BANKRUPTCY PREDICTION OF FIRMS LISTED AT THE NAIROBI SECURITIES EXCHANGE

BY

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D63/73046/2012

A RESEARCH PROJECT SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR THE AWARD OF THE DEGREE OF MASTER OF SCIENCE IN FINANCE, SCHOOL OF BUSINESS

UNIVERSITY OF NAIROBI

NOVEMBER 2013

DECLARATION

This project is my original work and has not been submitted for a degree to any other University.

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This research project has been presented for examination with my approval as the University Supervisor.

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DEDICATION

To my Dad and Mum, You are the best. To my adorable husband Issack Fish. You are my inspiration

ACKNOWLEDGEMENT

My greatest gratitude goes to the Almighty Allah whose Grace and Mercy has been abundant for me all through my entire MSc Finance course. I sincerely want to thank all those who stood by me during my entire studies and contributed in one way or another.

First, I would like to appreciate my dear husband for his constant support and love. This thesis would not have been possible unless I have had our warm family environment and his deep understanding. Issack, thank you for listening to me, bearing with me and encouraging me by your motivating words. I appreciate your patience when I was too busy with this course. You are a wonderful husband to help me become successful.

Secondly, I owe my deepest gratitude to Dr. Josiah Aduda for his valuable comments and useful suggestions. He has made available his support in a number of ways from the initial to the final level, enabling me to develop an understanding of the subject.

Thirdly, I would like to thank the team of CORDAID Foundation–Drought Emergency Assistance Department especially Mr. Najir Ahmed Khan and BroadReach Healthcare especially Philip Wambua, Ahmed Arale and Cassandra Blazer for their helpful advice and encouragement in the entire course.

Fourthly, it is an honour for me to thank my parents who have always been my biggest motivators and supporters in life.

Lastly to all my MSc Finance colleagues for their encouragement and for the ideas we shared from their experiences and backgrounds that made my studies a success

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LIST OF ABBREVIATIONS

ARM-	Athi River Mining
CBK-	Central Bank of Kenya
CMA-	Capital Markets Authority
EA-	East Africa Packaging
EAPCC-	East Africa Portland Company
EMH-	Efficient Market Hypothesis
LA-	Logit Analysis
MDA-	Multivariate Discriminant Analysis
NSE-	Nairobi Securities Exchange

ABSTRACT

Businesses are enterprises which produce goods or render services for profit motive. To be able to predict the financial soundness of a business has led to many research works. Financial ratios are a key indicator of financial soundness of a business. Financial ratios are a tool to determine the operational & financial efficiency of business undertakings. There exist a large number of ratios propounded by various authors. Altman developed a z-score model using ratios as its foundation. With the help of the Z- Score model, Altman could predict financial efficiency/bankruptcy up to 2-3 years in advance. The paper assesses the utility of statistical technique mostly termed as multiple discriminant analysis (MDA) in bankruptcy prediction of firms listed in Nairobi Stock Exchange in Kenya during the period of 2008 to 2012 and also delisted firms from NSE from the period of 1996 to 2012. The Capital Market Authority (CMA) has a regulatory responsibility to keep surveillance of firms listed in Nairobi Stock Exchange (NSE) with regards to capital, liquidity and other aspects with overall aim of ensuring financial stability of these firms. The expectation is therefore that the firms will be financially prudent and healthy which in turn will attract investors. There is therefore a need to critically assess the financial position of the listed firms and suggest ways of improving the performance of NSE. This study utilizes Altman's (1993) Z"-score multi discriminant financial analysis model which provides the framework for gauging the financial performance of the firms.

This is in addition to the use of the Statistical Package for Social Sciences software in support of the evidences from the Z-score model. The sample constituted selected firms listed in Nairobi Stock Exchange divided into five different sectors. The results of failed firms clearly stated that the model was intended for non-manufacturing firms since most of the failed firms that were classified in distress zone have scores of safe zone or grey zone. This is an indication that the model is not sufficient. Thus the study recommended that the NSE should make financial stability an integral driver of its policy framework.

CHAPTER ONE

INTRODUCTION

1.1Background of the Study

In the field of corporate finance any individual, firm or organization that establishes some form of relationship with a corporate entity (i.e. as an investor, creditor or stockholder) is interested on the performance and viability of the firm under consideration, an issue that is closely related to the analysis of business failure risk. Financial statements basically show the historical performance or record of the company at some previous point of time. By the time when financial statements are made public, changes are many economical areas such as market conditions, currency exchange rate and inflations can change the values of assets and liabilities. In this case there often exist discrepancies between book value of assets and their market values.

The information provided in the financial reports could be used for a number of purposes. One of the purposes would be to judge the performance of the entity. This is through comparison with other economic entities or with that of its past performance. Another would be to judge how well the directors and managers have governed the entity. This is in accordance to the second specific use of accounting information stated by Financial Accounting Standards Board (FASB).

"Financial reporting should provide information about the economic resources of an enterprise, the claims to those resources… and the effects of the transactions events and circumstances that change its resources and claims to those resources (FASB: 1978)

Management can also use accounting information to make various internal decisions though it is also important that managers have a lot more information available to them other than the one contained in the financial reports. Accounting information might also be used by investors to make investment decisions. Therefore accounting information has been used to predict corporate failure among other predictions.

The prediction of business failures or bankruptcy has for a long time caught the attention of managers, investors, stakeholders, scholars among many more. The failure of the business resulted in heavy losses to various stakeholders among them being; creditors, government, investment by shareholders, employees and general economic slowdown. These losses were costly and hence attracted a lot of research to be carried out. Most of the researches were concerned on how to avoid and eliminate the losses therein associated. When company is facing financial distress, book value of company liabilities can become worth more than the market value of the same liabilities. If this happen, then firm is in danger of not meeting its obligations to creditors. In this case creditors may not be paid and in worst of financial distressed time, the creditors may receive nothing in interest or principal, if the firm files for bankruptcy. Therefore this research will focus on the bankruptcy prediction of firms listed under the Nairobi Securities Exchange in Kenya. Detailed description of the topic is explained below.

1.1.1 Bankruptcy Prediction

O'Leary (2001) argues that Prediction of bankruptcy probably is one of the most important business decision-making problems. Affecting the entire life span of a business, failure results in a high cost from the collaborators (firms and organizations), the society, and the country's economy (Ahn, Cho, and Kim, 2000). Thus, the evaluation of business failure has emerged as a scientific field in which many academics and professionals have studied to find other optimal prediction models, depending on the specific interest or condition of the firms under examination.

Over the last 35 years, the topic of company failure prediction has developed to a major research domain in corporate finance. Academic researchers from all over the world have been developing a gigantic number of corporate failure prediction models, based on various types of modeling techniques. Besides the classic cross-sectional statistical methods, which have produced numerous failure prediction models, researchers have also been using several alternative methods for analyzing and predicting business failure. To date, a clear overview and discussion of the application of alternative methods in corporate failure prediction is still lacking.

Though one of the best-known models for predicting corporate financial distress is the Altman's Z-Score model (Altman, 1993). Altman's work has shown that the Z-Score and its variants have a very high degree of accuracy in predicting corporate financial distress in the U.S as well as in the emerging markets (Altman, Hatzell and Peck, 1995). The purpose of this study is to provide an out-of-sample test of the Z-Score model of 1993 and its variants by applying them to a sample of firms listed in the Nairobi Securities Exchange. The results provide us with evidence of the validity of a set of financial ratios, identified with reference to the Nairobi Securities Exchange listed firms, in predicting bankruptcies. The study covers 62 firms listed in the Nairobi Securities Exchange during the period 2008-2012.

1.1.2 Nairobi Securities Exchange

This study of bankruptcy prediction will be focusing on firms listed in Nairobi Securities Exchange. The NSE is regulated by the Capital Market Authority in Kenya. The interest in the area of bankruptcy prediction has increased due to considerable number of corporate failures around the globe in recent years especially since the early 1990s. The Nairobi Securities Exchange was constituted as *Nairobi Stock Exchange* in 1954 as a voluntary association of stockbrokers in the European community registered under the Societies Act.

In 1954 the Nairobi Stock Exchange was then constituted as a voluntary association of stockbrokers registered under the Societies Act. Since Africans and Asians were not permitted to trade in securities, until after the attainment of independence in 1963, the business of dealing in shares was confined to the resident European community. At the dawn of independence, stock market activity slumped, due to uncertainty about the future of independent Kenya. Therefore Nairobi Securities Exchange has been operating now for 59 years but failed to pick the growth momentum and currently the market has just 61 listed firms. Nairobi Securities Exchange has a responsibility to develop and regulate the market operations to ensure efficient trading. Therefore the companies listed under the Nairobi Securities Exchange are expected to be financially healthy so as to end business failures. While there are about 61 companies listed in NSE, not all are in a financially sound position. Although at the point of listing, these listed companies must meet the listing requirement of NSE, given time, the company's financial position and business direction can change for better or for worse. There are many reasons for these changes especially governance, management, financial appetite, or risk profile. Therefore surveillance in the market is necessary to ensure efficient trading hence economic growth of the country.

Notable failures include Global Crossing, Enron, Adelphia, WorldCom, HH Insurance, One Tel, and Ansert Airlines in 2001, and most recently FIN Corp in 2007. The predicting of financial distress is an early warning signal to keep investors from being in loss. It has been more than 70 years, since Ramser& Foster, and Fitzpatrick in 1931-1932, and 44 years, since Beaver (1966) but still they have not found the theory of financial distress. They were more statistical consideration then the intuitive models or fundamental causes of financial distress (Ooghe & Prijcker, 2007; Balcean & Ooghe, 2004). Since The Altman's model widely used among the investors, though it is not an intuitive model, once a firm is predicted having a financial distress next year, it has been treated as it has been financial distress currently, Whtaker (1999).Therefore significance of predicting bankruptcy has been on the rise due to its severe effects on firm's operations, its environment (management, credit institutions, stakeholders, investors, employees) and whole economy, Arnold (2007). Evidence show that the market value of distressed firms decline substantially, Warner (1977).

