PREDICTION OF FINANCIAL DISTRESS IN LIGHT OF FINANCIAL CRISIS: A CASE OF LISTED FIRMS IN KENYA

EMMY CHEROTICH KOECH

A Research Thesis Submitted to the Department Of Accounting, Finance and Management Science in Partial Fulfillment of the Requirements for the Award of A Masters Degree In Business Administration

EGERTON UNIVERSITY
NOVEMBER 2018

DECLARATION AND RECOMMENDATION

Declaration

I, the undersigned, declare that this research proposal is an original work and has never been submitted to any institution of higher learning for the Award of a degree or diploma other than Egerton University.

Signature: ……………………… Date………………………….

Emmy Cherotich Koech

CM11/00549/09

Recommendation

This research proposal has been submitted for examination with our approval as University supervisors.

Signature:……………………… Date………………………..

Dr. F. M Kalui (PhD)

Department of Accounting, Finance and Management Science, Egerton University

DEDICATION

I dedicate this work first to my God, who has been there for me giving me strength to pull through. It is also dedicated to my husband Mark Lorette and our two boys Perur and Kalya who have been my source of strength and encouragement. Lastly to my parents Mr. and Mrs. Stanley Koech who have continuously encouraged and prayed for me.

ACKNOWLEDGEMENT

I am greatly indebted to the Almighty God for granting me the opportunity to pursue this MBA program. His abundant care, love and grace have enabled me to soldier on despite many upheavals in my quest for a postgraduate degree.

I would like to appreciate Egerton University for creating a good environment for my studies and for their continued support in my endeavor to attain this degree.I would like to pay my grandest homage to all persons who in one way or the other significantly contributed to the eventual completion of my research. My honest gratitude and appreciation go to my supervisors Mr. Mugo Robert, Mr. Akuno Nyangaya R.O and Dr. F. M Kalui whose competent supervision was integral to the completion of this study. Special thanks go to the Capital Markets Authority librarian Geoffrey Chebwai who availed all the data that was pertinent to this research.

Lastly, I feel deeply grateful to my parents and siblings for their tremendous support, my friends for their encouragement and constant prayers.

ABSTRACT

The purpose of this study was to predict financial distress in Kenyan listed firms. The specific objectives were to determine the contribution of financial ratios towards the prediction of corporate financial distress, to evaluate the predictive ability of the logistic regression model in making accurate forecasts of financial distress, to determine the predictive accuracy of the model in predicting financial distress before and during financial crisis, and also to compare the predictive accuracy of the model in predicting financial distress over the two periods, that is, before financial crisis (2004- 2006) and during financial crisis (2007- 2009). The study adopted a correlational research design. The target population included all the firms listed at the Nairobi Securities Exchange as at 2008 which were 66 firms. Secondary data were used in this study and were obtained from the Capital Markets Authority. Purposeful sampling was employed. Both descriptive statistics such mean, mode, median and standard deviation. Also inferential statistics such as correlation to determine the association between financial ratios and financial distress. Regression analysis were performed to test the hypotheses. The results indicated that an increase in the ratio of working capital to total assets, EBIT to total assets, current liabilities to total assets, and retained earnings to total assets of the surveyed firms was likely to increase the financial distress of the surveyed firms. However, the ratio of debt to total assets was found to be marginally related to financial distress. It was concluded that the earnings before interest and tax to total assets ratio significantly affected financial distress; having large amounts of retained earnings could possibly increase financial distress; and that financial ratios played a crucial role in determination of financial distress among listed firms. The study recommended that the listed firms should maintain high liquidity, be appropriately leveraged and have a positive trajectory of profitability in order to effectively mitigate financial distress.

TABLE OF CONTENTS

DECLARATION AND RECOMMENDATION .... **ii**

COPYRIGHT .... **iii**

DEDICATION.. **iv**

ACKNOWLEDGEMENT ....**v**

ABSTRACT .... **vi**

LIST OF TABLES .... **ix**

LIST OF FIGURES ....**x**

LIST OF ACRONYMS.. **xi**

CHAPTER ONE...**1**

INTRODUCTION...**1**

1.1 Background of the study **1**

1.2 Statement of the Problem 6

1.3 Objectives of the Study 6

1.3.1 General objective 6

1.3.2 Specific objectives 6

1.4 Research Hypotheses...7

1.5 Significance of the Study. 7

1.6 Scope of the Study..8

1.7 Limitations of the Study 8

1.8 Operational Definition of Terms 9

CHAPTER TWO **10**

LITERATURE REVIEW...**10**

2.1 Concept of Financial Distress 10

2.2 Financial Distress Prediction Models..11

2.3 Theoretical Literature 17

2.3.1 Entropy Theory...17

2.3.2 Cash Management Theory...18

2.4 Empirical Literature 18

2.5 Research Gaps...27

2.6 Conceptual Framework **28**

CHAPTER THREE **30**

RESEARCH METHODOLOGY **30**

3.1 Research Design..30

3.2 Target population 30
3.3 Sampling Design and Size 31
3.4 Data Collection Method 31
3.5 Data Analysis 31
CHAPTER FOUR 33
RESULTS AND DISCUSSION 33
4.1 Introduction 33
4.2 Descriptive Statistics 33
4.2.1 Working Capital to Total Assets Ratio 33
4.2.2 Sales to Total Assets Ratio 34
4.2.3 EBIT to Total Assets Ratio 36
4.2.4 Current Liabilities to Total Assets Ratio 37
4.2.5 Debt to Total Assets Ratio 38
4.2.6 Retained Earnings to Total Assets Ratio 40
4.2.7 Financial Distress 41
4.3 Inferential Statistics 43
4.3.1 Relationship between Financial Ratios and Financial Distress 43
4.3.2 Effect of Financial Ratios on Financial Distress 46
4.4 Test of Hypothesis 50
CHAPTER FIVE 54
SUMMARY, CONCLUSIONS AND RECOMMENDATIONS 54
5.1 Introduction 54
5.2 Summary of Findings 54
5.3 Conclusions of the Study 55
5.4 Recommendations of the Study 56
5.5 Suggestions for Further Research 57
REFERENCES 58
APPENDICES 63
Appendix I: Companies under financial distress for the period under review 63
Appendix II: Data collection sheet for Discreet Hazard model 64

