altman's

model, any firm with a Z score value above 2.60 is classified as being in a safe zone. This clearly indicates that in the three years analyzed, Kakuzi was in a safe zone.

Kapchorua was in a safe zone in both year 2014 and 2015 with Z scores of 10.27 and 9.54 respectively. This proves the applicability of Altman's prediction model in predicting business financial distress. The study found that EAAGAD, Z score falls within a range of between 7.15 and 11.12 for the year 2012 and year 2013. According to Altman's model if a Z score falls within this range the firm is considered to be in a safe zone. The Z scores in Williamson Tea were 11.4 in 2014 and 10.76 in 2015. Williamson Tea is therefore considered to be operating in the safe zones.

### 4.5.4 Construction and Allied

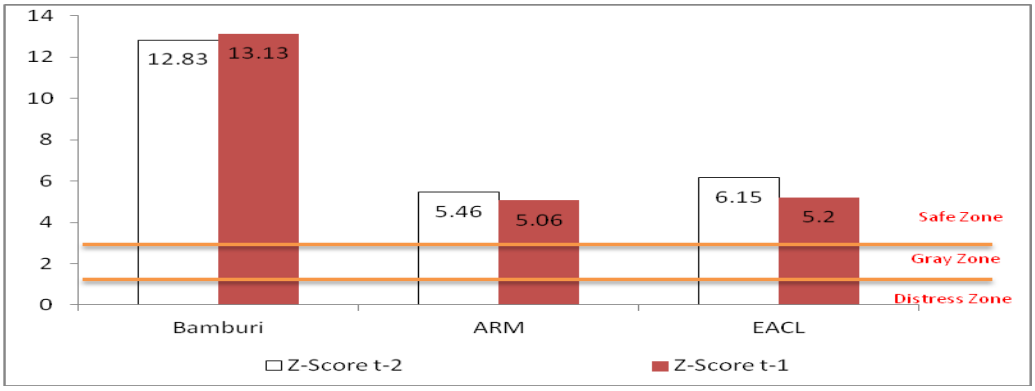


**Figure 4.7 Construction and Allied**

Bamburi is classified as one of the non-distressed companies. In the years 2011 to 2014 the firm's Z score values were in the range of between 9.90 and 13.12. This indicates that Bamburi was in a safe zone. Thus, Altman's model was right in this prediction. The Z score values for ARM were; 5.25 in 2010, 4.74 in 2011, 5.45 in 2012 and 5.06 in 2013. All Z score values for 2010, 2011, 2012 and 2013 indicate that the company was in a safe zone. This was also seen in EACL which had all period Z score above 2.6. In summary, for the construction and Allied sector, Altman model was able to correctly classify the companies in their right zone, thus the model is applicable to predict financial distress (or lack of) of the firms.

### 4.5.5 Manufacturing and Allied sector

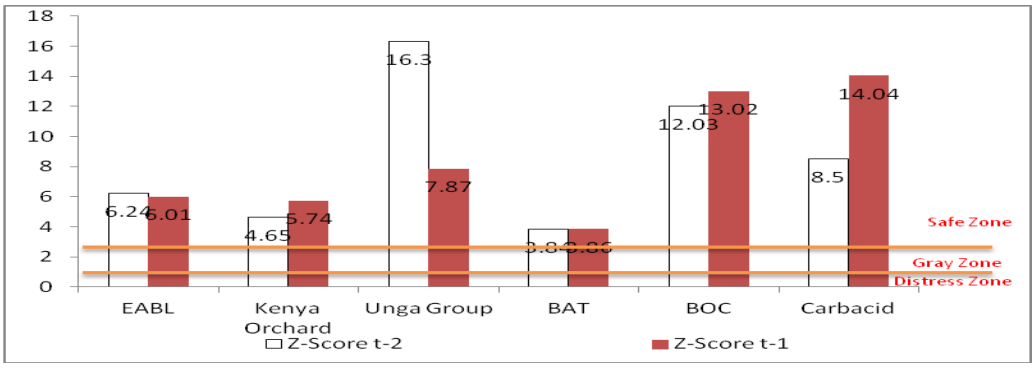


**Figure 4.8 Manufacturing and Allied sector**

EABL was in a safe zone in the years 2013 and 2014 as per the Z-score calculation. This means that Altman's model was applicable to predict non-distress of this company. The study found that Kenya Orchards Z score fall within a range of between 4.34 and 5.73 from 2011 to 2014. According to Altman's model if a Z score falls within this range the firm is considered to be in a safe zone. In this case, the model was applicable to predict non-financial distress of Kenya Orchard.

Unga Limited is classified as one of the non-financial distressed. In the years 2012 to 2014 the firm's Z score values were in the range of between 7.86 and 16.96. This indicates that Unga Limited was in a safe zone. This proves the applicability of Altman's business prediction model. From the findings BAT registered Z score of between 3.83 and 4.25 from 2013 to 2015. The company had Z scores were greater than 2.60, the company in the safe zone. These results prove the applicability of Altman's models since BAT was classified as a non-distressed firm over the period.

BOC had a Z score of 13.04 in 2003, 12.03 in 2004 and 13.02 in 2005. From these results Both BOC was in a safe zone. This research established that Carbacid had Z scores of 8.83 in 2003, 8.50 in 2004 and 14.03 in 2005. This result shows that Carbacid was in the safe zone. This indicates that Altman's model is applicable to predict the financial non-distress of the company.

### 4.5.6 Energy and Petroleum

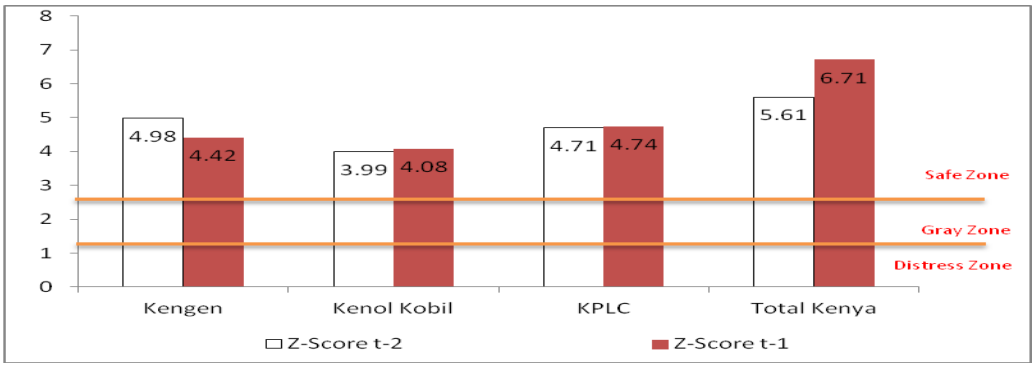


**Figure 4.9 Energy and Petroleum**

This study revealed that Kengen was in safe zone in the years 2013 and 2014. This was a correct classification from the model. In all the years, Z value was above 2.60 putting the firm in a safe zone. For Kenol Kobil the company registered Z score above 2.60 an indication that the company was in a safe zone. These results prove the applicability of Altman's model. KPLC, Z score values of 2009, 2010 and 2011 indicate that the firm was in a safe zone which means that the model is applicable to predict non-financial distressed firm. From the findings, Total Kenya score values were varying from 5.32 to 6.70. This indicates that Total Kenya was in a safe zone in the years 2012, 2013 and 2014. This proves the applicability of Altman's emerging market prediction model in predicting business failure.