1.2Research Problem

Companies are often assumed to have a perpetual life while in reality companies fail and this infinite assumption collapses. This leads to heavy losses to all stakeholders. Therefore this raises concern to all on how to predict probable failure. Early sign of failure detection will minimize failure associated costs. For instance the shareholders could withdraw their investments, the consumer in the economy will look for alternative markets, and the executive management will make better refined strategies to curb upcoming failures while the suppliers will look for more stable firms to supply their items in order to maintain their supply chain. Therefore in order to predict bankruptcies each stakeholder seeks information through classical and non-classical failure prediction models. Some of the leading studies have also been summarized in the following paragraphs.

Beaver (1966) applies a business failure prediction based on financial ratios. Using a Univariate Discriminant Analysis, he categorizes 30 financial ratios into six groups, and then chooses one ratio from each group with lowest percentage error. He drives the ability of each ratio in failure prediction one at a time and concludes that the ratio analysis can be employed in the prediction of failures even five years prior to failure.

Altman (1968) argues that the traditional univariate analysis could be confusing in failure prediction, since a firm could be considered as failure, based on a specific financial ratio but a non-failure on the basis of another one. Altman (1968) in his studies titled, "Financial Ratios Discriminant Analysis and the prediction of corporate Bankruptcy" which was published in the journal of Finance advanced a Z-score MDA model. The MDA could predict occurrences of bankruptcy 94% and 72% correctly one year and two years respectively before its actual occurrence. His model emerged with the following ratios as the most significant as far as bankruptcy prediction was concerned: Working capital to total assets, Retained Earnings to total assets, Earnings before interest to total assets, Market value equity to book value of total debt and sales to total assets. In also another study on corporate failure, Altman and Mcough (1974) carried out an analysis of the relationship between bankrupt companies and auditors reports prior to bankruptcy. Their work resulted in the conclusion that Altman's model can signal going-concern problems earlier than the auditors' opinion in a company that eventually enters bankruptcy.

In Kenya, many studies have been done to establish the bankruptcy prediction of firms. Keige, (1991) researched on business failure prediction using discriminant analysis who argues that it is possible to predict failure with up to 90% accuracy two years before the event. Issack Mwangi, (1991) researched on prediction of corporate failure using price adjusted accounting data. He argues that the most critical ratios in the financial ratios were the liquidity and debt service ratios. Barasa, (2007) also researched on the evolution of prediction models from classical to non-classical failure prediction models where he stated that Kenyan [an East African country] history of bank failures is evidence that this is not a foreign problem, but a problem similarly experienced in and within its surrounding. The scenario depicts equally depressing trends in 1980s' and 1990s'1. Kenyan as an illustration of countries in the Eastern Africa recorded seventeen (17) bank failures since December 1984 up to September 2007 along with twenty four (24) financial institutions within the same period (CBK, Inspectorate Report, 2007).Therefore time has passed and there is the gap of incorporating the classical and non-classical with the current existing technology and this has motivated my study on bankruptcy prediction of listed firms at the Nairobi Securities Exchange. This study therefore differs from the above studies done in that the bankruptcy prediction in firms listed in the Nairobi Securities Exchange using the latest Altman's Z" Score of 1993.

1.3Research Objectives

The study is set to achieve the utility of statistical technique mostly termed as multiple discriminant analysis (MDA) in bankruptcy prediction of NSE listed firms.

1.4Value of the Study

This study is likely to be of interest to the following;

The government and policy makers may be interested in the study of bankruptcy prediction of firms listed in the NSE. The study will give insight to the government and its policy role especially in the Ministry of Finance on the impact of bankruptcy prediction on long term financial stability of the economy. It will also help them seek trainings on the importance of bankruptcy prediction. The Ministry of Education and higher education will also gain insight on the need for making exclusive bankruptcy prediction education a part of the school curriculum. The result of the study will inform the ongoing financial sector reforms in the country. The Capital Market Authority which is a regulatory and oversight body may also find important to benefit from this study by enhancing maintenance of appropriate legal and regulatory framework.

The study can also chip in during the review of policies and making recommendation to the Government on new policy issue that could enhance market development. This will in return promote the guidance given to the market operators like Nairobi Securities Exchange and improve surveillance of the firms listed in the Nairobi Securities Exchange with regard to capital, liquidity and other aspects with overall am of ensuring financial stability of the listed firms. This study will also benefit the Nairobi Securities Exchange in terms of capacity building and enhancing the listed firms to maintain strong financial stability before and after the listing. NSE will also pick its growth momentum from 61 listed firms currently to capture at least three quarter of the firms in the economy of the Kenyan market and also extended to more regional markets with East and Central Africa. NSE can also benefit from the study by doubling its responsibility for development and regulation of the market operations to boost trading efficiencies.

The study will be also useful to investors in that there will be able to know about the status of companies listed in the Nairobi Securities Exchange and will boost their knowledge of the importance of bankruptcy prediction. It will be a preventive tool to them so that they can avoid situations of hostile takeover due to business failures which can be taken care of. This will hence ease the stringent rules of preventing mangers from going for training which might have boosted the company since most stockholders see it as waste of company resources. Therefore in the long the management of companies will be well acquainted with current information and give them more capacity in terms of strategizing on the tools to combine for effective bankruptcy prediction.

Employee, clients and suppliers of different firms in the economy of Kenya will also benefit from this study. The study will enable see the performance of the firm they work for and see whether it is growing or collapsing. With this information at hand, the employees will be able to advice the management on ways of preventing business failure through different models of bankruptcy prediction. In so doing this will also boost their skills and growth to their career. The clients, this information will help them see which firms are financial stable or not so that they can plan themselves on the consistency of getting services from these firms. The suppliers will be able to analyze their credit rating strategies to firms they lend. With this in place, they will be assured of future payments of their accounts receivable and consistency chain of supply through consistent production.

Scholars and researchers may use this study as a base for further research in the local environment. The study will contribute to the existing body of knowledge on bankruptcy prediction in Kenya. It will also stimulate prospective researchers to replicate the study in other sectors of the economy and in other regions of the country.

CHAPTER TWO

LITERATURE REVIEW

2.1Introduction

The bankruptcy prediction has attracted the attention of both academic researcher and business management. Several prediction models have evolved over a long period. Since late 1960's serious investigation into possibility of developing suitable business failure prediction models to help avert enormous loss resulting from business bankruptcy commenced (Altman, 1984; Dimitras, et al 1996, Altman and Narayanan 1997). Consequently many types of models and methods of predicting business failure have been developed with varying assumptions and computational complexities. The classical cross-sectional methods have proved to be the most popular business failure prediction methods (Zavgren, 1983; and Atiya, 2001).

2.2Review of Theories

2.2.1 Valuation Models

Valuation is a processed set of procedures used to estimate the economic value of an owner's interest in a business. Valuation is used by financial market participants to determine the price they are willing to pay or receive to perfect a sale of business. There are two valuation methods which have since been used to value the marketable securities. These are Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Model (APM). The CAPM model was developed concurrently by Treynor (1961) and Sharpe (1963, 1964). A typical CAPM model was $E(Ri)=Rj + [E(Rm)-Rf]Bi$ where $E(Ri)$ is the expected rate of return on asset i, Rf is the risk-free rate of return, $E(Rm)$ is the expected market rate of return, B is the variance of risky asset i. This when plotted on a graph will give the security market line.

Second model is the Arbitrage Pricing Model (APM) which was developed by Ross, (1976). It is based on the idea that the asset's returns can be predicted using the relationship between the same asset's and many common risk factor. This theory predicts a relationship between the returns of a portfolio and the returns of a single asset through a linear combination of many independent of many macro-economic variables. It is often viewed as an alternative to Capital

Asset Pricing Model, since the APT has more flexible assumption requirements. Therefore the analysis shows that period-specific probabilities of business failure are instrumental to the assessment of expected values of cash flows in such models. Under somewhat restrictive conditions the failure risk can alternatively be accommodated through an adjustment of the discount rate, i.e. expected values of future cash flows conditioned on business survival can simply be discounted with such a discount rate. The result holds both in bond and equity DCF valuation modeling. In order for the accounting-based residual income valuation model to appropriately capture the failure risk, an additional accounting “failure loss recognition” principle as well as a novel term in the model specification have been identified.

2.2.2 Option Pricing Theory

The most commonly used models today are the Black-Scholes model and the binomial model.

The basic intuition behind option pricing or contingent claims model (e.g. Merton, 1974, 1977) is that the equity of a levered firm can be viewed as a call option to acquire the value of the firm’s asset by paying off the face value of the debt at the debt’s maturity. From this perspective, a firm will be insolvent if the value of the firm’s asset falls below what the firm owes its creditors at debt maturity. In that event, equity holders will default on the debt (file for bankruptcy) and simply hand over the firm’s assets to its creditors and walk away free (protected by their limited liability rights. The probability of default at debt maturity in this case (the firm’s assets are less than the face value of the debt) is driven by the five primary option pricing variables: the natural logarithm of the book value of total liabilities due to maturity representing the option’s exercise price, the logarithm of the current market value of the firm’s assets, the standard deviations of percentage firm value changes, the average time to the debt’s maturity representing the option’s expiration , and the difference between the expected asset return and the firm’s payout yield (interest and dividend payments as proportion of asset value).

Both theories on options pricing have wide margins for error because their values are derived from other assets, usually the price of a company's common stock. Time also plays a large role in option pricing theory, because calculations involve time periods of several years and more. Marketable options require different valuation methods than non-marketable ones, such as those given to company employees.