LIST OF TABLES

Table 4.2: Sales to Total Assets Ratio 36

Table 4.3: EBIT to Total Assets Ratio 37

Table 4.4: Current Liabilities to Total Assets Ratio 38

Table 4.5: Debt to Total Assets Ratio 40

Table 4.6: Retained Earnings to Total Assets Ratio 41

Table 4.7: Financial Distress 43

Table 4.8: Correlation Matrix for Financial Ratios and Financial Distress 45

Table 4.9: Regression Weights for Overall Model 47

Table 4.10: Significant Test Results 48

Table 4.11: Results for Overall Model 48

Table 4.11: Results for Overall Model 50

Table 4.10: Significant Test Results 51

Table 4.12: Significant Test Results for 2004 – 2006 52

Table 4.13: Significant Test Results for 2007 – 2009 53

LIST OF FIGURES

Figure 2.1: Conceptual Framework..**30**

LIST OF ACRONYMS

CBK Central Bank of Kenya

CMA Capital Markets Authority

EBIT Earnings before Interest and Tax

GDP Gross Domestic Product

IMF International Monetary Fund

KNBS Kenya National Bureau of Standards

MDA Multivariate Discriminant Analysis

NSE Nairobi Securities Exchange

CHAPTER ONE

INTRODUCTION

1.1 Background of the study

The National Bureau of Economic Research (NBER, 2010) defines recession as a significant decline in the economic activity across the country lasting more than a few months and normally visible in real GDP growth, real personal income, employment, and industrial production and wholesale- retail sales. These factors are very important in determining whether there is a recession or not (Rachlin, 2009). The study by Koksal and Ozgul (2007), found that managers are usually asked to either delay or abandon investment projects altogether during an economic downturn and get back to normal operations after that period is over in order to avoid risks. It is worth therefore noting that companies that are affected more severely during economic crisis may be forced to either liquidate and cease business or curtail their operations, retrench some of their workers, ask employees to accept a smaller compensation package and find ways and means to cut costs so as to remain competitive.

The year 2008 saw economies in the world dip into a recession. This economic downturn began with industrialized countries and then moved to developing economies creating big cracks in the global world economy. Shortly after that credit flows froze and lender confidence dropped, investors stopped investing in countries and ultimately the value of stocks and domestic currencies plunged (IMF, 2009). A study by Cirmizi, Klapper and Uttamchandani (2012), found that this financial crisis had a big effect on companies around the world resulting in reduced demand for goods and services, reduction in availability of business financing and a declining flow of inter-border investment funds. There was also a rise in the level of insolvency among business entities due to declining demand for goods and services and decreasing availability of external finance.

Another study by Erkens, Hung and Matos (2012) stated that since there was a large number of collapsing financial institutions around the world, there was a freeze of global credit markets that required widespread government interventions. Developing economies may not have played a big part in the recession but due to the fact that their economies are not resilient enough to counter the actions of the global markets, the sudden turn of events affected them. For many countries that do not hold United States securities, the impact of the crisis was initially transmitted through the exchange rate and the financial markets. With rapidly changing asset prices, the deteriorating financial conditions became a very important source of macroeconomic vulnerability. In their January 2009 update on World Economic Outlook, IMF points out that global growth was projected to slow from less than 3½percent to about ½ percent in 2009 before recovering in 2010.This means that as a result of the recession, the world economy faced a deep downturn.

The Kenya National Bureau of Standards (KNBS, 2009) highlights key economic indicators of financial downturn for the main Organization for Economic Co-operation and Development (OECD) countries. In the United States for example, the economy experienced a slackened real GDP growth estimated at 1.4 per cent in 2008 compared to 2.0 per cent in 2007.In Japan, the expansion of the economy experienced a slowdown following the recession in the global economy. The country's real GDP grew at an estimated 0.5 per cent compared to 2.1 per cent in 2007. This was occasioned by external shocks leading to contraction in the country's export markets, reduction in domestic demand, and an appreciation of the Japanese Yen against other major currencies. The unemployment rate in the country increased from 3.9 per cent in 2007 to 4.1 per cent in 2008. In the United Kingdom Real GDP was estimated to have grown at 0.8 per cent in 2008 with the economy facing adjustments in the construction sector, falling house prices and decelerated domestic demand.

Unemployment is estimated to have increased by 0.1 percentage points to 5.5 per cent in 2008. For Germany the real GDP growth is estimated to have reduced from 2.6 per cent recorded in 2007 to 1.4 per cent in 2008. In China real GDP growth is estimated to have contracted in 2008 to 9.5 per cent compared to 11.9 per cent in 2007 and in the emerging Asian economies, countries in experienced slowed real GDP growth in 2008 at a rate of 7.7 per cent compared to 9.3 per cent in 2007. The Global recession was also felt in African countries and the ways in which it affected it include a significant contraction in their trade globally and a related collapse in exports of primary commodities, which many countries are dependent. Foreign investment and remittances to migrant workers decreased significantly. Some analysts also predicted that the recession would lead to cuts in foreign aid in the medium term with persistence of the crisis. Economies considered being the most powerful in Africa proved to be the most vulnerable to the downturn: South Africa experienced a recession for the first time in nearly two decades, and Nigeria and Angola reported revenue shortfalls due to the fall in global oil prices. Several countries seen as having solid macroeconomic governance, notably Botswana, sought international financial assistance to cope with the impact of the crisis. (Alexis, Martin & Vivian, 2010).

Many analysts argue that even with the recent reforms in the economy, growth and development in many African countries is hampered by policies that restrict competition. According to World Bank (2008), Africa is the world's second most trade-restrictive region after South East Asia. The region, also displays the worst attributes in business environment, governance, logistics, and other trade facilitation indicators (World Bank, 2008)

The Kenyan economy did not also escape the recession period and according to the Kenya National Bureau of Standards (KNBS, 2009) Economic Survey report, the economic growth in Kenya was restrained by the 2008 post-election violence, the global financial crisis and high fuel and food prices and though the post-election violence was experienced only in the first quarter of 2008, its spill-over effects were manifest throughout 2008 resulting in substantial declines in growths of most of the sectors of the economy leading to a slump in economic growth from 7.1% in 2007 to 1.7% in 2008. Similarly, employment creation was adversely affected by the slow economic growth, in the same period, the annual average inflation rate almost tripled from 9.8 per cent in 2007 to 26.2 per cent in 2008, a record high since that of 28.8 per cent in 1994. This led to a reduction in real average earnings by 16.2 per cent, the stock market also saw a downturn with the 20 share index shedding 1924 points at the end of 2008, while market capitalization remained at 854 billion Kenya shillings in 2008.

The effects of the global financial turmoil explains this stagnation that resulted in reduced investor confidence who offloaded their investments in the Nairobi Securities Exchange due to the anticipation of a global credit crunch and falling stock prices. The Kenya Shilling also weakened against the US dollar to record an average exchange rate of 69.18 Kenya shillings in 2008 compared to 67.32 Kenya shillings per US dollar in 2007. In addition, the earnings from tourism sector which deteriorated in 2008, impacted negatively on the foreign exchange rate. The Central Bank of Kenya (CBK, 2009) on the other hand reported the 91 day Treasury bill rates for January 2008 to be at 6.950 while that of 2009 was at 8.464.The composite consumer index for lower income groups with October 2005 as the base year was 124.88 in 2008 and 142.08 in 2009.The treasury bill rate for Jan 2009 was 8.464 up from 6.950 in Jan 2008.