**Table 4.2: Findings Summary**

| | | **TRUE** | **FALSE** |
|---|---|---|---|
| **Decision** | **1 & 2 Year prediction** | Classified as non-financial distressed | Classified as financially distressed |
| Fail to Reject | Financial distress Not observed by the model | 71% | **16% Type II error** |
| Reject | Financial distress was observed by the model | 0 (0%) **Type I error** | 13% |

From the thirty-one companies, companies that were used to evaluate the applicability of the Altman's emerging market model, 84% of the companies were correctly classified (71% being classified as non financial distress and the model was able to observe this while 13% classified as distress and the model was able to show this). The study observed a Type II error; the Altman's model had failed to show financial distress of 16% of the companies that were facing financial distress.

### 4.6. Models used to Determine Financial Distress in Kenya Non-Financial Sector

The second objective was to determine other models used to predict financial distress in Kenya non-financial sector. This was done by collecting primary data from Kenya non-financial sector executives and mainly those in risk management department. It was done through a guided questionnaire seeking to identify whether Kenyan companies predict financial distress, and if they do, what models they are using.

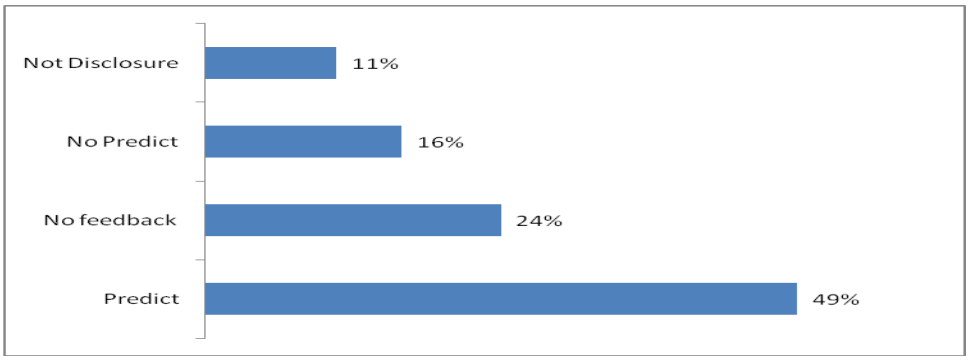


**Figure 4.10 Questionnaire Feedbacks on Organizations**

A total of 37 questionnaires were distributed, with a response rate of 76%. The study revealed that 49% of the companies do predict presence or absence of a financial distress while 16% of the companies do not predict, 11% of the companies did not disclose about this as they thought it was sensitive information.

44% of the companies that predict financial distress (or lack of distress) used the Probability of Default model (PD) and the Loss given Default (LGD), while 54% of the companies use their own calculations including basic excel calculations. These companies further explained that though they had their internal customized models, they were made from a combination of several other models.

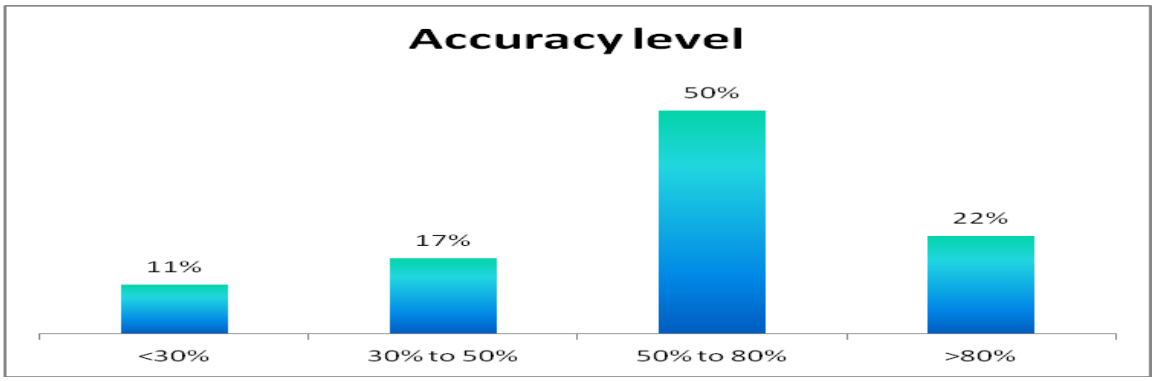


**Figure 4.11: Accuracy of Other Financial Distress Model Used**

22% of the companies that predicted financial distress said that their model is above 80% accurate in predicting the distress 1 or 2 years before a distress, 50% of the companies had 50% to 80% accuracy rate, 17% of these companies were between 30% to 50% accuracy rate, while 11% were below 30%.

100% of the companies said that financial distress prediction is done on annual basis. 20% of the companies use Altman's model to predict financial distress, but together with their in-house models and incase the two model's conflicts, they take results of their in-house models. 80% of the companies do not use Altman's emerging market model, but about 50% agreed that some of the ratios used in their in-house models were derived from Altman's emerging market model. These companies said that Altman's emerging market model has left out some key considerations like, human manipulation of financial figures, does not take into account one off events like bad debts write off and does not take into account the qualitative aspects of the firms like company strategic plans.

### 4.7. Inferential Statistics

The regression model for the study is presented in the table below. The model shows the extent to which each individual variable influences the dependent variable. Each model has its unique independent variables which are elaborated in the following equations. The study further gives a combined model from the other four models.

#### 4.7.1. Emerging market score model

$Z = 3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$.

Where;

X1 = Working Capital / Total Assets.

X2 = Retained Earnings / Total Assets.

X3 = Earnings before Interest and Taxes / Total Assets.

X4 = Book Value of Equity / Total Liabilities.

**4.7.2. Ohlson's O-score Model (1980)**

O-score = -1.32 – 0.407*AS + 6.03*LM – 1.43*WCM + 0.757*ICR – 2.37*ROA – 1.83*FTDR -1.72*DCLM + 0.285*DCRA – 0.521*CINI

Probability of Failure = P = exp (O-score)/1+exp (O-score)

Where

Adjusted Size: Ohlson measures a company's size as its total assets adjusted for inflation. Smaller companies are deemed to be more at risk of failure.

AS = log (Total assets/GNP price-level index)

Where GNP price-level index = (Nominal GNP/Real GNP)*100

Leverage Measure: Designed to capture the indebtedness of a company, the more leveraged the more at risk the company is to shocks.

LM = Total liabilities/Total assets

Working Capital Measure: Even if a company is endowed with assets and profitability, it must have sufficient liquidity to service short-term debt and upcoming operational expenses to avoid going bust.

WCM = Working capital/Total Assets

Inverse Current Ratio: This is another measure of a company's liquidity.

ICR = Current liabilities/Current assets

Discontinuity Correction for Leverage Measure: Dummy variable equaling one if total liabilities exceeds total assets, zero otherwise. Negative book value in a corporation is a very special case and hence Ohlson felt the extreme leverage position needed to be corrected through this additional variable.

Return on Assets: An indicator of how profitable a company is, assumed to be negative for a close to default company.

ROA = Net income/Total Assets

Funds to Debt Ratio: A measure of a company's ability to finance its debt using its operational income alone, a conservative ratio because it does not include other sources of cash. If the ratio of funds from operations to short-term debt is less than one the company may have an immediate problem.

FTDR = Funds from operations/Total liabilities

Where Funds from operations = pretax income + depreciation

Discontinuity Correction for Return on Assets: Dummy variable equaling one if income was negative for the last two years, zero otherwise.

Change in Net Income: Designed to take into account any potential progressive losses over the two most recent periods in a company's history.

CINI = (Net income(t) - Net income(t-1)) / (Net income(t) + Net income(t-1))

The O-score is transformed into a probability using a logistic transformation whereby P>0.5 indicates an at risk company and P<0.5 a safe one.

A study in 2007 from Marquette University asserts a rather spectacular success rate of 96% in both the 1 and 2 year prediction time frames.