2.2.3 Efficient Market Hypothesis Theory

Fama, (1970) defined an efficient financial market as "one in which prices always fully reflect available information". [1] the most common type of efficiency referred to in financial markets is the allocative efficiency, or the efficiency of allocating resources. This includes producing the right goods for the right people at the right price. A trait of allocatively efficient financial market is that it channels funds from the ultimate lenders to the ultimate borrowers in a way that the funds are used in the most socially useful manner.

Fama, (1970) identified three levels of market efficiency. One of them being Weak-form efficiency which states that prices of the securities instantly reflect full information of the past prices. This means future price movements cannot be predicted by using past prices. It is simply to say that, past data on stock prices are of no use in predicting future stock price changes. Everything is random. In this kind of market, should simply use a "buy-and-hold" strategy. Semi-strong efficiency as second level of market efficiency which states that asset prices fully reflect all of the publicly available information. Therefore, only investors with additional inside information could have advantage on the market. Any price anomalies are quickly found out and the stock market adjusts. Strong-form efficiency as the third level of market efficiency states that asset prices fully reflect all of the public and inside information available. Therefore, no one can have advantage on the market in predicting prices since there is no data that would provide any additional value to the investors. Fama also created the efficient-market hypothesis (EMH) theory, which states that in any given time, the prices on the market already reflect all known information, and also change fast to reflect new information. Therefore, no one could outperform the market by using the same information that is already available to all investors, except through luck.

Tobin, (1958) also identified four efficiency types that could be present in a financial market and they include information arbitrage efficiency which states that asset prices fully reflect all of the privately available information (the least demanding requirement for efficient market, since arbitrage includes realizable, risk free transactions). Arbitrage involves taking advantage of price similarities of financial instruments between 2 or more markets by trading to generate losses. It involves only risk-free transactions and the information used for trading is obtained at no cost. Therefore, the profit opportunities are not fully exploited, and it can be said that arbitrage is a result of market inefficiency. This reflects the weak-information efficiency model. Fundamental valuation efficiency a second efficiency states that asset prices reflect the expected past flows of payments associated with holding the assets (profit forecasts are correct, they attract investors). Fundamental valuation involves lower risks and less profit opportunities. It refers to the accuracy of the predicted return on the investment. Financial markets are characterized by predictability and inconsistent misalignments that force the prices to always deviate from their fundamental valuations. This reflects the semi-strong information efficiency model. Full insurance efficiency a third efficiency type ensures the continuous delivery of goods and services in all contingencies. Finally functional/Operational efficiency states that products and services available at the financial markets are provided for the least cost and are directly useful to the participants. Therefore every financial market will contain a unique mixture of the identified efficiency types.

2.3Review of Empirical Studies

Previous bankruptcy research had identified many ratios that were important in predicting bankruptcy. Among the most popular financial ratios used by researchers were; Beaver (1966) estimated a univariate financial distress model. Altman (1968) analyzed the financial distress problem of a firm by employing a multiple discriminant analysis (MDA), Martin (1977) and Ohlson (1980) investigated the profitability of a company under Logit model. The application of a financial distress models includes static univariate analysis, multivariate discriminant analysis, Logit model, probit model and neural network, and dynamic Merton model, CUSUM and so on.

Several recent papers have also served to emphasize the need for a timely model of UK financial failure prediction, the parameters of which are fully in the public domain. First, Campbell, Hilscher and Szilagyi (2008) show that financially distressed firms have delivered anomalously low returns in the US. There is no UK equivalent to the model they use to estimate distress risk, something we attempt to address in this paper. Second, Pope (2010) suggests that factor mimicking portfolios based on financial distress risk may help deliver more powerful factor models of expected returns. In respect of the UK, this suggestion pre-supposes that an appropriate model is available. Of course, with regard to the latter one can make the case for using a model that is well-understood, such as the z-score models of Taffler (1983, 1984) and this is precisely the approach followed in Agarwal and Taffler (2008a), which provides some fascinating evidence that momentum may be a proxy for distress risk.

However, in doing so it provides UK evidence that is consistent with the Campbell et al (2008) finding, leaving the conundrum that markets, apparently, do not adequately price distress risk. This alone motivates the search for a “better” distress prediction model that might resolve this anomaly. Third, Agarwal and Taffler (2007) note the dramatic increase in UK firms with “at risk” z-scores from 1997 onwards, which might imply the need for an updated UK prediction model. Fourth, Shumway (2001) shows that a “hazard” or “dynamic logit” model gives better predictive power than a simpler logit model. Chava and Jarrow (2004) develop this further by adding industry controls, and show that such a model can easily be estimated using standard statistical packages. As far as we are aware, these approaches to modeling, combined with the Campbell et al (2008) innovations, have not been attempted in the UK. However, in the current financial climate one scarcely needs to allude to the academic literature to justify an interest in a timely measure of failure prediction – the likely interest from the wider community in such a model is, regrettably, all too obvious.

In Kenya, Keige (1991) did a study on business failure prediction using discriminant analysis. Kiragu (1993) did another study on the prediction of corporate failure using price adjusted data. Kogi (2003) did an analysis of the discriminant corporate failure prediction model based on stability of financial ratios.

In this paper, we will focus on statistical technique called multiple discriminant analysis as an efficient predictor of corporate bankruptcy. We will examine the models predictive ability on several completely holdout samples of firms listed under the NSE in Kenya.

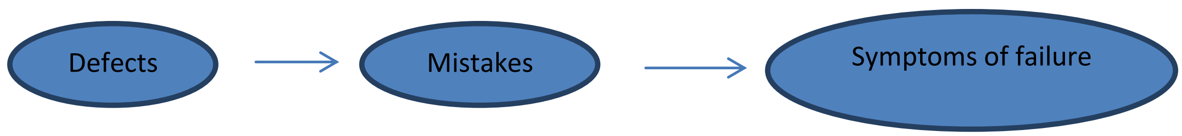
2.4Bankruptcy Prediction Models

Business failure models can be broadly divided into two groups: quantitative models, which are based largely on published financial information; and qualitative models, which are based on an internal assessment of the company concerned. Both types attempt to identify characteristics, whether financial or non-financial, which can then be used to distinguish between surviving and failing companies (Robinson and Maguire, 2001).

2.4.1. Qualitative Models

This category of model rests on the premise that the use of financial measures as sole indicators of organizational performance is limited. For this reason, qualitative models are based on nonaccounting or qualitative variables. One of the most notable of these is the A score model attributed to Argenti (2003), which suggests that the failure process follows a predictable sequence:

Figure 2.4.1: Failure process



2.4.2. Quantitative Models

Quantitative models identify financial ratios with values which differ markedly between surviving and failing companies, and which can subsequently be used to identify companies which exhibit the features of previously failing companies (Argenti, 2003). Commonly-accepted financial indicators of impending failure include: low profitability related to assets and commitments low equity returns, both dividend and capital poor liquidity high gearing high variability of income.

2.4.2.1. Multi-Discriminant Analysis

One of the quantitative models is Multi-Discriminant Analysis (MDA) model. It is a linear combination, so-called bankruptcy score of certain discriminatory variables. The bankruptcy score sorts firms into bankrupt and non-bankrupt groups according to their characteristics. It is stated that MDA still is the most popular technique in business failure identification and appears set standard for comparison of bankruptcy prediction models (Altman *et al.,* 2000). It was concluded that MDA models ranked number 1 out of 16 model types and is expected to provide a reliable bankruptcy prediction method. The MDA model had an average accuracy of more than 85% in bankruptcy prediction (Aziz *et al.*, 2006). Avoiding Type I and Type II errors is also essential since misclassification can be costly to stakeholders. The error rates for MDA models showed 15%for Type I errors and 12% for Type II errors reassuring their significance as practical prediction models. One of the advantages of the MDA is the reduction of the space dimensionality where it is transformed to its simplest form of one dimension since the purpose is to identify either if the companies are bankrupt or non-bankrupt. The object is classified using a single discriminant score namely the outcome of a discriminant function that transforms individual variable values. In 1993, Altman revised his model to incorporate a “four variable Z-Score” prediction model (Altman, 1993). Altman felt this revised model significantly improved the predictive ability of his model and made it simpler to incorporate. Altman’s 1968 model took the following form -:

$$Z'' = 6.56X1 + 3.26X2 + 6.72X3 + 1.05X4$$

Where: X1 = (Current Assets - Current Liabilities)/Total Assets

X2 = Retained Earnings/Total Assets

X3 = Earnings Before Interest and Taxes/Total Assets

X4 = Book Value of Equity/Total Liabilities

$Z'' > 2.60$ - “Safe” Zone
$1.1 < Z'' < 2.60$ - “Grey” Zone
$Z'' < 1.1$ - “Distress” Zone

Additionally, two adaptation of the 1968’s Z-score model are presented: the Z’-score and the Z”-score. These models are summarized in order to clarify the differences and why the study is testing the Z-Score of 1993.

Table2.4.2.1 below including the variables present to each model.

Table 2.4.2.1: Most popular Altman's discriminant functions

Year	Discriminant Function	Decision Criteria
1968	Z = 1.2 X1 + 1.4 X2 + 3.3 X3 + 0.6 X4 + 1.0 X5	Z < 1.81 bankrupted Z > 2.67 non-bankrupted Z = 1.81 to 2.67 gray area
1993	Z' = 0.717 X1 + 0.847 X2 + 3.107 X3 + 0.420 X4 + 0.998 X5	Z' < 1.23 bankrupted Z' > 2.90 non-bankrupted Z' = 1.23 to 2.90 gray area
1993	Z" = 6.56 X1 + 3.26 X2 + 6.72 X3 + 1.05 X4	Z" < 1.10 bankrupted Z" > 2.60 non-bankrupted Z" = 1.10 to 2.60 gray area

Where:

X1 = Working Capital/Total Assets (WC/TA)

X2 = Retained Earnings/Total Assets (RE/TA)

X3 = Earnings Before Interest and Taxes /Total Asset (EBIT/TA)

X4 = Market value of Equity/ Book Value of Total Liabilities MVE/TL)

X5 = Sales/Total Asset (S/TA)

X6 = Net Worth (Book Value)/Total liabilities (NW/TL)

Source; Altman, 1993

The models in Table above were built to apply to privately held firms and for non-manufacturers respectively. Both models substitute the book value of equity for the market value in X4, making these models a little less reliable than the original.