Recession can therefore be seen as a threat to the world economy at large since it has far reaching effects on both individual and corporate businesses. According to Wanjohi, (2011) the global economic slowdown and the accompanying cash crunch have hit businesses across all sectors forcing them to take drastic measures like reduce expenses in order to keep afloat. Distress is certainly not desirable and so the ability to adequately predict failure is crucial for both investors and creditors. This is because they have an incentive in early detection given that they would never like to make a decision that is disadvantageous to them. According to (Altman, 1993) the prediction of company distress and failure has gained much attention to financial economists and accountants alike and although values like corporate governance and ethics have been used to prevent financial distress, early detection of distress is still essential for protection of investments. Early failure prediction enables firms to take action to reduce bankruptcy costs, avoid failure to all stakeholders and contribute towards stability of the financial environment (Gharaibeh et al., 2013).

According to Vuran (2009), the development and use of models can be very important in two different ways. First, as early warning systems, such models are very useful to managers and other authorities. Second, they can be useful in aiding decision making of financial institutions in firms' evaluation and selection. There are many research projects that have been conducted in order to find the early warning signs of distress. Finding a method to identify corporate financial distress as early as possible is clearly a matter of considerable interest to investors, creditors, auditors and other stakeholders. The significance of this issue has stimulated a lot of research concerning the prediction of corporate bankruptcy or financial distress. These studies often used the statistical approach or iterative learning approach to develop prediction models. Researchers used statistical models in the 60s to identify ratios that could help classify companies into failed and non-failed .This statistical approach includes univariate and multivariate models. In his work, Beaver (1966) used a dichotomous classification test to identify financial ratios for corporate failure prediction. He used 30 financial ratios and 79 pairs of companies (failure/non-failure). The best discriminant factor was the working capital/debt ratio, which correctly identified 90 percent of the firms one year prior to failure. The second best discriminant factor was the net income/total assets ratio, which had 88 percent accuracy. Altman (1968) was the first researcher to develop a multivariate statistical model to discriminate failure from non-failure firms. He used multivariate discriminant analysis (MDA), Martin (1977) used the logit model for bank failure prediction.

This study will evaluate the impact of accounting information on the prediction of financial distress for Kenyan Listed firms using the logistic regression approach. Ohlson (1980) pioneered the application of Logistic Regression Analysis in prediction of bankruptcy and described the Logit model as a non-linear transformation of the linear regression and a technique that weights independent variables and assigns a score. The logit approach incorporates non-linear effects and uses the logistic cumulative distribution function to maximize the joint probability of default for the distressed firms and the probability of non-failure for the healthy companies in a sample. Much of the early research in the area of financial distress focused on MDA and then in later years on logit analysis.

Logistic Regression Analysis (logit analysis) involves the determination of conditional probabilities of variables in a sample using the logistic regression model (logit model).
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 of any of these. Generally, the dependent or response variable is dichotomous, such as presence/absence or success/failure. Logistic regression combines independent variables to estimate the probability that a particular event will occur, i.e. a subject will be a member of one of the groups defined by the dichotomous dependent variable. If the probability for group membership in the modeled category is above some cutoff point, the subject is predicted to be a member of the modeled group. If the probability is below the cutoff point, the subject is predicted to be a member of the other group. For any given case, logistic regression computes the probability that a case with a particular set of values for the independent variable is a member of the modeled category. The logit model however suffers a shortcoming with respect to data collection of bankrupt firms. According to Ohlson (1980), realistic evaluation of a model's predictive relationships requires that the predictors are (would have been) available for use prior to the event of failure. The shortcoming arises because annual audited reports would not be publicly available at the end of the financial year; since audit takes place the following year. The timing issue can be expected to be serious for firms which have a large probability of failure in the first place. Another researcher who used conditional probability models, and more specifically Logit Analysis, to predict financial distress was Zavgren (1985). She argued that models which generated a probability of failure were more useful than those that produced a dichotomous classification as with the MDA.

1.2 Statement of the Problem

Financial distress and bankruptcy prediction models have become increasingly popular among researchers in the academic field ever since William H. Beaver (1966) demonstrated the usefulness of financial ratios in the prediction of firm failure.

Many failure prediction models have been developed (Altman, 1968; Ohlson, 1980; Zmijewski, 1984; Zavgren, 1985) and several issues have been noted. . Mensah (1984) warned that, in addition to the selection of different ratios in the final prediction model, researchers typically analyse data across several years without considering the underlying economic events in those years. Zavgren (1985) and Holmen (1988) showed that, in the course of time, prediction models have performed less well to a certain extent since financial distress prediction models lose their predictive power over time.

Natasa and Marina (2011) did a study on comparing financial distress prediction models before and during recession in Croatia using a logistic regression model. This study concluded that if economic conditions are stable, the same model can achieve adequate precision over the years but if the conditions are changing the first step is changing the cut-off policies after which development of the new model follows.

With a view of the findings of Natasha and Marina (2011), this study sought to find out whether the logistic regression model, if applied in the Kenyan context would achieve precision before and during financial crisis

1.3 Objectives of the Study

1.3.1 General objective

The general objective of the study was to predict financial distress in Kenyan Listed firms in the light of financial crisis using the logistic regression model.

1.3.2 Specific objectives

This study was based on the following specific objectives:

i. To determine the financial ratios which contribute significantly to the prediction of financial distress.
ii. To evaluate the predictive ability of the model in making accurate forecasts of financial distress.

iii. To determine the predictive accuracy of the model in predicting financial distress before financial crisis.

iv. To determine the predictive accuracy of the model in predicting financial distress during financial crisis.

v. To compare the predictive accuracy of the model in predicting financial distress before and during financial crisis.

1.4 Research Hypotheses

This study tested the following null hypotheses:

HO_1: There are no financial ratios which significantly contribute to the prediction of financial distress.

HO_2: The model has no significant predictive ability to make accurate forecasts of financial distress.

HO_3: The model has no significant predictive accuracy in predicting financial distress before financial crisis.

HO_4: The model has no significant predictive accuracy in predicting financial distress during financial crisis.

HO_5: There is no significant difference in the predictive accuracy of the model in predicting financial distress before and during financial distress.

1.5 Significance of the Study.

Potential investors who wish to make investment decisions in certain companies will benefit from understanding financial distress and particularly the statistical variables to look out for and thus make an informed investment decision. Similarly, shareholders can use the findings of this study to make disposal or investment decisions. Financial institutions will be able to determine their debt repayment capability and thus the probability of default and other inherent risks. Suppliers who wish to enter into business relationships with potential buyers can use the model to make credit policy decisions. Suppliers would be most interested in a model that evaluates working capital patterns as supplies form a core component of working capital (Current Assets minus current liabilities). The model would be used to evaluate the strength of cash flows. Hence, credit policy decisions such as creditor days, trade discounts, late payment penalties, and cash trading can be made based on results of default model. The academicians and researchers will also benefit from further insights into the predictive ability of the hazard model which may form the basis for further research. The findings of this study may generate further research questions that may be investigated further.

1.6 Scope of the Study

The study was delimited to the prediction of financial distress in Kenya in the light of financial crisis. According to the Kenya National Bureau of Standards (KNBS, 2009) Economic Survey report, the economic growth in Kenya was restrained by the global financial crisis. The term financial distress was used interchangeably with bankruptcy and for the purpose of this study firms which made losses or experienced a 25% decline in profits were considered as financially distressed, supported by the Capital Markets Authority.