### 4.7.3. Zmiejewski (1984) Model

Zmijewski = - 4.3 - 4.5X1 + 5.7X2 + .004X3

Where;

X1 = Net income / Total assets

X2 = Total liabilities / Total assets

X3 = Current assets / Current liabilities

**4.7.4. Shumway (2001) Model**

Financial Distress $_{it}$ =

$$= \left\{ 1 + \exp\left( - \begin{bmatrix} \alpha + \beta_1 NITL_{it} + \beta_2 TLTA_{it} + \beta_3 \text{RESIZE}_{it} \\ + \beta_4 LEXRETURN_{it-1} \\ + \beta_5 LAGSIGMA_{it-1} + \varepsilon_{it} \end{bmatrix} \right) \right\}^{-1}$$

Where

RESIZE; Log (the number of outstanding shares multiplied by year-end share price then divided by total market value).

LEXRETURN: Cumulative annual return in year t-1 minus the value-weighted NSE index return in year t-1.

LAGSIGMA: Standard deviation of the residual derived from regressing monthly stock return on market return in year t-1.

**4.7.5. Combined Model**

Financial Distress $_{it}$ =

$$= \left\{ 1 + \exp\left( - \begin{bmatrix} \alpha + \beta_1 X2_{it} + \beta_2 X_{3it} \\ + \beta_3 OENEG_{it} + \beta_4 INTWO_{it} \\ + \beta_5 NITL_{it} + \beta_6 CACL_{it} + \varepsilon_{it-1} \end{bmatrix} \right) \right\}^{-1}$$

Where, all the variables are defined in the previous models, this model was expected to have more predictive power than any other model.

**Table 4.3: Results of the Regression Model (from Stata)**

| **Results** | **Altman (2000) Model** | **Ohlson (1980) Model** | **Zmiejewski (1984) Model** | **Shumway (2001) Model** | **Combined Model** | P>\|t\| P-value |
|---|---|---|---|---|---|---|
| **Intercept** | 0.18 | -12.87 | -8.00 | -16.94 | -2.22 | 0.035 |
| $X_1$ | -0.21 | | | | -0.76 | 0.016 |
| $X_2$ | -0.33 | | | | -9.87 | 0.03 |
| $X_3$ | -0.54 | | | | | 0.04 |
| $X_4$ | 0.03 | | | | | 0.00 |
| OLSIZE | | -0.14 | | | | 0.00* |
| TLTA | | 16.23 | 13.43 | 18.54 | | 0.07 |
| WCTA | | -3.45 | | | | 0.08 |
| CLCA | | -0.43 | | | | 0.00* |
| OENEG | | -0.21 | | | 1.32 | 0.004 |
| NITA | | -2.43 | | | | 0.00* |
| FUTL | | -3.64 | | | | 0.048 |
| INTWO | | 5.43 | | | 0.55 | 0.00* |
| CHIN | | -0.43 | | | | 0.00 |
| NITL | | | -2.24 | -7.98 | -0.86 | 0.03 |
| CACL | | | -0.001 | | 0.02 | 0.00* |
| RESIZE | | | | 0.03 | | 0.007 |
| LEXRETURN | | | | -3.42 | | 0.00* |
| LAGSIGMA | | | | -0.43 | | 0.00* |

The estimation results of Altman (2000) model indicate that $X_1$ (-0.21), $X_2$ (-0.33) and $X_3$ (-0.54) have a negative and significant relationship with dependent variable (Financial distress) at the 1% significance level and $X_4$ (0.03) has a positive relation with dependent variable.

In the Ohlson (1980) model, TLTA (16.23) and the dummy variable of INTWO (5.43) are significant at the 1% level and in Zmiejewski (1984) model TLTA (13.43) and NITL (-2.43) are significant at the 1% level. The results of Shumway (2001) model indicates that TLTA (18.54) and NITL (-7.98) are significant. Finally, the combined model shows that X2 (-9.87) and OENG (1.32) are both significant at the 1% level.

**Table 4.4: Prediction Power Metrics**

| Results | Altman (2000) model | Ohlson (1980) model | Zmiejewski (1984) model | Shumway (2001) model | Combined model |
|---|---|---|---|---|---|
| Adjusted $R^2$ | 71.2 | 80.32 | 76.24 | 73.24 | 86.34 |
| F stat | 387.43 | 856.54 | 798.43 | 798.56 | 1243.32 |
| Voung Z | 15.14 | 6.02 | 10.1 | 13.1 | |

The results of likelihood ratio (LR) for Altman model (387.43), Ohlson model (856.54), Zemijewsky model (798.43), Shumway model (798.43) and the combined model is (1243.32) show that all models are significant at 1% level, generally. The In-sample prediction power (adjusted $R^2$) of the combined model (86.34%) is higher than that of Altman model (71.2%), Ohlson model (80.32%), Zemijewsky model (76.24%) and Shumway model (73.24%). The results of Voung (1989) test show that the differences between the prediction power of combined model and Altman model (15.14), Ohlson model (6.02), Zemijewsky model (10.1) and Shumway model (13.1) are all significant at the 1% level.

Thus, the results indicate that the prediction power of the combined model in predicting financial distress is higher than that of other previous models. Thus, logit type financial distress prediction model significantly outperforms other models.

### 4.8 Chapter Summary

This section compared Financial Distress Prediction Models used in Listed Non-Financial Sector in Kenya. Altman's financial distress prediction model in the emerging market is found to be appropriate in financial prediction of non-financial firms quoted at Nairobi Securities Exchange. Further it was revealed that most of the firms have developed an inhouse model which they use to predict financial distress and it's done annually in most cases. The section also outlined other models and their predictive power with final result showing that a combined model would be better in predicting financial distress.

# CHAPTER FIVE: SUMMARY, CONCLUSION AND RECOMMENDATIONS

## 5.1 Introduction

This chapter presents a summary of the key findings of the study as well as the conclusions and recommendations for further research. The general objective was to compare Financial Distress Prediction Models used in Listed Non-Financial Sector in Kenya.

## 5.2 Summary of the Findings

### 5.2.1 Test Level of Applicability of Models used to Determine Financial Distress in

This paper compares the applicability of bankruptcy prediction models namely Altman (1968), Ohlson (1980) and Zmijewski (1984) and Shumway model on Listed Non-Financial Sector in Kenya. Overall, the results show clearly that Ohlson (1980) logit model performed most accurate; meaning that the selected financial ratios of the Ohlson model (1980) is most accurate in predicting bankruptcy likelihood. As expected by common literature, the bankruptcy prediction models perform highly different in their accuracy rate.

As observed in common literature, e.g. Grice (2001) and Grice & Ingram (2003) the accuracy rate of the Altman model (1968) declines during the investigation period. In more depth, Hay et al. (2010) studied the Altman model (1968) and came to the conclusion that although Altman´s model (1968) is a reliable method for bankruptcy prediction, Altman´s model (1968) is sensitive to small companies and industries. Grice (2001), Agarwal (2008) and Hays et al. (2001) therefore suggest that this problem can be overcome by re- estimating the coefficients of the models using a sample of firms approximated the proportion of distressed and non- distressed companies in the population (Grice, 2001).

Moreover, the findings on the on Listed Non-Financial Sector in Kenya suggest that the models perform less accurate than of the combined model which has and an adjusted $R^2$ of 86.32%.

### 5.2.2 To find out other Models Used to Predict Financial Distress in Kenya Non-Financial Sector

The study shows that Kenya companies in the non-financial sector do use Altman's emerging market model in predicting financial distress especially in combination with other models. This was consistent with the inferential statistics that showed that a combination of four models produced a better prediction capability than using a single model. Further most of the firms have developed an inhouse model which they use to predict financial distress and it's done annually.