The Z”-score unlike the Z’-score, does not consider the variable X5- Sales/total assets in order to minimize the potential industry effect of asset turnover and the effects of different types of assets financing, like lease capitalization(see Table above).

The accuracy of the Z-score models in predicting bankruptcy has been of 72-80% reliability meaning the percentage of companies that are correctly classified in a sample of estimations. These Z-score models measure the financial health of companies and are believed to be a good diagnostic tool to predict a bankruptcy of a company. The models have gained wide acceptance for the past two decades by auditors, management consultants, courts of law and even used in database systems used for loan evaluations (Eidleman, 1995). Eidleman (1995) stated five points that many practitioners argue for the use of Z-scores approach and the disadvantages of these models.

It is more precise and leads to clearer conclusions than contradictory ratios as well as they measure the extent of uncertainty. It is uniform and leaves less room for inaccuracies of judgment. It is more reliable and can be evaluated statistically. This approach is based on past experience rather than on someone's unverified opinion. It is faster and less costly to work with than traditional tools. They can weed out the two extremes if the spectrum in an economical fashion. This allows the analyst to focus on the grey area where experience and judgment are needed to compensate for what the computer misses.

Eidleman also mentioned several pitfalls in using this approach; such as that models do not always give a clear result. The outcome is also never better than the numbers it is based on but people can be blinded by the model’s clear accuracy if they do not fully understand how inaccurate information can be. The Z-score models are not recommended for predicting corporate failure of financial companies. This is because the ratios that are used in the model are based on financial statements and financial firms often have off-balance sheet items that are not captured by the ratios used in the Z-score model. The Z’-score model developed by Altman for companies in United States of America has demonstrated potential to predict bankruptcy in Argentinean companies. The researcher find it’s more appropriate to use Altman’s privately held company model (Z’-score) since it has worked in Argentineans companies which is believed to have the same economic condition like in Kenya. In addition, it is possible to see the different strength and performance of the companies using this model (Porporato*et al.*, 2008).

The financial ratios in Z-score calculated by multiplying each of several financial ratios by an appropriate co-efficient and summing the results. The ratios rely on working capital, total assets, retained, EBIT, market value of equity, net worth. Working Capital is equal to Current Assets minus Current Liabilities (Milkkete, 2001). Total Assets is the total of the Assets section of the Balance Sheet. Retained Earnings is found in the Equity section of the Balance Sheet. EBIT (Earnings before Interest and Taxes) includes the income or loss from operations and from any unusual or extraordinary items but not the tax effects of these items. It can be calculated as follows: Find Net Income; add back any income tax expenses and subtract any income tax benefits; then add back any interest expenses. Market Value of Equity is the total value of all shares of common and preferred stock. The dates these values are chosen need not correspond exactly with the dates of the financial statements to which the market value is compared (Milkkete, 2001). Net Worth is also known as Shareholders' Equity.

2.4.2.2. 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.Springate 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 (also owners), 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. Formula is as below;

$Z = 1.03A + 3.07B + 0.66C + 0.4D$

$Z < 0.862$; then the firm is classified as "failed"

WHERE A = Working Capital/Total Assets

B = Net Profit before Interest and Taxes/Total Assets

C = Net Profit before Taxes/Current Liabilities

D = Sales/Total Assets

2.4.2.3. Blasztk Model (Canadian)

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. An advantage of this method is that it does compare the company being evaluated with companies in the same industry (Bilanas, 2004).

2.5Chapter Summary

A look at studies done on bankruptcy prediction indicates that the accounting data are capable to predict bankruptcy in the firms. However there is no consensus about the kind of the financial ratios which are used in prediction of financial distresses. The yielded results have been according to different financial ratio and different methods of research. In this study Edward Altman’s model is used to predict bankruptcy of firms listed in the Nairobi Securities Exchange in Kenya.

The main conclusions of this study are: (i) while the z-score model is marginally more accurate, the difference is statistically not significant, (ii) relative information content tests find that both approaches yield estimates that carry significant information about failure, but neither method subsumes the other, although most importantly, (iii) in a competitive loan market, a bank using the z-score approach would realize significantly higher risk-adjusted revenues, profits, and return on capital employed than a bank employing the comparative market-based credit risk assessment approach. Our results demonstrate that traditional accounting-ratio-based bankruptcy risk models are, in fact, not inferior to KMV-type option-based models for credit risk assessment purposes, and dominate in terms of potential bank profitability when differential error misclassification costs and loan prices are taken into account. The apparent superiority of the market-based model approach claimed by Hillegeist et al. (2004) reflects the poor performance of their comparator models, not a particularly strong performance by their option-pricing model.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1. Introduction

This chapter presented an outline of the research methodology used in the study. It covered the research design, target population, described the sample population, outlines the data collection procedures and sources and described the data analysis tools.

3.2. Research Design

The main purpose of this research was to determine the bankruptcy prediction of firms listed in the NSE. The researcher used descriptive research design. This was deemed appropriate as it involved a depth of study of the bankruptcy prediction of firms listed in NSE which helped the researcher to describe the state of current affairs of firms and assess the characteristics of the situation. The research was established for a period between 2008- 2012. This period was considered by the researcher to be adequate for establishing any bankruptcy prediction of the NSE listed firms.

3.3. Population of the study

The population of this study comprised of all firms listed on the NSE. Failed firms were considered to be those that had either been suspended or delisted from the NSE to date. They were only10 firms during this period. Non-failed firms were all entities listed in the NSE since the year 1989-2008. To fall under this study's category of non-failed firms, the firms had been suspended or delisted for the period under focus. As at September 2013 there were 62 firms listed on the NSE. This statistic was received from NSE and the Capital Markets Authority (CMA) website. This was convenient due to the fact that financial statements of listed firms were readily available and reliable.

3.4. Sample Selection

The sample size comprised of at least one firm from each of the twelve sectors listed on the NSE (Appendix 1) depending on the availability of data. Convenient sampling technique was used to establish bankruptcy prediction of firms across all industries/ sector of the NSE and the data is easily accessible and reliable for listed firms.

3.5.Data Collection

Data was obtained from financial reports of the listed companies at the Nairobi Securities Exchange and the Capital Markets Authority. The secondary data was in form of current assets and liabilities, total assets, retained earnings, earnings before interest and taxes, book value of equity, and sales. The period covered by the study was extended to five years, starting from 2008-2012.Discriminant analysis was used. Specifically a discriminant function was formulated from the ratios. The function was in the form; $Z=a1X1 + a2X2 + a3X3 +\ldots. + anXn$ where Z= discriminant score, a1, a2,…an =discriminant coefficients and X1, X2,…Xn= independent variables.

3.6.Data Analysis

The field of research on bankruptcy prediction has revealed a large number of significant predictors of failure (Beaver, 1968a; Blum, 1974; Altman, 1968; Altman, et al., 1977; Chatterjee et al., 1966; Back et al., 1996). The variables were classified into profitability, liquidity, and solvency, degree of economic distress, leverage, efficiency, variability and size. The selected variables were used in discriminant analysis to develop a model for failure prediction

Discriminant analysis model was used in the data analysis, reason being that it was termed as an efficient predictor of corporate bankruptcy. Discriminant analysis is a multivariate technique that seeks to determine whether a set of variables significantly differentiate among two or more sets of data, as well as determine specific combination variables that most efficiently differentiate among groups. In this case the aim was to determine that sets of ratios that maximize the differences between failed and non-failed firms.

The Z-score is a linear combination of four or five common business ratios, weighted by coefficients. The coefficients were estimated by identifying a set of firms which had been declared bankrupt. These were matched by sample of firms which had survived, matching being done by industry and asset size. Five measures were objectively weighted and summed up to arrive at an overall score that then becomes the basis for classification of firms into one of the prior groupings (distressed and non-distressed).

Z’’ = 6.56X1 + 3.26X2 + 6.72X3 + 1.05X4

Where: X1 = (Current Assets - Current Liabilities)/Total Assets

X2 = Retained Earnings/Total Assets

X3 = Earnings Before Interest and Taxes/Total Assets

X4 = Book Value of Equity/Total Liabilities

Z” Score Bankruptcy Model:

Z’’ = 6.56X1 + 3.26X2 + 6.72X3 + 1.05X4

Zones of Discrimination:

Z’’ > 2.60 - “Safe” Zone

1.1 < Z’’ < 2.60 - “Grey” Zone

Z” < 1.1 - “Distress” Zone

All the companies which had a Z score below 1.1werecategorized as companies in distress zone; companies with a Z score of between 1.1 and 2.60werecategorized as companies in a grey zone while those with a Z score above 2.6werecategorized in a safe zone. In a distress zone there was a high prospect of bankruptcy for firms, in a grey zone there was the uncertainty as to whether the firm went bankrupt or not while firms in the safe zone had a low likelihood of becoming bankrupt.

CHAPTER FOUR

DATA ANALYSIS, RESULTS AND DISCUSSIONS

4.1. Introduction

Data analysis is a process of gathering, modeling and transforming data with the goal of highlighting useful information, suggesting conclusions and supporting decision making. This chapter shows the analysis, results and discussion of findings of the study as set out in chapter three. The Statistical Package for Social Sciences software and MS Excel Application were used and the findings were presented as descriptive statistics and tables. Data was collected from audited financials reports for the selected companies as set out in the appendices.