The population of the study comprised of all the companies listed in the Nairobi Securities Exchange particularly, the listed companies which made losses in 2008 or experienced profit reductions of 25% and above. Data were obtained from secondary sources, collected from financial reports of the companies from the Capital Markets Authority (CMA) records for 5 years prior to 2008 which is the time the companies experienced distress.

In order to provide an in- depth analysis of the predictive accuracy of the model, tests were done using data for the period immediately prior to the financial crisis, which was, 2004 - 2006 and during financial crisis which was 2007- 2009 The research design was correlational in nature which is a research design which measures two or more variables and assess the relationship between or among them.

1.7 Limitations of the Study

The first limitation of the study was that the study restricted itself only to those listed companies that failed in 2008 leaving out other firms that failed in other years and secondly, the study generalized the findings from one period of financial crisis to other periods of financial crises which may not necessarily be the case. The study delimited itself to only those companies whose profits declined by 25% and above and those which made losses in the year under review since they were defined as financially distressed. Secondly, the study focused on the period from 2003 to 2008, since according to the Kenya National Bureau of Standards (KNBS, 2009) Economic Survey report, the economic growth in Kenya was restrained by the global financial crisis and high fuel and food prices. Lastly, the study focused on only the companies which were listed at the Nairobi Securities Exchange (NSE) for the period under study since this information was publicly available in the Capital Markets Authority website which ensured reliability and validity.

1.8 Operational Definition of Terms

Bankruptcy: This is a term used interchangeably with financial distress.

Company failure: This is a state of being in financial distress or being bankrupt.

Financial distress: This is a state where a company makes losses or reduces profits by 25% and over.

Financial crisis: This is a period of economic downturn where there is a decline in economic activity leading to poor performance and very low to no profits at all. In this document, it has been used interchangeably with recession.

Financial ratios: These are indicators that compares two numeric values obtained from financial statements of a given entity that ordinarily reflect the financial situation and performance of a firm.

Predictive ability: This refers to the capacity of the model to forecast the financial situation (distress) of a firm.

Predictive accuracy: This is the degree of precision that the model is able to forecast financial distress or situation of a firm.

CHAPTER TWO

LITERATURE REVIEW

2.1 Concept of Financial Distress

The literature on the forecasting of financial distress is not without inadequacies. According to Jamshed (2012), one of these problems is that different authors use different criteria to indicate the presence of distress. Pandey (2005) looks at financial distress in terms of ability to meet obligations and concludes that when a firm is unable to meet its obligations then it is in a state of financial distress. The same opinion is shared by Jahur and Quadir (2012) who define financial distress as the inability of a firm to pay its current obligations on the dates that they are due. That is, a firm cannot pay lenders, suppliers, shareholders, or a bill is overdrawn or the firm is bankrupt according to the law (Vuran, 2009). This means that an institution is having operational, managerial and financial difficulties. (Adeyemi, 2011). This, according to Steyn, Buwer and Hamman (2006) means that the firm cannot continue operating in its current form and therefore includes delisting or a major restructuring of the overall organization. Outecheva (2007) looks at financial distress in terms of leverage and concludes that a combination of very low volume of liquidity, negative cash flow and high levels of leverage leads to financial distress among many corporate firms. As soon as firms have reached a certain level of leverage but do not strategically conform to their business plans, financial distress can occur even if the economic times are favorable. Equity values become vulnerable when there is high leverage in the firms accompanied by increasing volatility. This leads to a situation where each possible decline in the value of the enterprise may rapidly impair equity. (Altman and Hotchkiss, 2006). Amoa-Gyarteng (2014) also argues that highly leveraged firms may face bankruptcy if they are unable to meet their repayment schedules in a timely manner.

The onset of looming financial distress has with it signs that are evident long before the actual failure occurs in the firm. In the run up to business failure, companies are most likely to be on the receiving end of different types of negative news. This will in most cases include the reporting of poor financial results, administration issues, factory closures and redundancies. In any case, early warning signs to distress should be identifiable in advance (Ritchie, 2012).Theoretically, according to Gitman (2009), the assumption is that the business enterprise operates eternally and its main goal is to gain profit. While those business enterprises continue their successful operations, some of them cannot reach their goals and fall into financial failure mostly in the first two years of their lives but others' growth and expansion does not mean that they will never come across failure or distress. The signals about financial distress which are deemed to be most important can be received from the analysis of financial ratios of a company. Researchers on corporate distress have found out varying signs of distress. Companies that, compared to the market rate for similar investments, consistently generate low rate of returns, have an average return that is lower compare to the cost of capital or do not have adequate revenue to meet the costs that they incur can all be classified as experiencing business failure.(Baharin and Sentosa, 2013). A reduction in profits is also a cause for concern as it also indicates poor performance and according to the Capital Markets authority, a reduction in profits by 25% and over is a sign of financial distress. This is done by comparing the profits for the current year and that of the previous year and then dividing the result by the figure for the previous year and then calculating the percentage change.

A study by Usdin and Boom (2012) identified nine signs of financial distress as: the company not being able to pay its creditors in time; the company being sued in collection matters; the company suffering a significant event that will not recur; the secured lender of the company threatening to shut down business operations; a union threatening some kind of action against the company; a major supplier threatening to terminate its services to the company; the company not being able to perform its contracts in time or unable at all; the liabilities of the company being greater than its assets and finally the business model of the company being no longer viable. Sami (2013) also points out that a firm that has encountered distress meets three hardships: the managers lose a lot of time in the quest to solve financial distress; the demand for its product can reduce and production cost increase; it loses the right to make certain decisions without legal approval. However, Zhuang and Chen (2014) indicate that the state of a company in financial terms often cannot be observed directly but only through observing the signal indicators associated with the financial state.

2.2 Financial Distress Prediction Models

According to Joseph (2011), the very first studies concerning ratio analysis for the prediction of bankruptcy are called univariate studies which mostly involve using t- tests in analyzing the individual ratios and comparing the ratios of failed companies to the ones for the successful companies. This analysis was championed by Beaver (1966) who found that the many indicators of financial distress would discriminate between both bankrupt and non-bankrupt firms for a period as long as five years prior to company failure. In this approach it is worth noting that the information found in financial statements presents both present and future conditions of the firm.

According to Abudo (2011) the univariate model was improved by the introduction of the multivariate discriminant model for prediction of possible bankruptcy. Altman (1968) spearheaded the use of multivariate discriminant analysis using the Z-Score model which was based on a sample composed of 66 manufacturing companies with 33 firms in each of two matched-pair groups. The independent variables in this model was the financial data of the fiscal years before bankruptcy and the dependent variables were the bankrupt and non-bankrupt companies. This model was able to predict financial crisis with an accuracy rate of 95% in the year before such a crisis happened. Altman's discriminant function used five weighted ratios to calculate the z-score acting as the "cutoff" threshold discriminating failed from non-failed companies. Based on the sample, all firms having a Z-Score greater than 2.99 fell into the non-bankruptcy sector, while those firms having a Z-Score below 1.81 were bankrupt. Scores of between 1.81 and 2.99 lied in the grey area.