The common three models used by companies included the Probability of default (PD) model, the loss given default (LGD) and the Exposure at Default (EAD). Probability of default model is used in a variety of credit analysis and risk management framework. PD is generally associated with financial characteristics such as inadequate cash flow to service debt, declining revenue, declining profit margins, high leverage, marginalized liquidity, and inability to implement a business plan. It is closely linked to expected loss which is related to the contractual terms between parties. The risk of default is derived by analyzing the obligor's capacity to repay the debts in accordance with contractual terms.

Exposure at default is a parameter used in calculating the economic capital for companies. It is the gross exposure under a facility upon a default of an obligor. EAD is an estimation of the extent to which a company may be exposed to counterparty in the event of, and at time of default.

### 5.2.3. To compare Altman (1968), Ohlson (1980), Zmijewski (1984) and Shumway (2001) financial distress models.

**Table; 5.1; Adjusted $R^2$ results**

| Results | Altman (2000) model | Ohlson (1980) model | Zmiejewski (1984) model | Shumway (2001) model | Combined model |
|---|---|---|---|---|---|
| Adjusted $R^2$ | 71.2 | 80.32 | 76.24 | 73.24 | 86.34 |

The study found out that when compared to other models like the O-score model, Zmiejewsky, Shumway model and a combination of these entire four models, Altman's had the least prediction score of 71.2%. It was found that a combination of the four models would be more applicable to predict financial distress with 86.34% capability.

### 5.3 Conclusion

From the above findings, this study can authoritatively have concluded that firms are more likely to experience bankruptcy if they have relatively lower earnings before interest and tax to total assets, a larger decline in net income, relatively low working capital to total assets, or high total liabilities to total assets. After comparing the empirical performance of a range of bankruptcy prediction models using a series sample performance metrics. Across all of these metrics, this study concludes that the combined model significantly outperforms models from the extant literature.

The study further concludes that organizations have developed their internal models to detect financial distress which have been created as combinations of several other models, including Altman's model. From the inferential statistics, it was found out that a combination of many models had a better prediction power of about 86% compared to single model used to predict.

### 5.4 Recommendations

The study recommend that a combination of models could be used to predict financial distress of firms that are faced with the distress, this should take into account such things as data smoothing from management, one off financial event like write off and the non-financial factors likely to affect the financial performance of the companies.

From the findings of this research, the study recommends that Kenya market regulators like Capital market authority and Central bank should explore avenues to create models that can be used to predict financial distress of companies and by so doing; they can easily monitor and ensure stability of the economy. This could assist the regulator to create some awareness of a likely financial distress of a firm and early intervention would be implemented. The regulator would also be able to create Policies that can be applicable in detecting a financial distress.

The research identifies the need for a better model for investors to predict a financial distress or non-financial distress in a firm. This will enable the investor to increase their return on capital for their investments as they are likely to hold stocks in companies that are not experiencing financial difficulties. Investors will also be able to know when to buy new stock or even to sell depending on the results of the predicting models.

The creditors also need to know the credit worthiness of a company, from the research, we find that Altman's model can be used to give this prediction and that better models need to be created especially a combination of several models. With a model to predict financial distress, the creditors will be able to make judgment whether to lend more to their customers.

This research study shows that Altman's model is 71.20% applicable to determine financial distress of the NSE listed non-financial sector, this creates a gap for academicians and scholars to find out which other models can be more applicable to predict a financial distress, to what extent the model can predict such distress and what causes the 30% prediction gap. The study recommends that studies should be done on how to eliminate the type II errors.

### 5.5 Limitations of the Study

The study used an accounting based models, accounting-based models is doubtful since they present accounting information that include past performance. This numbers may be subject to manipulation by management and conservatism and historical cost accounting may cause that the true asset values may be very different from the recorded book values (Agarwal & Taffler, 2008). Furthermore, they state that many accounting-based bankruptcy prediction models are too sample specific, which results a lack of generalization power.

The findings are limited as the sample size used here is small as per the NSE listed non-financial company in Kenya. The variable could probably change if a large sample is used. When analyzing financial statements in any depth it is necessary to compute a good number of ratios, but relatively few are really significant and not all of these ratios are

independent in the sense that they could not be logically derived from other ratios without reference to the original figures.

Qualitative aspects such as the company's strategy, age of the firm and quality of management need to be considered in the interpretation of the result. As Beaver et al. (2005,) state; market-based variables can be measured with "a finer partition of time". Furthermore Agarwal & Taffler (2008) state that market-based variables "provide a sound theoretical model for firm financial distress; in efficient markets, stock process will reflect all information contained in accounting statements and will also contain information not in the accounting statements; market variables are unlikely to be influenced by firm accounting policies; market prices reflect future expected cash flows, and hence should be more appropriate for prediction purposes; the output of such models is not time or sample dependent".

This study cannot escape the defects and drawbacks that are inherent in every human endeavor. This included financial constraints and challenges.

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APPENDICES

## A. Z-score calculation & financial report extracts

### Kenya Airways

| Amount in Kenya shillings "M" | KQ 2012 | KQ 2013 | KQ 2014 |
|---|---|---|---|
| Working Capital | -1923 | -22233 | -34120 |
| Total Assets | 77432 | 122670 | 148657 |
| Retained Earnings | 21298 | 13441 | 10070 |
| Earnings before Interest and Taxes | 3487 | -8919 | -2437 |
| Book Value of Equity | 23023 | 31209 | 28186 |
| Total Liability | 54409 | 91461 | 120428 |
| Working Capital / Total Assets X1 * 6.56 | -0.02 | -0.18 | -0.23 |
| Retained Earnings / Total Assets X2 * 3.26 | 0.28 | 0.11 | 0.07 |
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | 0.05 | -0.07 | -0.02 |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 0.42 | 0.34 | 0.23 |
| Constant | 3.25 | 3.25 | 3.25 |
| Z Value | 4.73 | 2.29 | 2.10 |

### Uchumi Supermarket

| Amount in Kenya shillings "M" | Uchumi 2011 | Uchumi 2012 | Uchumi 2013 | Uchumi 2014 |
|---|---|---|---|---|
| Working Capital | -145 | -610 | -723 | -1450 |
| Total Assets | 4005 | 4942 | 5574 | 6919 |
| Retained Earnings | 952 | 1331 | 1598 | 2010 |
| Earnings before Interest and Taxes | 515 | 403 | 486 | 433 |
| Book Value of Equity | 1327 | 1327 | 1327 | 1327 |
| Total Liability | 1726 | 2284 | 2648 | 3582 |
| Working Capital / Total Assets X1 * 6.56 | -0.04 | -0.12 | -0.13 | -0.21 |

| | | | | |
|---|---|---|---|---|
| Retained Earnings / Total Assets X2 * 3.26 | 0.24 | 0.27 | 0.29 | 0.29 |
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | 0.13 | 0.08 | 0.09 | 0.06 |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 0.77 | 0.58 | 0.50 | 0.37 |
| Constant | 3.25 | 3.25 | 3.25 | 3.25 |
| Z Value | 5.46 | 4.48 | 4.45 | 3.63 |

**Mumias Sugar Company**

| Amount in Kenya shillings "M" | Mumias 2012 | Mumias 2013 | Mumias 2014 |
|---|---|---|---|
| Working capital | 1451 | -1360 | -6282 |
| Total assets | 27400 | 27148 | 23563 |
| Retained Earnings | 9312 | 7055 | 4510 |
| Earnings before Interest and Taxes | 1494 | -2567 | -3067 |
| Book Value of Equity | 15723 | 13288 | 10641 |
| Total Liability | 11675 | 13858 | 12921 |
| Working Capital / Total Assets X1 * 6.56 | 0.05 | -0.05 | -0.27 |
| Retained Earnings / Total Assets X2 * 3.26 | 0.34 | 0.26 | 0.19 |
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | 0.05 | -0.09 | -0.13 |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 1.35 | 0.96 | 0.82 |
| Constant | 3.25 | 3.25 | 3.25 |
| Z Value | 6.49 | 4.14 | 2.12 |