4.2. Data Presentation

4.2.1 Descriptive Successful Firms

Table 1: Descriptive Successful Firms

	N	Minimum	Maximum	Mean	Std. Deviation
X1: Working Capital / Total Assets	45	0.0000	.2654	.096660	.0879764
X2: Retained Earnings / Total Assets	45	.0263	.5368	.275520	.1347436
X3: EBIT / Total Assets	45	0.0000	.3273	.133607	.0938585
X4: Equity Book Value / Total Liabilities	45	.1900	2.5916	.997264	.6400104
Valid N (list wise)	45				

Table 1 above shows that the average X1 for the 45 observation made from 9 successful companies from the year 2008 to 2012 is 0.097 with a standard deviation of 0.088 varying from a range of 0.000 to a maximum X1 of 0.265; the average X2is 0.276 with a standard deviation of 0.135 varying from a minimum of 0.026 to a maximum X2 of 0.537; the average X3is 0.134 with a standard deviation of 0.094 varying from a minimum of 0.000 to a maximum X3 of 0.327

4.2.2 Analysis of Successful Firms

Table 2: Altman Z'' (1993) Score for Successful Firms

N	Name	Year	X1	X2	X3	X4	Altman (1993) Z" Score	Remarks
1	ARM	2008	0.01	0.21	0.11	0.50	2.02	Gray Zone
2	ARM	2009	0.00	0.16	0.08	0.52	1.58	Gray Zone
3	ARM	2010	0.06	0.15	0.07	0.39	1.76	Gray Zone
4	ARM	2011	(0.03)	0.19	0.07	0.42	1.27	Gray Zone
5	ARM	2012	0.05	0.18	0.07	0.35	1.76	Gray Zone
6	Bamburi	2008	0.22	0.45	0.24	1.43	6.02	Safe Zone
7	Bamburi	2009	0.24	0.46	0.30	1.87	7.07	Safe Zone
8	Bamburi	2010	0.16	0.48	0.23	1.85	6.09	Safe Zone
9	Bamburi	2011	0.25	0.54	0.16	2.59	7.16	Safe Zone
10	Bamburi	2012	0.22	0.44	0.13	2.53	6.38	Safe Zone
11	EAPCC	2008	0.16	0.20	0.16	0.80	3.66	Safe Zone
12	EAPCC	2009	0.13	0.30	0.12	0.96	3.67	Safe Zone
13	EAPCC	2010	0.09	0.28	0.01	0.99	2.58	Gray Zone
14	EAPCC	2011	0.08	0.29	0.05	0.78	2.61	Safe Zone
15	EAPCC	2012	0.03	0.18	0.04	0.53	1.62	Gray Zone
16	EABL	2008	0.26	0.32	0.33	1.93	6.97	Safe Zone
17	EABL	2009	0.27	0.32	0.31	1.80	6.73	Safe Zone
18	EABL	2010	0.15	0.28	0.33	1.63	5.81	Safe Zone
19	EABL	2011	0.02	0.23	0.25	1.18	3.75	Safe Zone
20	EABL	2012	(0.08)	0.27	0.28	0.19	2.44	Gray Zone
21	KenolKobil	2008	0.17	0.17	0.12	0.65	3.19	Safe Zone
22	KenolKobil	2009	0.19	0.17	0.08	0.58	2.92	Safe Zone
23	KenolKobil	2010	0.22	0.20	0.11	0.65	3.56	Safe Zone
24	KenolKobil	2011	0.16	0.16	0.11	0.34	2.63	Safe Zone
25	KenolKobil	2012	(0.02)	0.03	(0.27)	0.25	(1.66)	Distress Zone
26	Kenya Airways	2008	0.10	0.27	0.18	0.52	3.33	Safe Zone
27	Kenya Airways	2009	(0.03)	0.21	0.21	0.29	2.24	Gray Zone
28	Kenya Airways	2010	(0.04)	0.24	0.24	0.37	2.49	Gray Zone
29	Kenya Airways	2011	0.02	0.26	0.06	0.42	1.81	Gray Zone
30	Kenya Airways	2012	(0.02)	0.26	0.03	0.42	1.32	Gray Zone

31	Mumias Sugar	2008	0.08	0.29	0.11	1.77	4.11	Safe Zone
32	Mumias Sugar	2009	0.08	0.30	0.07	1.35	3.37	Safe Zone
33	Mumias Sugar	2010	0.18	0.35	0.12	1.50	4.67	Safe Zone
34	Mumias Sugar	2011	0.15	0.34	0.11	1.66	4.63	Safe Zone
35	Mumias Sugar	2012	0.05	0.34	0.06	1.35	3.30	Safe Zone
36	Safaricom	2008	(0.17)	0.49	0.27	1.34	3.74	Safe Zone
37	Safaricom	2009	(0.20)	0.48	0.17	1.28	2.73	Safe Zone
38	Safaricom	2010	(0.11)	0.49	0.20	1.49	3.80	Safe Zone
39	Safaricom	2011	(0.11)	0.49	0.16	1.45	3.50	Safe Zone
40	Safaricom	2012	(0.13)	0.49	0.14	1.45	3.20	Safe Zone
41	Total Kenya	2008	0.16	0.15	0.07	0.53	2.54	Gray Zone
42	Total Kenya	2009	0.07	0.07	0.02	0.40	1.25	Gray Zone
43	Total Kenya	2010	0.09	0.09	0.05	0.46	1.66	Gray Zone
44	Total Kenya	2011	0.07	0.07	0.00	0.35	1.05	Distress Zone
45	Total Kenya	2012	0.16	0.07	(0.00)	0.76	2.08	Gray Zone

The table 2 above shows the different values of X1, X2, X3, X4, Altman Z” Scores for the 1993 model as well as the remarks for the finding as per Altman explanation of different scores. Altman’s (1993) Z’’ score model was applied for the nine listed successful firms and results were shown alongside with remarks of the categories which they fall into. However, 35.6 % of the observed firms that ought to be classified in the safe zone had z’’ scores that classified them in the gray zone whereas two observations that rendered to Total and Kenol Kobil in the distress zone in the years 2011 and 2012 respectively.

Table 3: Summary of Classification of Successful Firms

Classification	**Frequency**	**%age Freq.**
Distress Zone	2	4.4%
Gray Zone	16	35.6%
Safe Zone	27	60.0%
Total	45.00	100.0%

It can be noted that Altman's (1993) Z'' score model correctly classified 60% of the observed firms and 4.4% were classified in the distress zone whereas a big portion of successful firms were in the gray zone 35.6% of observed firms which greatly increases uncertainty about their future classification. This shows that the model should be used with utmost caution for classifying firms as either failed or successful since there's a greater margin of error. Altman's (1993) Z'' score model was intended for non-manufacturing firms and has only four variables which he thought could best predict bankruptcy and more so he presumed that all the multi discriminant assumptions were satisfied and he went ahead to run such a model. However contemporary critiques advocate for the use of logistic regression because of the many assumptions of multi discriminant analysis that are rarely in reality satisfied which ultimately reduce errors of wrong classification. The findings agree with those of Alareeni and Branson (2012) who found that Altman Z'' score (1993) model had limited predictive power as compared to that of Altman Z score of 1968.

4.2.3 Descriptive Failed Firms

Table 4: Descriptive Failed Firms

	N	Minimum	Maximum	Mean	Std. Deviation
X1: Working Capital / Total Assets	35	.0390	.7844	.214566	.1473904
X2: Retained Earnings / Total Assets	35	0.0000	.0979	.054457	.0189915
X3: EBIT / Total Assets	35	.0041	.2134	.053306	.0650929
X4: Equity Book Value / Total Liabilities	35	.0458	.7927	.203809	.2422248
Valid N (list wise)	35				

Table 4 above shows that the average X1for the 35 observations made from 7 failed companies from the year 1997 to 2005 is 0.215 with a standard deviation of 0.147 varying from a range of 0.039 to a maximum X1 of 0.784; the average X2is 0.055 with a standard deviation of 0.019 varying from a minimum of 0.000 to a maximum X2 of 0.099; the average X3is 0.053 with a standard deviation of 0.065 varying from a minimum of 0.004 to a maximum X3 of 0.213 and finally the last descriptive statistics for the failed firms is X4 having an average of 0.204 with a standard deviation of 0.242 varying from a minimum of 0.046 to a maximum X4 of 0.793.

4.2.4 Analysis of Failed Firms

Table 5: Altman Z’’ (1993) Score for Failed Firms

N	Name	Year	X1	X2	X3	X4	Altman (1993) Z" Score	Remarks
1	Pearl Drycleaners	2001	0.2094	0.0971	0.0622	0.0513	2.16	Gray Zone
2	Pearl Drycleaners	2000	0.2187	0.0958	0.0599	0.0547	2.21	Gray Zone
3	Pearl Drycleaners	1999	0.2283	0.0979	0.0625	0.0553	2.29	Gray Zone
4	Pearl Drycleaners	1998	0.2362	0.0940	0.0735	0.0573	2.41	Gray Zone
5	Pearl Drycleaners	1997	0.2162	0.0921	0.0657	0.0598	2.22	Gray Zone
6	Theta Group	2001	0.0751	0.0464	0.0091	0.0916	0.80	Distress Zone
7	Theta Group	2000	0.0837	0.0481	0.0094	0.0916	0.87	Distress Zone
8	Theta Group	1999	0.0796	0.0495	0.0105	0.0941	0.85	Distress Zone
9	Theta Group	1998	0.0869	0.0501	0.0112	0.0901	0.90	Distress Zone
10	Theta Group	1997	0.0947	0.0501	0.0119	0.0915	0.96	Distress Zone
11	Lonhro EA Ltd	2001	0.2060	0.0504	0.0041	0.0536	1.60	Gray Zone
12	Lonhro EA Ltd	2000	0.2118	0.0520	0.0044	0.0492	1.64	Gray Zone
13	Lonhro EA Ltd	1999	0.1711	0.0477	0.0118	0.0458	1.41	Gray Zone
14	Lonhro EA Ltd	1998	0.1477	0.0478	0.0105	0.7002	1.93	Gray Zone
15	Lonhro EA Ltd	1997	0.1513	0.0476	0.0101	0.4493	1.69	Gray Zone
16	Kenya National Mills	2001	0.7844	0.0523	0.2134	0.2494	7.01	Safe Zone
17	Kenya National Mills	2000	0.4061	0.0513	0.2002	0.3001	4.49	Safe Zone
18	Kenya National Mills	1999	0.3376	0.0493	0.0716	0.1436	3.01	Safe Zone
19	Kenya National Mills	1998	0.3630	0.0498	0.1891	0.1536	3.98	Safe Zone
20	Kenya National Mills	1997	0.4034	0.0523	0.1771	0.1550	4.17	Safe Zone
21	Regent Undervalued Assets Ltd	2001	0.0788	0.0488	0.0097	0.0916	0.84	Distress Zone
22	Regent Undervalued Assets Ltd	2000	0.0757	0.0508	0.0100	0.0916	0.83	Distress Zone