According to Warutere (2013) logistic regression puts together independent variables so as to estimate that a particular event will occur. If the probability for group membership in the modeled category is above some cutoff point, the subject is predicted to be a member of the modeled group. If the probability is below the cutoff point, the subject is predicted to be a member of the other group. Generally, the dependent variable will be dichotomous for example, presence/ absence or success / failure. Ohlson (1980) was the pioneer of the logistic regression analysis for the prediction of bankruptcy and described the logit model as a technique that measures the weight of independent variables and then assigns a score. Ohlson (1980) model consisted of nine variables that were deemed to be helpful in bankruptcy prediction and the nine variables X1 is total assets / GNP price level index; Where GNP price-level index = (Nominal GNP/Real GNP), X2 is total liabilities / total assets, X3 is working capital / total assets, X4 is current liabilities / current assets, X5 = 1 if total liabilities > total assets, else 0, X6 is net income / total assets, X7 is funds from operations / total liabilities, X8 is 1 if a net loss for the last two years, 0 otherwise, X9 is Change in net income. The cut-off point of p = 0.5 was used, consistent with Ohlson. Non-bankrupt firms lay below the cutoff point and bankrupt firms lay above the cutoff value. Martin (1977) also used the logit model for prediction of bank failure.

Shumway (2001) developed the hazard model which is estimated as a dynamic logit model using maximum likelihood estimation method. It uses a combination of both accounting and market information that vary over time to estimate the probability of financial distress. The hazard rate can be defined as the probability of a firm going bankrupt at time *t* conditional upon having survived up to time *t*. This therefore means that the probability of bankruptcy changes through time. The sample that Shumway (2001) used was composed of 300 bankrupt firms for the period between 1962 and 1992.The firms were declared bankrupt within five years of delisting. The model was differentiated from the others in the literature through the calculation of firms' trading years, in order to reduce the loss of firms from the sample over.

The Cox Proportional Hazard model is as a result of the works by Cox (1972) who found that there are two significant innovations, the proportional hazards model and the maximum partial likelihood. The proportional hazards model is in the form: $\lambda_i(t) = \lambda_0(t)e^{\beta x}$ With $\lambda_0(t)$ as an arbitrary unspecified baseline hazard rate that measures the effect of time for an individual with covariates which have values of zero. ***X*** is the vector of covariates that influences the hazard and $\boldsymbol{\beta}$ is the vector of their coefficients. The Cox model is popular mainly because the semi parametric approach it uses does not require a particular probability distribution to represent times of survival.

The Springate model was developed by Gordon L.V Springate in 1978 who, after the procedure developed by Altman in the U.S, came up with a step-wise multiple discriminate analysis in order to select four out of nineteen financial ratios that were popular in distinguishing between healthy businesses and those that actually failed. The interpretation is that if Z < 0.862, then the firm is classified as failed. With the 40 companies tested by Springate, this model achieved a 92.5% accuracy rate.

The probit model is a financial distress prediction model by Zmijewski (1984) who looked at the choice- base sample bias and the sample selection bias usually faced by researchers on financial distress and presented two estimation biases, one from oversampling distressed firms and the other from using only complete data. Contrary to the common 1:1 failure / non-failure matching, Zmijewski used the probit model on six sets of data where the ratio varied from 1:1 to 1:20 respectively. Zmijewsky (1984) based the selection of independent variables on how well the variables predicted in the previous models. A firm with a probability greater than 0.5 is classified as bankrupt, and a firm with a probability smaller than 0.5 is classified as non-bankrupt.

According to Amir (2001), research studies on the use of neural networks for bankruptcy prediction started in 1990 and since then has generated considerable research interest. Neural networks are tools in which mental aspects are considered together with the application of the statistics. One network consists of many units called neurons which are processing elements whose work is to receive and process the inputs the delivers an output signal. An artificial neural network is layered; each of these layers has several neurons that are connected to other neurons belonging to the preceding and following layer. The structure of the network can be classified as either single- layer, multi-layer, irreversible or feedback. This network will classify all the companies which are in financial distress in an appropriate group based on data for one year before bankruptcy. In general this approach has been successful in bankruptcy prediction due to its low error value (Saeideh, 2012). When it comes to prediction of financial distress on the basis of profitability, solvency and liquidity ratios, the number of variables that are presented to the network is equal to 3 and the single variable for estimation is the bankruptcy of the company. When the company is in a healthy state, the output neuron is equal to 0 and when it is bankrupt the output neuron takes the value of 1.

Decision trees are a form of distress prediction tool that have been popularly used for the classification of problems. This is possible because the rules involved are easy both to understand and communicate. According to Ravi Kumar and Ravi (2007), decision trees divide a large heterogeneous set of data into smaller and more homogeneous groups with respect to a particular value of the target variable by producing a set of if-then rules. The decision trees can be built using different algorithms such as classification and regression trees (CART), chi squared automatic interaction detection (CHAID), Quest, C4.5, C5.0 or entropy reduction algorithm.

The Case- Based Reasoning approach to bankruptcy prediction can be looked at in the same way as the decision making process of a human being in that it provides a solution to a new problem mainly by looking back at a library of old cases which is called a case base. It is basically a mirror of the manner in which human beings solve current problems by referring to past experiences. Here, new problems are solved from the basis of how the previous cases were solved and their solutions meaning that the previous problem is referred to when making a decision about the new problem. According to Li and Sun (2008) the algorithm of the solution in this approach is based on a distance function and a combination function where, the distance function calculates the distance between two records and the combination function combines the results from several neighbors to arrive at an answer. Something interesting about this method is that solutions that are arrived at are very comprehensive and can be reused to solve problems that are newly encountered.

The Operations Research Approach to financial distress prediction an interdisciplinary mathematical science that traces its origin to military efforts before the Second World War and whose main focus is on the effective use of the technological advances by organizations. According to Gass and Assad (2005) operations research applies mathematical programming techniques to the making of decisions, aiming at optimal or near- optimal solutions to problems that are complex in nature. This method of problem solving does not rely on strict assumptions like the statistical methods and are also able to perform correctly with a broader variety of data. Further, the fitted model in this approach is less influenced by any outlier observations.

Another bankruptcy prediction tool is the support vector machine which according to Yoon (2010) is a statistical learning algorithm which involves looking for optimal screen separators by the supporting vectors which enables solving classified problems. It is one among the latest techniques that have been developed and used to predict bankruptcy in the corporate world introduced by Boser, Guyon andVapnik (1992) and Vapnik and Cortes (1995).The main idea here is to map the vector for input into some feature space with a high dimension with the help of some nonlinear mapping chosen a priori. A linear decision surface is constructed and in it, put special properties that ensure a high networking ability. Support vector machines are simple in nature and therefore can be analyzed using mathematics. According to Pai and Lin (2005) the regression function in use is formulated as: $y = w\,(x) + b$. The vector machines can be applied in many information processing tasks including data classification, pattern recognition and function estimation.