**A Baumann**

| Amount in Kenya shillings "M" | A Baumann ( 2005) | A Baumann ( 2006) | A Baumann ( 2007) |
|---|---|---|---|
| working capital | 55 | 39 | 38 |
| total assets | 188 | 155 | 138 |
| retained Earnings | 127 | 85 | 49 |
| Earnings before Interest and Taxes | -121 | -42 | -35 |
| Book Value of Equity | 147 | 104 | 68 |
| Total Liability | 42 | 51 | 69 |
| Working Capital / Total Assets X1 * 6.56 | 0.29 | 0.25 | 0.28 |
| Retained Earnings / Total Assets X2 * 3.26 | 0.67 | 0.55 | 0.36 |
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | -0.64 | -0.27 | -0.26 |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 3.48 | 2.05 | 0.99 |
| Constant | 3.25 | 3.25 | 3.25 |
| Z Value | 6.70 | 6.99 | 5.55 |

**Eveready East Africa**

| Amount in Kenya shillings "M" | Eveready 2012 | Eveready 2013 | Eveready 2014 |
|---|---|---|---|
| Working capital | 181 | 239 | 191 |
| Total assets | 1144 | 941 | 930 |
| Retained Earnings | 139 | 185 | 7 |
| Earnings before Interest and Taxes | 68 | 102 | 55 |
| Book Value of Equity | 349 | 396 | 218 |
| Total Liability | 795 | 546 | 712 |

| | | | |
|---|---|---|---|
| Working Capital / Total Assets X1 * 6.56 | 0.16 | 0.25 | 0.21 |
| Retained Earnings / Total Assets X2 * 3.26 | 0.12 | 0.20 | 0.01 |
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | 0.06 | 0.11 | 0.06 |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 0.44 | 0.73 | 0.31 |
| Constant | 3.25 | 3.25 | 3.25 |
| Z Value | 5.54 | 7.05 | 5.34 |

**Express Group**

| Amount in Kenya shillings "M" | Express Group 2012 | Express Group 2013 | Express Group 2014 |
|---|---|---|---|
| Working Capital | -98 | -58 | -52 |
| Total Assets | 496 | 481 | 478 |
| Retained Earnings | -76 | -74 | -77 |
| Earnings before Interest and Taxes | 17 | 6 | -62 |
| Book Value of Equity | 198 | 199 | 180 |
| Total Liability | 297 | 282 | 298 |
| Working Capital / Total Assets X1 * 6.56 | -0.2 | -0.12 | -0.11 |
| Retained Earnings / Total Assets X2 * 3.26 | -0.15 | -0.15 | -0.16 |
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | 0.03 | 0.01 | -0.13 |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 0.67 | 0.7 | 0.61 |
| Constant | 3.25 | 3.25 | 3.25 |
| Z Value | 2.38 | 2.78 | 1.77 |

**Sameer Group Africa**

| Amount in Kenya shillings "M" | Sameer Group Africa 2011 | Sameer Group Africa 2012 |
|---|---|---|
| Working Capital | 1523 | 1725 |
| Total Assets | 2371 | 2459 |
| Retained Earnings | 1392 | 1392 |
| Earnings before Interest and Taxes | 148 | 301 |
| Book Value of Equity | 2250 | 2327 |
| Total Liability | 875 | 1073 |
| Working Capital / Total Assets X1 * 6.56 | 0.64 | 0.70 |
| Retained Earnings / Total Assets X2 * 3.26 | 0.59 | 0.57 |
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | 0.06 | 0.12 |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 2.57 | 2.17 |
| Constant | 3.25 | 3.25 |
| Z Value | 12.50 | 12.79 |

**Marshalls East Africa**

| Amount in Kenya shillings "M" | Marshalls East Africa 2012 | Marshalls East Africa 2013 | Marshalls East Africa 2014 |
|---|---|---|---|
| Working Capital | 23 | -73 | -124 |
| Total Assets | 567 | 515 | 604 |
| Retained Earnings | 166 | 59 | 61 |
| Earnings before Interest and Taxes | -166 | -110 | -2 |
| Book Value of Equity | 392 | 282 | 280 |
| Total Liability | 175 | 233 | 324 |
| Working Capital / Total Assets X1 * 6.56 | 0.04 | -0.14 | -0.21 |

| | | | |
|---|---|---|---|
| Retained Earnings / Total Assets X2 * 3.26 | 0.29 | 0.12 | 0.10 |
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | -0.19 | -0.19 | -0.08 |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 2.24 | 1.21 | 0.86 |
| Constant | 3.25 | 3.25 | 3.25 |
| Z Value | 5.56 | 2.66 | 2.61 |

**CMC**

| Amount in Kenya shillings "M" | CMC (2009) | CMC (2010) |
|---|---|---|
| working capital | 3327 | 3437 |
| total assets | 13294 | 14666 |
| retained Earnings | 4122 | 4342 |
| Earnings before Interest and Taxes | 1069 | 931 |
| Book Value of Equity | 5273 | 5455 |
| Total Liability | 8020 | 9212 |
| Working Capital / Total Assets X1 * 6.56 | 0.25 | 0.23 |
| Retained Earnings / Total Assets X2 * 3.26 | 0.31 | 0.30 |
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | 0.08 | 0.06 |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 0.66 | 0.59 |
| Constant | 3.25 | 3.25 |
| Z Value | 7.13 | 6.80 |

**Standard Group**

| Amount in Kenya shillings "M" | Standard group | Standard group | Standard group | Standard group | Standard group |
|---|---|---|---|---|---|

| | 2010 | 2011 | 2012 | 2013 | 2014 |
|---|---|---|---|---|---|
| Working Capital | 334 | 93 | 130 | 222 | 268 |
| Total Assets | 3306 | 3512 | 3502 | 4137 | 4102 |
| Retained Earnings | 814 | 996 | 1168 | 1365 | 1534 |
| Earnings before Interest and Taxes | 454 | 232 | 265 | 301 | 326 |
| Book Value of Equity | 1536 | 1654 | 1839 | 2028 | 2208 |
| Total Liability | 1770 | 1858 | 1663 | 2108 | 1894 |
| Working Capital / Total Assets X1 * 6.56 | 0.10 | 0.03 | 0.04 | 0.05 | 0.07 |
| Retained Earnings / Total Assets X2 * 3.26 | 0.25 | 0.28 | 0.33 | 0.33 | 0.37 |
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | 0.14 | 0.07 | 0.08 | 0.07 | 0.08 |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 0.87 | 0.89 | 1.11 | 0.96 | 1.17 |
| Constant | 3.25 | 3.25 | 3.25 | 3.25 | 3.25 |
| Z Value | 6.55 | 5.73 | 6.25 | 6.25 | 6.66 |

**Longhorn Kenya**

| Amount in Kenya shillings "M" | Longhorn Kenya 2013 | Longhorn Kenya 2014 |
|---|---|---|
| Working Capital | 185 | 236 |
| Total Assets | 685 | 748 |
| Retained Earnings | 330 | 378 |
| Earnings before Interest and Taxes | 151 | 147 |
| Book Value of Equity | 386 | 434 |
| Total Liability | 299 | 313 |
| Working Capital / Total Assets X1 * 6.56 | 0.27 | 0.32 |
| Retained Earnings / Total Assets X2 * 3.26 | 0.48 | 0.51 |

| | | |
|---|---|---|
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | 0.22 | 0.20 |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 1.29 | 1.39 |
| Constant | 3.25 | 3.25 |
| Z Value | 9.43 | 9.75 |