23	Regent Undervalued Assets Ltd	1999	0.0781	0.0523	0.0113	0.0941	0.86	Distress Zone
24	Regent Undervalued Assets Ltd	1998	0.0930	0.0529	0.0120	0.0901	0.96	Distress Zone
25	Regent Undervalued Assets Ltd	1997	0.0943	0.0514	0.0127	0.0915	0.97	Distress Zone
26	Uchumi Supermarket	2005	0.0390	-	0.2002	0.3332	1.95	Gray Zone
27	Uchumi Supermarket	2004	0.3376	0.0493	0.0716	0.6965	3.59	Safe Zone
28	Uchumi Supermarket	2003	0.3687	0.0491	0.0681	0.7573	3.83	Safe Zone
29	Uchumi Supermarket	2002	0.3584	0.0485	0.0806	0.7848	3.87	Safe Zone
30	Uchumi Supermarket	2001	0.3639	0.0477	0.0790	0.7927	3.91	Safe Zone
31	EA Packaging	2002	0.2171	0.0485	0.0042	0.0523	1.67	Gray Zone
32	EA Packaging	2001	0.2122	0.0483	0.0044	0.0510	1.63	Gray Zone
33	EA Packaging	2000	0.1829	0.0456	0.0123	0.0517	1.49	Gray Zone
34	EA Packaging	1999	0.1496	0.0457	0.0109	0.0587	1.27	Gray Zone
35	EA Packaging	1998	0.1493	0.0455	0.0105	0.0591	1.26	Gray Zone

The table 5 the different values of X1, X2, X3, X4, Altman Z" Scores for the 1993 model as well as the remarks for the finding as per Altman explanation of different scores. Since all the above failed firms were eventually listed Altman's (1993) Z'' score model should have captured this and classified under the distress zone for all the 35 observations that were made.

However, on application Altman's (1993) Z'' score model, most of the firms that ought to be classified in the distress zone had z'' scores that classified them as either on the safe zone or gray zone.

Table 6: Delisting Year of Failed Firms

	Company	Year Delisted
1	Pearl Drycleaners	2001
2	Theta Group	2001
3	Lonhro EA Ltd	2001
4	Kenya National Mills	2002
5	Regent Undervalued Assets Ltd	2001
6	Uchumi Supermarket	2005
7	EA Packaging	2003

The table 6 above shows the seven failed firms that were delisted from the Nairobi Securities Exchange which were subjected to Altman's 1993 Z'' Score Model.

The failed firms should have all been classified in the distress zone by Altman's (1993) Z'' score model but the following table shows how actual classification was done.

Table 7: Summary of Classification of Failed Firms

Classification	**Frequency**	**%age Freq.**
Distress Zone	10	28.6%
Gray Zone	16	45.7%
Safe Zone	9	25.7%
Total	35.00	100.0%

It can be noted that Altman's (1993) Z'' score model correctly classified 28.6% of the observed firms and 25.7% wrongly classified firms as safe even though they were delisted from NSE and 45.7% of observed firms were in the gray zone which greatly increases uncertainty about their future classification. This shows that the model should be used with utmost caution for classifying firms as either failed or successful since there's a greater margin of error.

As for the successful firms, Altman's (1993) Z'' score model ought to have classified the firms properly into their respective categories but the following table shows how actual classification was done.

4.3. Summary and Interpretation of Findings

The research employed nine sample firms form the successful firms which translated to forty five observations and seven failed firms which also translated to thirty five observations. The five financial ratios mentioned above were used as indicators in the equation for judging the financial soundness of NSE listed firms for the period 2008 to 2012. So far the study indicated that the Altman's *Z*"-scores was helpful in predicting corporate defaults as well as an easy-to-calculate measure of control for financial distress status of companies in academic studies. The Z-Score above 2.6 indicates a company to be healthy. Besides, such a company is also not likely to enter bankruptcy. However, Z-Scores ranging from 1.1-2.6 were taken to lie in the grey area while scores below 1.1 indicated distressed or more precisely failed companies. The results showed that the model was successful to predict non-failed firms but did not satisfy the classifications of failed firms as explained below.

It can be noted that Altman's (1993) Z'' score model correctly classified 28.6% of the observed firms and 25.7% wrongly classified firms as safe even though they were delisted from NSE and 45.7% of observed firms were in the gray zone which greatly increases uncertainty about their future classification. This shows that the model should be used with utmost caution for classifying firms as either failed or successful since there's a greater margin of error. As for the successful firms, Altman's (1993) Z'' score model ought to have classified the firms properly into their respective categories. After the analysis of the data presented from successful firms it was eminent that Altman's (1993) *Z*"-score model correctly classified 27 observations of successful firms in the safe zone. This meant that these firms had a low likelihood of becoming bankrupt and hence had a stable financial position. Eight of the successful firms were precisely from the construction sector, nine from the manufacturing sector, four from energy and petroleum sector, five from the telecommunication sector and one from commercial services. These firms were therefore summarized to meet their maturing short term obligations, efficient management in manufacturing, sales administration and other activities due to its cumulative profitability over time represented by the retained earnings over total asset variable. From the findings of the successful firms in the safe zone, it was also noted that the management of these firms had overall effectiveness as shown by the returns generated.

The model also classified 16 observations out of the 45 from the successful firms of the observed firms in the gray zone. This means that there is uncertainty of the future financial stability of these firms. The firms could either go into financial distress in which they might be subjected to hostile takeover or collapse of the business entity. It can also be said that financial aspect of the above firms in the gray zone may rise and become stable to perform both its long term and short term obligations. The construction sector represented the most uncertain sector in terms of financial stability. Seven observations in that sector therefore operate under uncertain environment. Under the commercial sector also 5 observations (from Kenya Airways) operated under uncertain environment. This meant that external factors like political stability put the firm into uncertain situations.

Finally the findings of the analyzed successful firm also indicate that the model classified 2 observations out of the 45 into distress zone. These firms were Kenol Kobil during the year 2012 and Total Kenya in 2011 and both of the firms fall under the sector of energy and petroleum in the Nairobi Securities Exchange list. From the analysis, this finding indicated the firms went into financial distress during those years.

The model also analyzed the firms that were termed as failed and delisted from Nairobi Securities Exchange from the period 1996 to 2012. The firms also had similar zones of classification though their margin of error is high. 10 out of the 35 observations were classified in the distress zone hence going into financial distress or bankruptcy. Those firms were the likes of Theta Group from the year 1997 to 2001 and Regent Undervalued assets limited from the year 1997 to 2000. From our findings these firms were unable to meet their financial obligations and hence went into insolvency.

Most of the firms that ought to be classified in the distress zone had Z”-scores that categorized them as either safe or gray zones. The firms that were classified in the safe zone were the likes of Kenya national Mills during the period of 1997 to 2001 and Uchumi supermarket during the period of 2001 to 2004. The findings indicated that these firms were financially healthy while in the real sense that was not the case. Kenya National Mills was acquired by another firm while Uchumi supermarket had the financial crises which all over the Kenyan market news.

The remaining 16 observations out of the 35 failed observations were classified in the zone of uncertainty which mostly termed as the gray zone. Since time has passed these firms have either gone into financial distress or stabilized in their financial performance. Examples of these were Pearl Drycleaners from the period of 1997 to 2001; Lonhro EA limited from the period of 1997 to 2001; Uchumi supermarket in 2005; East Africa Packaging from 1998 to 2002. Except Uchumi all the other three firms are not currently listed in NSE and that might be an indication that the firms went into financial distress.

However, the study noted that Altman's (1993) Z"-score model was not sufficient to differentiate between failed and non-failed firms. Altman's (1993) Z'' score model was intended for non-manufacturing firms and appropriate model for retail firms. The model has only four variables which he thought could best predict bankruptcy and more so he presumed that all the multi discriminant assumptions were satisfied and he went ahead to run such a model. This showed that the model should be used with utmost caution for classifying firms as either failed or non-failed firms since there was a greater margin of error for the failed firms. Contemporary critiques advocate for the use of logistic regression because of the many assumptions of multi discriminant analysis that are rarely in reality satisfied which ultimately reduce errors of wrong classification. The findings therefore agree with those of Alareeni and Branson (2012) who found that Altman Z'' score (1993) model had limited predictive power as compared to that of Altman Z score of 1968.The study therefore indicated that the model of Altman's (1993) Z"-score is suitable for non-manufacturing firms and retail firms as the model was intended for such firms.

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATION

5.1. Summary

The study involved the bankruptcy prediction of firms listed in the Nairobi Securities Exchange. It used the data from audited financial statements of firms listed and it was derived from the portal of Capital Market Authority and Nairobi Securities Exchange. The Altman's (1993) *Z*" score model was used to do the study due to its popularity in the failure prediction studies to other prediction models in the recent years. This research also explored the analysis of failed firms using the same model so as to compare the utility of the statistical model. To test this I sort firms whose data was available and which were delisted from Nairobi Securities Exchange from the period 1996 to 2012.