The gains of the Soft Computing approach as a method of bankruptcy prediction can be seen by the way it combines many individual techniques to maximize the advantages while at the same time minimizing the combined model weaknesses. The gains that are achieved through precision and certainty as with other techniques like logit are according to Kumar and Ravi (2007) not adequately justified by the costs that are involved.. This technique has recently become very popular among researchers and practitioners and is seen as one of the latest trend in corporate prediction modeling (Demyanyk and Hasan, 2010).

This, according to Bilanas (2004), the Blasztk System model is the only business prediction model that was not developed with the use of the multiple discriminate analysis. The way this system works is that the financial ratios of the company to be evaluated are calculated, weighted and then finally compared with the ratios calculated for average companies in that same industry. This is done in order to predict its state as compared to the others.

The development of the Ca- Score model was done using a step-wise multiple discriminate analysis where thirty financial ratios were analyzed in a sample of 173 Quebec manufacturing businesses with annual sales range of $1-20million.According to Bilanas (2004) this model has an average reliability of 83% and is restricted to the evaluation of companies in the manufacturing sector.

2.3 Financial ratios and financial distress

Various financial variables can be used to determine the factors driving the default behavior of manufacturing firms. Prior research suggests many different approaches. The most popular became the scores created by Beaver (1966), Altman (1968), Ohlson (1980), and Zmijewski (1984), who use accounting ratios to find the probability of default using a static model. Altman (1968) finds that the company is likely to go bankrupt if it is highly leveraged, unprofitable and experiences cash-flow problems. In his O-score Ohlson (1980) identifies four basic factors as being statistically significant in determining the default probability: size of the company (log of total assets), measure of financial structure (total liabilities/ total assets), measures of performance (net income/total assets) and a measure of current liquidity (working capital/ total assets). Zmijewski (1984) confirms this by finding that bankruptcy is a decreasing function of return on assets (ROA), liquidity (current asset/current liabilities) and an increasing function of leverage (debt/total assets). These results seem to be very intuitive. Bankruptcy is often triggered by the inability to serve debt. This is more likely to occur when the company does not have access to external financing or has cash-flow problems. Therefore, we can expect the firm to go bankrupt if its current year cash-flow is insufficient to cover debt obligation. This is a direct connection to free cash-flow theory. Its main objective is to find a trade-off between lowering costs of asymmetric information by distributing cash-flow through dividends and thereby maximizing firm value and the increased probability of default (Jensen (1986)). To this end, the size of companies' indebtedness is an expected determinant of default probability. Next, large companies are expected to be less likely to have problems accessing external finance markets. The logarithm of total assets as a proxy for firm's size has traditionally been used to avoid the non-stationarity problem. Further, it is not unrealistic to hypothesize that a firm's profitability is a determinant of bankruptcy. Firms are more likely to default if they go through a low profitability period.

2.4 Model accuracy

Model accuracy is the most discussed dimension of model quality; however it is only one of several. Models can fail in two ways. Either the model predicts a company to survive when it actually fails (Type I error). In this case, an investor might lose promised interest payments, principal or both. She might also suffer from a decline in the obligation's market price. The model might also predict failure when a company in fact survives (Type II error). In this case, the investor might lose interest payments and fees when the loans are turned down or lost through non-competitive bidding. (Sobehart, Keenan, and Stein (2001)) In case of tradable obligations, she might sell them at disadvantageous market price even though the obligation could have been held to maturity without facing risk of default. Concluding from the above, a model should accurately classify defaulters and non-defaulters. One prediction rule might be to set P equal to 0.5, as one should predict default if it is more likely than not. However, Jones and Hensher (2008) argue that in unbalanced datasets, where there is only a small proportion of ones or zeros for the dependent variable, the aforementioned prediction rule might fail. Another popular rule is setting $P$to the sample proportion of defaults (=defaults/total number of firms in the sample).

2.5 Theoretical Literature

The approach here is that prediction models are constructed on the basis of some theoretic arguments. These theories predict financial distress by closely looking at the conditions of distress that are present in the firms. For the purposes of this study, these theories include entropy theory and cash management theory.

2.5.1 Entropy Theory

According to Aziz and Dar (2006), the entropy theory states that a careful look at the changes in the balance sheet of a firm is one way of identifying its financial distress position. This theory employs both Univariate analysis and Multiple Discriminant

Analysis (MDA) in examining the changes that occur in the structures of balance sheets. Univariate Analysis is the use of accounting based ratios for the distress risk assessment (Natalia, 2007), while MDA (Multivariate analysis) is a statistical analysis in which more than one variable are analyzed at the same time (Slotemaker, 2008).This means therefore, that the multivariate analysis serves to counter the defects of the univariate analysis for example, single ratios calculated by univariate analysis do not capture time variation of financial ratios. If the financial statements of a firm reflects significant changes in the assets and liabilities on the balance sheet, it means that it is more likely that it will have difficulties maintaining an equilibrium state in order to balance liquidity and leverage levels and if these changes are likely to become uncontrollable in future, one can foresee financial distress in these firms (Aziz and Dar, 2006).

2.5.2 Cash Management Theory

The concern of this theory is the management of cash flows into and of the firm. That is, cash flows within the firm and cash balances held by the firm due to financing deficit or investment surplus cash. According to Aziz and Dar (2006), the major concern of every firm is the short- term management of corporate cash balances. This is so because accurate prediction of cash flows is difficult especially inflows and there is no perfect coincidence between outflows and inflows. Pandey (2005) states that during certain periods, cash outflows will exceed inflows since tax payments or dividends will build up and at other periods cash inflows will be more than cash sales. The lack of balance between cash inflows and outflows would therefore mean the failure of the cash management function of the firm and may ultimately lead to a disruption in the profits of the firm. This is also dangerous since the persistence of such an imbalance may cause financial distress to the firm and ultimately business failure.

2.6 Empirical Literature

Natasha & Marina (2011) designed three separate models of financial distress prediction to track changes in the relative importance of financial ratios in three consecutive years which were based on financial data from 2000 privately owned small and medium- sized enterprises in Croatia from 2006 to 2009.These models were developed by means of logistic regression. The sample number was 1987 companies which was divided into financially healthy ones and the financially distressed ones. After data cleaning was done, the total sample consisted of

990 financially healthy companies and 997 financially distressed ones. There were 31 financial ratios together with region and industry used as predictors in logistic regression model. According to Natasha and Marina (2011) the financial ratios that weren't significant are the following: Operating Revenues/Operating Expenses, Current ratio, Quick Ratio, Cash/Sales, Cast/Total Liabilities, Long-Term Assets Turnover, Inventory Turnover, Days Sales in Inventory, Working Capital/Total Assets, Total Liabilities/Total Assets, Total Liabilities/Equity, Equity/Long-Term Assets, Total Liabilities/(Retained Earnings + Depreciation), Retained Earnings/Total Assets, Net Profit/Total Assets, and Net Profit Margin. The researchers then concluded that with stable economic conditions, the same model can achieve adequate precision but if conditions are changing, development of new models is inevitable. A more lasting and adequate solution to this problem was found to be to include macroeconomic variables in the financial distress prediction model.