**Scan Group**

| Amount in Kenya shillings 'M' | Scan Group 2008 | Scan Group 2009 |
|---|---|---|
| Working Capital | 1903 | 1658 |
| Total Assets | 3774 | 3933 |
| Retained Earnings | 518 | 781 |
| Earnings before Interest and Taxes | 544 | 541 |
| Book Value of Equity | 2079 | 2366 |
| Total Liability | 1694 | 1567 |
| Working Capital / Total Assets X1 * 6.56 | 0.50 | 0.42 |
| Retained Earnings / Total Assets X2 * 3.26 | 0.14 | 0.20 |
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | 0.14 | 0.14 |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 1.23 | 1.51 |
| Constant | 3.25 | 3.25 |
| Z Value | 9.26 | 9.17 |

**EACL**

| Amount in Kenya shillings 'M' | EACL 2012 | EACL 2013 | EACL 2014 |
|---|---|---|---|
| Working Capital | 499 | 837 | 553 |
| Total Assets | 6249 | 6809 | 7889 |
| Retained Earnings | 1289 | 1382 | 926 |
| Earnings before Interest and Taxes | 945 | 762 | 507 |

| | | | |
|---|---|---|---|
| Book Value of Equity | 2323 | 2412 | 3092 |
| Total Liability | 1045 | 3743 | 4798 |
| Working Capital / Total Assets X1 * 6.56 | 0.08 | 0.12 | 0.07 |
| Retained Earnings / Total Assets X2 * 3.26 | 0.21 | 0.20 | 0.12 |
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | 0.15 | 0.11 | 0.06 |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 2.22 | 0.64 | 0.64 |
| Constant | 3.25 | 3.25 | 3.25 |
| Z Value | 7.80 | 6.15 | 5.20 |

**Car and General**

| Amount in Kenya shillings "M" | Car and General 2010 | Car and General 2011 | Car and General 2012 | Car and General 2013 |
|---|---|---|---|---|
| Working Capital | 639 | 383 | 469 | 422 |
| Total Assets | 3871 | 5562 | 5705 | 6901 |
| Retained Earnings | 1240 | 1431 | 1666 | 1949 |
| Earnings before Interest and Taxes | 329 | 428 | 355 | 459 |
| Book Value of Equity | 1556 | 1920 | 2143 | 2504 |
| Total Liability | 2315 | 3642 | 3562 | 4397 |
| Working Capital / Total Assets X1 * 6.56 | 0.16 | 0.07 | 0.08 | 0.06 |
| Retained Earnings / Total Assets X2 * 3.26 | 0.32 | 0.26 | 0.29 | 0.28 |
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | 0.09 | 0.08 | 0.06 | 0.07 |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 0.67 | 0.53 | 0.60 | 0.57 |
| Constant | 3.25 | 3.25 | 3.25 | 3.25 |
| Z Value | 6.65 | 5.61 | 5.79 | 5.62 |

**Sasini Tea**

| Amount in Kenya shillings "M" | Sasini Tea 2012 | Sasini Tea 2013 | Sasini Tea 2014 |
|---|---|---|---|
| Working Capital | 524 | 564 | 710 |
| Total Assets | 8923 | 9054 | 14930 |
| Retained Earnings | 1240 | 1309 | 1428 |
| Earnings before Interest and Taxes | -85 | 158 | 62 |
| Book Value of Equity | 6427 | 6383 | 12121 |
| Total Liability | 2496 | 2671 | 2809 |
| Working Capital / Total Assets X1 * 6.56 | 0.06 | 0.06 | 0.05 |
| Retained Earnings / Total Assets X2 * 3.26 | 0.14 | 0.14 | 0.10 |
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | -0.01 | 0.02 | 0.00 |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 2.57 | 2.39 | 4.32 |
| Constant | 3.25 | 3.25 | 3.25 |
| Z Value | 6.73 | 6.76 | 8.43 |

**Kakuzi**

| Amount in Kenya shillings 'M' | Kakuzi 2012 | Kakuzi 2013 | Kakuzi 2014 |
|---|---|---|---|
| Working Capital | 1091 | 1023 | 1004 |
| Total Assets | 3426 | 3570 | 3680 |
| Retained Earnings | 2631 | 2723 | 2809 |
| Earnings before Interest and Taxes | 479 | 239 | 233 |
| Book Value of Equity | 2801 | 2904 | 2985 |
| Total Liability | 770 | 814 | 873 |
| Working Capital / Total Assets X1 * 6.56 | 0.32 | 0.29 | 0.27 |
| Retained Earnings / Total Assets X2 * 3.26 | 0.77 | 0.76 | 0.76 |
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | 0.14 | 0.07 | 0.06 |

| | | | |
|---|---|---|---|
| Book Value of Equity / Total Liabilities X4 * 1.05 | 3.64 | 3.57 | 3.42 |
| Constant | 3.25 | 3.25 | 3.25 |
| Z Value | 12.60 | 11.81 | 11.54 |

**Kapchorua**

| Amount in Kenya shillings 'M' | Kapchorua 2014 (March) | Kapchorua 2015 (March) |
|---|---|---|
| Working Capital | 500 | 530 |
| Total Assets | 1929 | 1983 |
| Retained Earnings | 1210 | 1183 |
| Earnings before Interest and Taxes | 182 | -30 |
| Book Value of Equity | 1381 | 1428 |
| Total Liability | 548 | 556 |
| Working Capital / Total Assets X1 * 6.56 | 0.26 | 0.27 |
| Retained Earnings / Total Assets X2 * 3.26 | 0.63 | 0.60 |
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | 0.09 | -0.01 |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 2.52 | 2.57 |
| Constant | 3.25 | 3.25 |
| Z Value | 10.27 | 9.55 |

**EAAGADS**

| Amount in Kenya shillings 'M' | EAAGADS 2012 | EAAGADS 2013 |
|---|---|---|
| Working Capital | 80 | 12 |
| Total Assets | 573 | 500 |
| Retained Earnings | 181 | 83 |
| Earnings before Interest and Taxes | 36 | -83 |

| | | |
|---|---|---|
| Book Value of Equity | 481 | 402 |
| Total Liability | 92 | 97 |
| Working Capital / Total Assets X1 * 6.56 | 0.14 | 0.02 |
| Retained Earnings / Total Assets X2 * 3.26 | 0.32 | 0.17 |
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | 0.06 | -0.17 |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 5.24 | 4.13 |
| Constant | 3.25 | 3.25 |
| Z Value | 11.12 | 7.16 |

**Williamson Tea**

| Amount in Kenya shillings 'M' | Williamson Tea 2014 (March) | Williamson Tea 2015 (March) |
|---|---|---|
| Working Capital | 2397 | 2429 |
| Total Assets | 8539 | 8559 |
| Retained Earnings | 5682 | 5519 |
| Earnings before Interest and Taxes | 794 | 70 |
| Book Value of Equity | 6581 | 6583 |
| Total Liability | 1959 | 1976 |
| Working Capital / Total Assets X1 * 6.56 | 0.28 | 0.28 |
| Retained Earnings / Total Assets X2 * 3.26 | 0.67 | 0.64 |
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | 0.09 | 0.01 |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 3.36 | 3.33 |
| Constant | 3.25 | 3.25 |
| Z Value | 11.41 | 10.77 |