In order to test the efficient utility of the model I also used Statistical Package for Social software. The research employs a database of 5sectors from the Nairobi Securities Exchange for non-failed firms of which nine firms were sampled for the period from 2008 to 2012 .Another database of failed firms was also employed and seven firms were sampled from the list of delisted firms from NSE.

The study showed that Altman's (1993) *Z*"-score correctly classified 28.6% of the observed firms from the sample of failed firms and wrongly classified 25.7% of the same as safe even though they were delisted from NSE. The remaining 45.7% were also classified in the grey zone and this increases the uncertainty about their future classifications. On the other hand, the study also shows the predictive ability of the model where it classified correctly 60% of the observed firms in safe zones and 4.4% classified in the distress zone. In addition the remaining 35.6% of observed firms were classified in the grey zone and this increases the uncertainty about their future classification in the current listed firms in NSE.

5.2.Conclusions

The motivation for empirical research in corporate bankruptcy prediction is clear in that the early detection of financial distress and the use of corrective measures are preferable to protection under bankruptcy law. This study has provided a critical analysis of large number of empirical studies on bankruptcy prediction based variously on statistical techniques. It appears that there is substantial disagreement over the most suitable methodology and substantial scope for model development. In general financial ratios can be used to predict bankruptcy. However the type of ratio that will best discriminate between failing and non-failing firms appears to differ from place to place. From the analysis presented, it would appear that current ratio, retained earnings to total asset, earnings before interest and taxes to total assets and book value of equity to total liabilities can be used to successfully predict failures. This therefore suggests that investors and stakeholders should pay attention to liquidity and activity ratios.

The review shows that multi-discriminant analysis model has been frequently used due to its consistently high predictive accuracy achieved in relatively large number of studies with smaller adjusted standard deviations. This therefore suggests that the MDA model overall the most reliable methods of bankruptcy prediction. From the above findings we conclude that Altman's (1993) *Z*" score model is efficient in predicting bankruptcy prediction. In recent years, bankruptcy prediction has gained widespread attention in increasing popularity in corporations. The study explores the utility of statistical technique mostly termed as MDA. This technique is used to predict a firm's going concern status from four variables. This model contained four predictive variables was used and was as follows:

Z" 6.56X1 + 3.26X2 + 6.72X3 + 1.05X4

Where Z" is the discriminant score

Xl is the working capital/Total Asset

X2 is the Retained Earnings/Total Asset

X3 is the Earnings Before Interest and Taxes/Total Asset

X4 is the Book Value of Equity/Total liabilities

5.3. Policy Recommendations

Several important policy implications emerge from this study. First, a disjoint was noted in correlation between is expected of listed firms in terms of financial performance and the benefit to be accrued from CMA surveillance on them. This is due to the fact that firms have been delisted from NSE due to other factors and not due to financial performance as per the analysis in chapter of failed firms. It has also been noted that NSE has been performing poorly as evidenced when it was suspended for 15 minutes on October 2008 after its 20-share index falling below 4,000 points. This points out that CMA and NSE role and responsibility needs to be strengthened. The NSE should make financial stability an integral driver of its policy framework through adoption of financial analysis models.

Second, we should be alert of the fact that at times the signs of a major financial distress exhibits within a very short time that the predictive ability of financial ratios become temporarily redundant. This situation is common during an expected downturn of the economy. Nonetheless, financial ratios would give vital information to different stakeholders under normal operations. It is therefore recommended that practical applicability of bankruptcy prediction should be checked after some period of time as the economy changes.

Finally the outcome of the study suggests that stakeholders in a business firm can predict failure before it occurs by paying attention to current ratios and performance ratios. The fact that such can help predict failure before it occurs implies that stakeholders in a firm can avoid the losses associated with failures by taking appropriate actions well in advance. This will also be an early warning system to other interested parties.

5.4. Limitations of the Study

Financial data is only one source of signal about corporate failure. In reality other non-quantifiable circumstances and reasons could lead to failure. Examples are the catastrophes and exogenous considerations like the effects of political instability in Kenya during the 2007 to 2008 periods. Therefore when these other factors are considered the researcher will have conclusive method for predicting bankruptcy of firms.

The publicly available information was inadequate especially in delisted firms. Data was not available from most firms which were delisted from due to the fact that most companies give minimum legal disclosures which have been found wanting. This has narrowed down the scope of the study to the few firms whose data was available.

The sample size used here is small and concentrated on few selected firms in the different sectors. The study could have been conclusive if conducted across all firms listed in the Nairobi Securities Exchange. It has left critical sectors like insurance and financial service sectors due to the fact that most companies give minimum legal disclosures which have been found wanting.

The coefficients would most probably change if a larger sample was used. This was mostly contributed due to the limited time frame that the study was conducted in.

5.5. Suggestions for Further Research

The study has tried to strengthen the position of existing work in bankruptcy prediction, particularly based on Altman's (1993) Z" score model. From the insights gained in the course of the investigation, the researcher offers the following suggestions, which should act as a direction to future researchers:

Another research area that could be extended is to test bankruptcy prediction models to non-listed firms, relatively smaller turnover sized firms where the incidences of business failure is greater than larger corporations. This will help determine financial position of all firms in the economy and give more insights to investors on their investment decisions. With this suggestion regulatory bodies like Nairobi Securities Exchange and Capital Market Authority will be in a position to capture wider market in terms of listing new firms.

A replication of this study should be done after some time to find out if there are any changes that have taken place. A comparison can then be done with the current data of that time. From this, a definite recommendation should be arrived at as to whether the model used was helpful in predicting bankruptcy failures

Researchers should investigate the development of bankruptcy prediction models using different statistical methodology other than multi-discriminant analysis, such as artificial neural networks (ANNs), logit or probit analysis, to compare and select the most efficient model. This will evaluate the progress towards bankruptcy prediction in firms across the economy and to find out whether they are valid, adequate and whether they provide early warning of bankruptcy. With this suggestion in place, there will be more available research studies on the bankruptcy prediction and will be of great importance to both academicians and investors in relating with the current market and best procedures in making conclusive decisions concerning firms in the economy.

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APPENDICES

Appendix 1: Firms Listed on the NSE

AGRICULTURAL
Eaagads Ltd Ord 1.25
Kapchorua Tea Co. Ltd Ord 5.00
Kakuzi Ord.5.00
Limuru Tea Co. Ltd Ord 20.00
Rea Vipingo Plantations Ltd Ord 5.00
Sasini Ltd Ord 1.00
Williamson Tea Kenya Ltd Ord 5.00
COMMERCIAL AND SERVICES
Express Ltd Ord 5.00
Kenya Airways Ltd Ord 5.00
Nation Media Group Ord. 2.50
Standard Group Ltd Ord 5.00
TPS Eastern Africa (Serena) Ltd Ord 1.00
Scangroup Ltd Ord 1.00
Uchumi Supermarket Ltd Ord 5.00
Hutchings Biemer Ltd Ord 5.00
Longhorn Kenya Ltd
TELECOMMUNICATION AND TECHNOLOGY
AccessKenya Group Ltd Ord. 1.00

Safaricom Ltd Ord 0.05
AUTOMOBILES AND ACCESSORIES
Car and General (K) Ltd Ord 5.00
CMC Holdings Ltd Ord 0.50
Sameer Africa Ltd Ord 5.00
Marshalls (E.A.) Ltd Ord 5.00
BANKING
Barclays Bank Ltd Ord 0.50
CFC Stanbic Holdings Ltd ord.5.00
I&M Holdings Ltd Ord 1.00
Diamond Trust Bank Kenya Ltd Ord 4.00
Housing Finance Co Ltd Ord 5.00
Kenya Commercial Bank Ltd Ord 1.00
National Bank of Kenya Ltd Ord 5.00
NIC Bank Ltd 0rd 5.00
Standard Chartered Bank Ltd Ord 5.00
Equity Bank Ltd Ord 0.50
The Co-operative Bank of Kenya Ltd Ord 1.00
INSURANCE
Jubilee Holdings Ltd Ord 5.00
Pan Africa Insurance Holdings Ltd 0rd 5.00
Kenya Re-Insurance Corporation Ltd Ord 2.50

Liberty Kenya Holdings Ltd
British-American Investments Company (Kenya) Ltd Ord 0.10
CIC Insurance Group Ltd Ord 1.00
INVESTMENT
Olympia Capital Holdings ltd Ord 5.00
Centum Investment Co Ltd Ord 0.50
Trans-Century Ltd
MANUFACTURING AND ALLIED
B.O.C Kenya Ltd Ord 5.00
British American Tobacco Kenya Ltd Ord 10.00
Carbacid Investments Ltd Ord 5.00
East African Breweries Ltd Ord 2.00
Mumias Sugar Co. Ltd Ord 2.00
Unga Group Ltd Ord 5.00
Eveready East Africa Ltd Ord.1.00
Kenya Orchards Ltd Ord 5.00
MANUFACTURING AND ALLIED
A.Baumann CO Ltd Ord 5.00
CONSTRUCTION AND ALLIED
Athi River Mining Ord 5.00
Bamburi Cement Ltd Ord 5.00
Crown Berger Ltd 0rd 5.00

E.A. Cables Ltd Ord 0.50
E.A. Portland Cement Ltd Ord 5.00
ENERGY AND PETROLEUM
Kenol Kobil Ltd Ord 0.05
Total Kenya Ltd Ord 5.00
KenGen Ltd Ord. 2.50
Kenya Power & Lighting Co Ltd
Umeme Ltd Ord 0.50
GROWTH ENTERPRISE MARKET SEGMENT
Home Afrika Ltd Ord 1.00