The study by Warutere (2013) assesses the probability of firm failure, a year before failure, using logistic regression model that was developed by Ohlson (1980). The study utilized secondary data collected from Capital Markets Authority and Nairobi Securities Exchange. The required data was collected from financial statements of a sample of sixteen companies; ten of which were in good financial health and six of which were financially distressed. The study covered a range of 14 years from 1997 to 2011. The study sample comprised companies that were delisted from NSE, those whose stocks were suspended from trading and surviving companies between 1996 and 2011.The sample comprised failed firms and non-failed firms. Failed firms were those firms whose stocks were delisted or suspended from the Nairobi Securities Exchange between1996 and 2011. For purposes of this study, the event of being delisted or suspended was treated as a clear signal of firm failure. The sample of failed firms comprised a mix of firms delisted and suspended from trading.The results of this study show that logistic regression analysis is applicable in 9 out of 10firms analysed which indicates a 90% successful application of the Ohlson (1980) model used in the study. The model is found to be successful in predicting business failure one year before it occurs. The study concludes that the logistic regression analysis model developed by Ohlson (1980) is applicable in predicting financial failure of companies and is a useful tool for investors in the Kenyan market. This study was different from the present study since it focused on the performance of the model a year before crisis while the present study is concerned with the period before financial crisis and during financial crisis.

The study by Macharia and Basweti (2017) seeks to apply selected bankruptcy prediction models to assess the going concern risk of listed firms in Kenya. The study intended to establish the practices of textual disclosures in going concerns and the extent of prediction of going concern risk using the selected bankruptcy predicting models and also to establish whether textual disclosures and selected bankruptcy predicting models were statistically significant in assessing the going concern risk of listed firms in Kenya. Thirteen firms reported as going concern firms were studied, from 2000 to 2015.The collected data was analysed using descriptive statistics, correlation and One- way ANOVA to test the presence of significant difference between textual disclosures practices and selected bankruptcy predicting models. To accomplish the objectives of the study, a regression analysis was adopted. An analysis of a sample of seven firms that were either delisted or placed under statutory management was done alongside thirteen going concern firms listed at the NSE within the same sectors and the samples of non- going concern firms which had been delisted were matched by sectors with the going concern firms. The study used secondary data which was collected from the CMA resource center using a data collection sheet. Descriptive statistics was used to analyze the collected data and the means of the scores for Altman, Fulmer and Springate models were computed. The study pointed out that Fulmer and Altman model can assess to a large extent the going concern risk in the telecommunication sector whereas Springate model was able to significantly assess risk in the manufacturing sector. The findings of the study revealed that an improvement in financial analysis of firm performance will be realised with adoption of bankruptcy prediction models and textual disclosures. This study also found that organizations that use Altman revised four variables models, Springate model and Fulmer model are expected to experience significant enhanced going concern assessment which can assist the financial analysts to establish critical issues in prudent financial management of firms.

Charalambakis (2014), in his study evaluates the contribution of market information and accounting to the prediction of financial distress for Greek firms using the discreet hazard approach. The accounting data and market data obtained from the Thomson Reuters DataStream for the period 2002- 2010.The analysis of the paper focused on the accounting ratios of the Z- score based on Altman (1968) and Taffler (1983) and in particular sales to total assets, EBITDA to total assets, current liabilities to total assets and current assets minus current liabilities scaled by total assets. The results show that a model that combines sales to total assets, profitability and financial risk with market capitalization, excess returns and stock return volatility best depicts the probability of financial distress for Greek firms. The model that combines the three accounting ratios with three market – based variables exhibits the highest predictive ability. Charalambakis (2014) also performed out of sample tests which confirmed that the model with the best in- sample predictive ability also allocates the highest percentage of bankrupt firms within the time of financial crisis, which clearly shows that the model provides an early warning signal of the upcoming financial crisis. In a study on corporate financial distress prediction. The findings showed that profitability, leverage, ratio of retained earnings to total assets, the ability of a firm to export, liquidity and the ability of a firm to pay out dividends are strong predictors of financial distress. The findings of the study strongly recommend accounting for industry effects when forecasting financial distress for private firms. The model that incorporates the six firm specific factors and considers industry effects exhibits the highest predictive ability based on the in- sample accuracy tests.

Ming- Chang (2014) carried out a study on firms listed in the Taiwan Stock Exchange and examined financial distress between 2003 and 2009 using the Cox Proportional Hazard Model. The researcher presented empirical results of the study regarding 12 financial ratios as predictors of financial distress using profitability, leverage, efficiency and valuation ratio variables. The study proved that the accuracies of classification of the model in overall accuracy of classification was 87.93%.

John, Jens & Jan (2010) consider the measurement and pricing of stocks in financial distress and present a model that predicts corporate failure using accounting and market- based variables. Their best model outperforms leading alternatives such as the model proposed by Shumway (2001) as well as distance-to-default, an approach popular in industry and one use by Vassalou and Xing (2004).In the second part of the paper John, Jens and Jan (2010) consider the performance of distressed stocks from 1981 to 2008.They found that distressed stocks have significantly underperformed and that they are risky they have high levels of volatility and high market betas. They conclude that the underperformance of distressed relative to safe stocks is present across all size and value quintiles, though it is more pronounced for portfolios that have a larger spread in failure probability, a fact that explains the more extreme underperformance of distressed stocks for small rms. Furthermore, the low performance of distressed stocks is concentrated in stocks with lower analyst coverage and lower institutional holdings.

Jose (2014) focused his study on survival analysis and its use in predicting company failure. In that research, the hazard rate was placed at the probability of bankruptcy as of time t, conditional upon having survived until time t. Many hazard models are applied in a context where the running of time naturally affects the hazard rate. The model employed in this paper uses the time of survival or the hazard risk as dependent variable, considering the unsuccessful companies as censured observations. Jose (2014) observed that the main advantage of the model used relies on the additional information it provides. With this approach the researcher gets a different perspective, since the survival curve of analysis of a particular company allows knowing the likelihood of a company survival beyond a given time period and hence the risk of falling into bankruptcy. However, similar to what happens with other methods, the accuracy of the model developed in the paper depended utterly on the quality of the data which supports the basis for its modelling. This model was found to rely on the proportionality of risks, which in reality may not be always the case. Another relevant limitation is the difficulty of obtaining the survival times, i.e., the time when the phenomenon that is being analyzed occurs.

Laitinen and Luoma (1991) also applied the Cox model to business failure. This paper was significant in the critical presentation of the advantages and disadvantages of using survival analysis to predict business failure. Laitinen and Luoma (1991) did an empirical classification of the Cox model with discriminant analysis and logit analysis using 36 failed Finnish limited companies and 36 successful ones and their predictions made by doing a division of the businesses into two based on their hazard ratios. The ones with the higher and lower hazard ratios were predicted to fail or succeed respectively. The discriminant analysis and logit analysis were found to be slightly superior to the Cox model. Nevertheless, Laitinen and Luoma (1991) argued that the Cox model approach was more appropriate, natural, and flexible and also incorporated more information.