**Bamburi**

| Amount in Kenya shillings "M" | Bambu | Bambu | Bambu | Bambu |
|---|---|---|---|---|

| | ri 2011 | ri 2012 | ri 2013 | ri 2014 |
|---|---|---|---|---|
| Working Capital | 8259 | 9451 | 1180 | 992 |
| Total Assets | 33502 | 43038 | 37035 | 34082 |
| Retained Earnings | 17983 | 18875 | 27115 | 24913 |
| Earnings before Interest and Taxes | 8466 | 7176 | 5516 | 5801 |
| Book Value of Equity | 24174 | 30861 | 31510 | 29119 |
| Total Liability | 9328 | 12177 | 5525 | 4963 |
| Working Capital / Total Assets X1 * 6.56 | 0.25 | 0.22 | 0.03 | 0.03 |
| Retained Earnings / Total Assets X2 * 3.26 | 0.54 | 0.44 | 0.73 | 0.73 |
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | 0.25 | 0.17 | 0.15 | 0.17 |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 2.59 | 2.53 | 5.70 | 5.87 |
| Constant | 3.25 | 3.25 | 3.25 | 3.25 |
| Z Value | 11.03 | 9.90 | 12.83 | 13.13 |

**ARM**

| Amount in Kenya shillings 'M' | ARM 2010 | ARM 2011 | ARM 2012 | ARM 2013 |
|---|---|---|---|---|
| Working Capital | 1034 | -697 | 1434 | -398 |
| Total Assets | 16565 | 20516 | 20450 | 22459 |
| Retained Earnings | 2782 | 3828 | 4946 | 6428 |
| Earnings before Interest and Taxes | 1113 | 1363 | 1790 | 2000 |
| Book Value of Equity | 5087 | 6078 | 7014 | 8124 |
| Total Liability | 9005 | 9637 | 19833 | 21482 |
| Working Capital / Total Assets X1 * 6.56 | 0.06 | -0.03 | 0.07 | -0.02 |
| Retained Earnings / Total Assets X2 * 3.26 | 0.17 | 0.19 | 0.24 | 0.29 |
| Earnings before Interest and Taxes / Total Assets X3 * | 0.07 | 0.07 | 0.09 | 0.09 |

| | | | | |
|---|---|---|---|---|
| 6.72 | | | | |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 0.56 | 0.63 | 0.35 | 0.38 |
| Constant | 3.25 | 3.25 | 3.25 | 3.25 |
| Z Value | 5.25 | 4.74 | 5.46 | 5.06 |

**EABL**

| Amount in Kenya shillings 'M' | EABL 2013 | EABL 2014 |
|---|---|---|
| Working Capital | -8014 | -7653 |
| Total Assets | 31114 | 35405 |
| Retained Earnings | 20352 | 22502 |
| Earnings before Interest and Taxes | 11115 | 10407 |
| Book Value of Equity | 6522 | 6859 |
| Total Liability | 50122 | 53765 |
| Working Capital / Total Assets X1 * 6.56 | -0.26 | -0.22 |
| Retained Earnings / Total Assets X2 * 3.26 | 0.65 | 0.64 |
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | 0.36 | 0.29 |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 0.13 | 0.13 |
| Constant | 3.25 | 3.25 |
| Z Value | 6.24 | 6.01 |

**Kenya Ochards**

| Amount in Kenya shillings 'M' | Kenya Orchards 2011 | Kenya Orchards 2012 | Kenya Orchards 2013 | Kenya Orchards 2014 |
|---|---|---|---|---|
| Working Capital | 8 | 9 | 11 | 13 |
| Total Assets | 56 | 56 | 59 | 34 |

| | | | | |
|---|---|---|---|---|
| Retained Earnings | 1 | 1 | 1 | 0 |
| Earnings before Interest and Taxes | 1 | 1 | 1 | 1 |
| Book Value of Equity | 0 | 0 | 2 | -23 |
| Total Liability | 70 | 69 | 68 | 73 |
| Working Capital / Total Assets X1 * 6.56 | 0.14 | 0.16 | 0.19 | 0.38 |
| Retained Earnings / Total Assets X2 * 3.26 | 0.01 | 0.01 | 0.01 | 0.01 |
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | 0.02 | 0.01 | 0.02 | 0.04 |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 0.00 | 0.00 | 0.04 | -0.31 |
| Constant | 3.25 | 3.25 | 3.25 | 3.25 |
| Z Value | 4.34 | 4.45 | 4.65 | 5.74 |

**Unga Group Limited**

| Amount in Kenya shillings 'M' | Unga Limited 2012 | Unga Limited 2013 | Unga Limited 2014 |
|---|---|---|---|
| Working Capital | 2677 | 2669 | 2762 |
| Total Assets | 6410 | 8317 | 8027 |
| Retained Earnings | 1558 | 1724 | 1841 |
| Earnings before Interest and Taxes | 513 | 662 | 568 |
| Book Value of Equity | 1449 | 1444 | 4687 |
| Total Liability | 158 | 156 | 4327 |
| Working Capital / Total Assets X1 * 6.56 | 0.42 | 0.32 | 0.34 |
| Retained Earnings / Total Assets X2 * 3.26 | 0.24 | 0.21 | 0.23 |
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | 0.08 | 0.08 | 0.07 |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 9.18 | 9.27 | 1.08 |
| Constant | 3.25 | 3.25 | 3.25 |

| | | | |
|---|---|---|---|
| Z Value | 16.96 | 16.30 | 7.87 |

**BAT**

| Amount in Euros 'M' | BAT 2013 | BAT 2014 | BAT 2015 |
|---|---|---|---|
| Working Capital | 1082 | 363 | 808 |
| Total Assets | 26881 | 26167 | 31515 |
| Retained Earnings | 2398 | 1578 | 1754 |
| Earnings before Interest and Taxes | 355 | -458 | 263 |
| Book Value of Equity | 6935 | 5814 | 5032 |
| Total Liability | 19946 | 14583 | 26483 |
| Working Capital / Total Assets X1 * 6.56 | 0.04 | 0.01 | 0.03 |
| Retained Earnings / Total Assets X2 * 3.26 | 0.09 | 0.06 | 0.06 |
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | 0.01 | -0.02 | 0.01 |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 0.35 | 0.40 | 0.19 |
| Constant | 3.25 | 3.25 | 3.25 |
| Z Value | 4.26 | 3.84 | 3.86 |

**BOC**

| Amount in Kenya shillings "M" | BOC 2003 | BOC 2004 | BOC 2005 |
|---|---|---|---|
| working capital | 534 | 527 | 579 |
| total assets | 1341 | 1466 | 1613 |
| retained Earnings | 785 | 859 | 968 |
| Earnings before Interest and Taxes | 211 | 221 | 291 |
| Book Value of Equity | 1075 | 1153 | 1267 |
| Total Liability | 268 | 346 | 313 |

| | | | |
|---|---|---|---|
| Working Capital / Total Assets X1 * 6.56 | 0.40 | 0.36 | 0.36 |
| Retained Earnings / Total Assets X2 * 3.26 | 0.59 | 0.59 | 0.60 |
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | 0.16 | 0.15 | 0.18 |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 4.01 | 3.33 | 4.05 |
| Constant | 3.25 | 3.25 | 3.25 |
| Z Value | 13.04 | 12.03 | 13.02 |

**Carbacid**

| Amount in Kenya shillings | Carbacid 2003 | Carbacid 2004 | Carbacid 2005 |
|---|---|---|---|
| Working Capital | 161 | 225 | 344 |
| Total Assets | 599 | 2533 | 996 |
| Retained Earnings | 285 | 2157 | 476 |
| Earnings before Interest and Taxes | 126 | 597 | 580 |
| Book Value of Equity | 490 | 753 | 2477 |
| Total Liability | 599 | 2533 | 853 |
| Working Capital / Total Assets X1 * 6.56 | 0.27 | 0.09 | 0.35 |
| Retained Earnings / Total Assets X2 * 3.26 | 0.48 | 0.85 | 0.48 |
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | 0.21 | 0.24 | 0.58 |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 0.82 | 0.30 | 2.90 |
| Constant | 3.25 | 3.25 | 3.25 |
| Z Value | 8.83 | 8.50 | 14.04 |