Appendix 2: Sample Data

Non- failed firms

Ref	Name	Year	Total Assets	Current Assets	Current Liabilities	Total Liabilities	Retained Earnings	Equity	EBIT
			Kes '000'	Kes '000'	Kes '000'	Kes '000'	Kes '000'	Kes '000'	Kes '000'
1	Athi River Mining	2008	6,352,478	1,885,011	1,842,931	4,225,935	1,362,975	2,127,543	705,450
		2009	12,141,091	3,362,746	3,353,762	8,012,161	1,886,662	4,128,930	948,714
		2010	16,564,899	4,240,061	3,206,459	11,921,297	2,499,082	4,662,168	1,112,962
		2011	20,549,023	3,756,304	4,453,136	14,446,497	3,827,809	5,998,657	1,362,912
		2012	26,953,100	7,936,410	6,502,840	19,832,580	4,945,503	7,013,771	1,790,296
2	Bamburi Cement Limited	2008	20,720,000	10,036,000	5,443,000	11,613,000	9,377,000	16,602,000	4,889,000
		2009	32,112,000	12,773,000	4,944,000	11,171,000	14,674,000	20,941,000	9,596,000
		2010	33,306,000	12,863,000	7,464,000	11,680,000	15,931,000	21,626,000	7,564,000
		2011	33,502,000	13,356,000	5,097,000	9,328,000	17,983,000	24,174,000	5,368,000
		2012	43,038,000	16,462,000	7,011,000	12,177,000	18,875,000	30,861,000	5,423,000
3	East African Portland Cement Company limited	2008	9,073,345	2,661,738	1,176,375	5,046,596	1,835,456	1,098,000	1,474,057
		2009	12,053,977	3,131,045	1,512,392	5,939,115	3,606,005	1,098,000	1,452,078
		2010	12,037,565	2,911,680	1,836,650	6336364	3,341,441	1,098,000	90,015
		2011	13,530,871	3,172,070	2,100,179	7,268,415	3,923,685	1,098,000	653,640
		2012	14,158,592	2,635,509	2,265,774	9,241,968	2,608,340	1,098,000	610,479
4	East African Breweries Limited	2008	33,254,248	17,534,514	8,867,918	11,137,405	10,509,910	3,272,698	10,883,834
		2009	35,832,389	18,941,137	9,432,296	12,464,145	11,332,702	3,272,698	11,038,838
		2010	38,420,691	17,456,435	11,684,390	14,716,239	10,768,656	3,272,698	12,568,087

		2011	49,519,364	16,320,457	15,509,186	22,764,183	11,261,368	3,272,698	12,258,989
		2012	54,584,316	18,057,773	22,483,782	45,868,436	14,985,679	3,272,698	15,253,049
5	Kenol Kobil	2008	27,708,592	21,111,387	16,301,749	16,792,732	4,578,815	5,239,938	3,441,673
		2009	31,288,857	25,170,657	19,293,187	19,834,229	5,419,719	5,239,938	2,387,146
		2010	32,216,630	26,062,068	18,879,407	19,511,118	6,455,764	5,239,938	3,667,452
		2011	45,974,304	40,145,862	32,794,177	34,323,843	7,144,143	5,239,938	4,933,783
		2012	32,684,166	24,540,381	25,340,816	26,238,441	859,568	5,239,938	(8,964,664)
6	Kenya Airways	2008	77,838,000	22,123,000	14,113,000	51,256,000	20,960,000	2,308,000	14,269,000
		2009	75,979,000	19,709,000	21,722,000	58,803,000	16,069,000	2,308,000	16,043,000
		2010	73,263,000	17,858,000	20,921,000	53,290,000	17,641,000	2,308,000	17,265,000
		2011	78,712,000	23,617,000	22,209,000	55,569,000	20,089,000	2,308,000	5,002,000
		2012	77,432,000	21,833,000	23,756,000	54,409,000	20,280,000	2,308,000	2,146,000
7	Mumias Sugar	2008	14,152,576	4,574,100	3,398,096	5,111,079	4,154,154	3,060,000	1,589,204
		2009	17,475,715	5,099,837	3,760,339	7,436,246	5,292,218	3,060,000	1,193,161
		2010	18,334,110	6,495,834	3,250,021	7,334,258	6,404,006	3,060,000	2,179,874
		2011	23,176,516	6,511,659	2,961,691	8,700,509	7,863,551	3,060,000	2,646,575
		2012	27,400,113	7,171,360	5,720,655	11,676,427	9,312,806	3,060,000	1,764,029
8	Safaricom	2008	74,366,313	12,887,438	25,243,720	31,723,720	36,792,593	3,850,000	19,945,160
		2009	91,332,223	17,352,654	35,321,856	40,001,856	43,480,367	3,850,000	15,304,027
		2010	104,120,850	22,570,645	33,819,970	41,825,732	50,691,160	3,850,000	20,966,670
		2011	113,854,762	21,701,296	34,117,726	46,400,671	56,002,747	3,850,000	18,361,363
		2012	121,899,677	21,194,195	37,615,900	49,818,879	59,940,584	3,850,000	17,369,400
9	Total	2008	14,526,784	11,763,581	9,508,962	9,508,962	2,174,978	2,842,844	1,031,368
		2009	31,528,196	20,745,441	18,588,085	22,566,085	2,219,900	6,742,291	733,699

		2010	30,375,677	20,114,577	17,519,824	20,795,824	2,837,562	6,742,291	1,388,425
		2011	35,198,166	25,338,951	22,982,764	26,003,348	2,452,527	6,742,291	57,850
		2012	32,980,604	23,348,459	17,933,163	18,787,928	2,250,385	11,942,291	(64,301)

Failed firms

Ref	Name	Year	Total Assets	Working Capital	Total Liabilities	Retained Earnings	Equity	EBIT
			Kes	Kes	Kes	Kes	Kes	Kes
1	Pearl Drycleaners	2001	713,278,000	149,368,000	693,899,000	69,267,000	35,568,000	44,398,000
		2000	723,647,000	158,257,000	685,378,000	69,357,000	37,456,000	43,380,000
		1999	736,182,000	168,041,000	687,201,000	72,091,000	37,980,000	45,993,000
		1998	738,378,000	174,369,000	689,479,000	69,378,000	39,478,000	54,270,000
		1997	801,279,000	173,276,000	691,379,000	73,836,000	41,378,000	52,682,000
2	Theta Group	2001	1,587,367,000	119,269,000	1,356,368,000	73,639,000	124,268,000	14,384,000
		2000	1,545,376,000	129,367,000	1,367,842,000	74,356,000	125,276,000	14,454,000
		1999	1,537,286,000	122,323,000	1,359,183,000	76,162,000	127,838,000	16,187,000
		1998	1,545,378,000	134,367,000	1,437,368,000	77,457,000	129,457,000	17,368,000
		1997	1,567,334,000	148,375,000	1,436,367,000	78,457,000	131,367,000	18,582,000
3	Lonhro EA Ltd	2001	2,767,287,000	569,998,000	7,989,098,000	139,425,000	428,453,000	11,256,000
		2000	2,661,970,000	563,801,000	8,486,689,000	138,450,000	417,543,000	11,785,000
		1999	2,649,064,000	453,203,000	8,770,427,000	126,265,000	401,507,000	31,319,000
		1998	2,556,356,000	377,453,000	568,935,000	122,245,000	398,367,000	26,789,000

		1997	2,554,234,000	386,456,000	877,653,000	121,673,000	394,325,000	25,678,000
4	Kenya National Mills	2001	3,231,287,000	2,534,598,000	1,289,908,000	168,958,000	321,678,000	689,642,000
		2000	3,269,097,000	1,327,458,000	1,050,000,000	167,789,000	315,113,000	654,358,000
		1999	3,436,761,000	1,160,253,000	1,905,000,000	169,602,000	273,492,000	246,032,000
		1998	3,452,279,000	1,253,267,000	1,792,000,000	171,784,000	275,263,000	652,826,000
		1997	3,327,278,000	1,342,287,000	1,865,678,000	173,865,000	289,267,000	589,295,000
5	Regent Undervalued Assets Ltd	2001	1,487,367,000	117,269,000	1,356,368,000	72,639,000	124,268,000	14,384,000
		2000	1,445,376,000	109,367,000	1,367,842,000	73,356,000	125,276,000	14,454,000
		1999	1,437,286,000	112,323,000	1,359,183,000	75,162,000	127,838,000	16,187,000
		1998	1,445,378,000	134,367,000	1,437,368,000	76,457,000	129,457,000	17,368,000
		1997	1,467,334,000	138,375,000	1,436,367,000	75,457,000	131,367,000	18,582,000
6	Uchumi Supermarket	2005	3,269,097,000	127,458,000	3,151,132,000	0	1,050,000,000	654,358,000
		2004	3,436,761,000	1,160,253,000	2,734,920,000	169,602,000	1,905,000,000	246,032,000
		2003	3,486,364,000	1,285,472,000	2,725,356,000	171,267,000	2,064,000,000	237,387,000
		2002	3,553,367,000	1,273,456,000	2,734,376,000	172,368,000	2,146,000,000	286,276,000
		2001	3,635,876,000	1,323,256,000	2,825,897,000	173,268,000	2,240,000,000	287,368,000
7	EA Packaging	2002	2,667,287,000	578,998,000	8,189,098,000	129,425,000	428,453,000	11,256,000
		2001	2,661,970,000	564,801,000	8,186,689,000	128,450,000	417,543,000	11,785,000
		2000	2,549,064,000	466,203,000	7,770,427,000	116,265,000	401,507,000	31,319,000
		1999	2,456,356,000	367,453,000	6,789,350,000	112,245,000	398,367,000	26,789,000
		1998	2,454,234,000	366,456,000	6,676,530,000	111,673,000	394,325,000	25,678,000