**Kengen**

| Amount in Kenya shillings ‘M’ | Kengen | Kengen |
|---|---|---|

| | 2013 | 2014 |
|---|---|---|
| Working Capital | 7455 | 2434 |
| Total Assets | 188673 | 250206 |
| Retained Earnings | 37729 | 41071 |
| Earnings before Interest and Taxes | 4027 | 4158 |
| Book Value of Equity | 73959 | 76710 |
| Total Liability | 114715 | 173496 |
| Working Capital / Total Assets X1 * 6.56 | 0.04 | 0.01 |
| Retained Earnings / Total Assets X2 * 3.26 | 0.20 | 0.16 |
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | 0.02 | 0.02 |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 0.64 | 0.44 |
| Constant | 3.25 | 3.25 |
| Z Value | 4.98 | 4.42 |

**Kenol Kobil**

| Amount in Kenya shillings 'M' | Kenol Kobil 2011 | Kenol Kobil 2012 | Kenol Kobil 2013 | Kenol Kobil 2014 |
|---|---|---|---|---|
| Working Capital | 7352 | -800 | -1357 | -811 |
| Total Assets | 13180 | 32684 | 28122 | 23915 |
| Retained Earnings | 7144 | 5166 | 5166 | 2068 |
| Earnings before Interest and Taxes | 6716 | -6285 | 558 | 1091 |
| Book Value of Equity | 11650 | 6446 | 6666 | 7330 |
| Total Liability | 34324 | 26238 | 21455 | 16585 |
| Working Capital / Total Assets X1 * 6.56 | 0.56 | -0.02 | -0.05 | -0.03 |

| | | | | |
|---|---|---|---|---|
| Retained Earnings / Total Assets X2 * 3.26 | 0.54 | 0.16 | 0.18 | 0.09 |
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | 0.51 | -0.19 | 0.02 | 0.05 |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 0.34 | 0.25 | 0.31 | 0.44 |
| Constant | 3.25 | 3.25 | 3.25 | 3.25 |
| Z Value | 12.46 | 2.57 | 3.99 | 4.08 |

**KPLC**

| Amount in Kenya shillings 'M' | KPLC 2009 | KPLC 2010 | KPLC 2011 |
|---|---|---|---|
| Working Capital | -2998 | 1737 | 4780 |
| Total Assets | 70648 | 66179 | 89508 |
| Retained Earnings | 7643 | 3716 | 4220 |
| Earnings before Interest and Taxes | 4782 | 5633 | 6255 |
| Book Value of Equity | 26461 | 28741 | 39743 |
| Total Liability | 43800 | 56285 | 80136 |
| Working Capital / Total Assets X1 * 6.56 | -0.04 | 0.03 | 0.05 |
| Retained Earnings / Total Assets X2 * 3.26 | 0.11 | 0.06 | 0.05 |
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | 0.07 | 0.09 | 0.07 |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 0.60 | 0.51 | 0.50 |
| Constant | 3.25 | 3.25 | 3.25 |
| Z Value | 4.41 | 4.71 | 4.74 |

**Total Kenya**

| Amount in Kenya shillings 'M' | Total 2012 | Total 2013 | Total 2014 |
|---|---|---|---|
| Working Capital | 5374 | 6517 | 7286 |
| Total Assets | 32981 | 39984 | 32542 |

| | | | |
|---|---|---|---|
| Retained Earnings | 2250 | 3437 | 4483 |
| Earnings before Interest and Taxes | -64 | 2085 | 2276 |
| Book Value of Equity | 14193 | 15379 | 16425 |
| Total Liability | 18788 | 24605 | 16116 |
| Working Capital / Total Assets X1 * 6.56 | 0.16 | 0.16 | 0.22 |
| Retained Earnings / Total Assets X2 * 3.26 | 0.07 | 0.09 | 0.14 |
| Earnings before Interest and Taxes / Total Assets X3 * 6.72 | 0.00 | 0.05 | 0.07 |
| Book Value of Equity / Total Liabilities X4 * 1.05 | 0.76 | 0.63 | 1.02 |
| Constant | 3.25 | 3.25 | 3.25 |
| Z Value | 5.32 | 5.61 | 6.71 |

**B. Questionnaire**

**Company Details**

Company Name; ……

Physical Address of Company; ……

Company Sector of business; ……

**Respondent Details**

Respondent Name (optional); ……

Respondent position in the organization (optional); ……

Respondent years of experience in the organization; ……

Gender; Male ☐ Female ☐

**Questions – Financial distress of an organization**

1. Does your organization predict likely hood of financial distress happening?

   Yes ☐ ☐ prediction ☐

2. What are some of the tools your organization is using to predict financial distress?
    a. Altman – style model ☐
    b. Discriminant analysis ☐
    c. logistic regression decision trees ☐
    d. Soft computing methods known as artificial neural net ☐
    e. cumulative sum (CUSUM) procedures ☐
    f. survival analysis ☐
    g. Financial data analysis ☐
    h. Others ……. ☐
3. To what extent can the financial distress model used in your organization be used to predict any financial distress ( lack of a distress)
    a. Below 30% accuracy ☐
    b. Between 30% and 50% ☐
    c. Between 50% to 80% ☐
    d. Above 80% ☐
    e. Others score ☐
4. ……..……..……
……..……..……..……
……..……..……..…
……How often do you use these tools to predict financial distress?
    a. Annually…… ☐
    b. Monthly…… ☐
    c. Semi-annually…… ☐
    d. Other period (State) …… ☐
    e. Others …… ☐
5. Have you used "Altman Z score emerging market model" in predicting financial distress?

    Yes ☐ ☐

**If Yes;**

a. Up to what period did you use to predict a distress (or lack of it)?

i) Below 1 Year prior
ii) 1 – 2 Year prior
iii) 3 – 5 Years Prior
iv) Above 5 Years Prior
v) Other periods

b. How long have your organization used the model

a. Over 5 years……
b. 3 to 5 years……
c. 2 to 3 years……
d. 0 to 2 years ……
e. Others ……

c. To what percentage was the Altman's model able to predict

i) 100% prediction
ii) 70% – 100% prediction
iii) 50% - 70% prediction
iv) 30% - 50% 5 prediction
v) Below 30% prediction

**If No;**

d. Why have you not used this model to predict financial distress (or lack of distress)

a. Over 5 years……
b. 3 to 5 years……
c. 2 to 3 years……
d. 0 to 2 years ……

**C. Summary of questionnaire feedback**

| | | Yes | No | No | No | Tot |
|---|---|---|---|---|---|---|

| | | | | | | |
|---|---|---|---|---|---|---|
| | | | | disclosure | feedback | al |
| 1 | Does your organization predict financial distress | 18 (49%) | 6 (16%) | 4 (11%) | 9 (24%) | 37 |
| 2 | Tools used to predict financial distress | PD, LGD, In-house model | | | | |
| | | <30% | 30% to 50% | 50% to 80% | >80% | |
| 3 | Accuracy of the financial distress model used in your organization be used to predict any financial distress | 11% | 17% | 50% | 22% | 18 |
| 4 | How often do you use these tools to predict financial distress? | 100% Annually | | | | |
| 5 | Have you used "Altman Z score emerging market model" in predicting financial distress | 20% Yes, but alongside an in house model, 80% No | | | | |