Shumway (2001) applied the very first survival analysis model to a large data set encompassing financial ratios and market- driven variables for more than 2000 companies over 31 years. Shumway (2001) found theoretical superiority of survival analysis over the logit and discriminant analyses. Additionally the model was also shown to empirically outperform both discriminant and logit analyses, However, less than 10% of the businesses in the data set were failed, which is much lower than the percentage in the real world. In addition, Shumway only considered Type I Error.

Abuga (2013) analyzed financial distress, its causes and its effects on firms funded by ICDC. The main objectives in this study were to first identify the nature of the causes of financial distress and then to establish the effects of financial distress. Weighted Mean Score and Factor Analysis were used to analyze the causes of financial distress which were classified into exogenous and endogenous. The sampling frame comprised of companies funded by ICDC. The researcher obtained primary data using questionnaires presented to managers and analyzed the various effects of financial distress using a Five-point Likert Scale. Abuga (2013) identified that the most significant causes of financial distress were; improper capital decisions, lack of access to credit, shortage of skilled workers, poor records, highly geared firms and poor internal management. The findings therefore affirmed that endogenous causes dominate the exogenous causes. This can be arrived at by doing the average of the mean weighted score of both the internal and external causes of financial distress.

Riku (2010) sought to find out the implications of financial distress. The study targeted all common shares traded in NYSE, AMEX and NASDAQ during the period between 1994 and 2009. The sample consisted of 9405 unique stocks. The researcher instead of relying on one model, combined the existing default models to arrive at a new one called a default index. This index consisted of parts which were developed by other authors namely; Altman Z- score, Ohlson O-score, Merton distance to default modified by Bharat and Shumway (2003) and Campbell's default score. The last component of the default index was the accounting ratio of total debt per total assets. The main finding of Riku (2010) was that financial distress affects both sales and cash flow in good and bad times alike while operating income dint seem to depend on financial distress as much. The regression results pointed out that the sales declines was most severe for highly distressed companies and that financial distress is detrimental to corporate performance but more detrimental to operational performance during periods of economic downturn .This study found out that companies at risk drift to a vicious cycle where mediocre profitability leads to financial distress which ultimately leads to bankruptcy. The study by Riku (2010) utilized the static trade – off theory, pecking order theory and the organization theory of capitalization.

Steven, Jayaraman, Shankar and Ally (2011) carried out a study to assess the performance of Malaysian companies after suffering financial distress. This was done by the improvement of stock prices and other financial ratios which indicated the company as performing better than the period before bankruptcy. Secondary data from published annual reports was used. The classic Z-score model was applied and Companies with a Z-score of greater than 2.99 fell into the "non-bankrupt" sector, while those firms with a Z-score below 1.81 were bankrupt. The researchers show that company performance, successful company reorganization and change of management all had a positive impact on stock prices. Another observation was that many companies post very high profits during their first few years which are in most cases not sustainable. This may lead the company into restructuring or winding up completely. Steven, Jayaraman, Shankar and Ally (2011) recommend that in order to avoid winding up or facing a restructuring petition, companies should be able to show results that are positive and improve their performance compared to the previous financial results which led to downturn. Many factors will need to be considered for example, management. Avoiding such things as poor management, poor business planning, poor financial planning, and poor marketing will certainly improve their condition. Understanding the position that the company is in after a distress condition is paramount to creating a suitable restructuring plan for the company to move forward.

Abudo (2011) carried out a study to determine how financial distress can be predicted in the banking industry using the Altman (1968) model. The argument was that many corporate firms are faced with financial inefficiency and are as a result not in a position to correctly predict their position in both long and short terms. The population of the study consisted of all the 43 banks in Kenya as per Kenya Bankers Association using a census survey. Data collection relied on the 43banks and from the data, each company and each year ratios were computed. The research design applied was a descriptive study and Data analysis used the following ratios: Working Capital/total assets (liquidity), retained Earnings/total assets (earned surplus, leverage), earnings before interest and taxes/total assets (earning power), Market value equity/book value of total liabilities (solvency), sales/total assets (sales generating capability. The study applied secondary data which was obtained from financial reports and returns filed with the Central Bank of Kenya. Altman (1968) model was applied for failed and non-failed banks. The testing model discriminated 20 failed banks versus 23 non failed ones. This study applied Modigliani and Miller capital structure irrelevancy theory and the financial life cycle theory. The finding of the study by Abudo (2011) was that the Altman (1968) model was accurate on 8 out of the 10 failed firms, that is 80% validity of the model and for the non-failed majority proved Altman’s financial distress prediction model was a 90% validity of the model. None of the activity and turnover ratios were found to be critical in predicting financial distress. These findings however differed with those of Altman (1968) whose conclusion was that efficiency and profitability ratios were most important and that liquidity ratios were insignificant. The recommendation of Abudo (2011) was that since the model presented in this study was based on stability of financial ratios, other measures of ratio stability such as the coefficient of variation and the standard error of estimate of the financial ratios could be applied to develop similar models and since the linearity assumption, that ratios are normally distributed, is inherent in this study, attempts should be made to develop a non-linear model such as logit and probit models.

Amalendu and Ruchira (2011) carried out a study that was of crucial importance in building up a model to develop predictive abilities for company failures in the Indian context. The study analyzed sixty-four private sector pharmaceutical companies with sixteen ratios using multiple discriminant analysis, that is, profitability, efficiency, liquidity and solvency based on their popularity as evidenced by their frequent usage in the finance and accounting literature. Financial Statement data from the annual reports of selected failed and non-failed private sector pharmaceutical companies were taken from a ten-year period starting 1996 until the end 2005.The data for the companies that failed were acquired for five years before failure. Thirty two failed manufacturing companies were matched with thirty two non-failed ones. They were used to construct a strong discriminant function and the results of the classification showed high predictive accuracy rates of between 86% and 96% for each of the five years prior to actual failure. Amalendu and Ruchira (2011) came to a conclusion that liquidity and profitability ratios are the most significant in predicting the financial health of a company and that there is a relationship between financial ratios, company health and business failures. Financial ratios have predictive power with regards to whether a company will fail or not. This study is a strong indicator that even with many new and advanced statistical tools, MDA is still a very reliable statistical tool.

Robert (2014) carried out a study to confirm whether financial ratios are suitable for prediction of financial distress in the non-financial sector of companies listed in the NSE. The study was descriptive with secondary data obtained through review of literature including articles, journals and published financial reports. The study examined some financial ratios in the financial reports of both sound and financially distressed firms for the period between 2003 and 2011.The aim was to determine the most reliable and significant ratios that can be used for the prediction of company financial distress. Robert (2014) drew the sample from companies listed in the NSE in the non-financial sector from 2002 to 2006 which came to a total of 41 companies. After the ratios were selected, they were analyzed using the backward stepwise method to determine the statistically significant ones. Discriminant analysis method was used to estimate the model that predicts financial distress. Statistical models were then used to test the predictive power of the ratios which led to the conclusion that the variables that reveal financial distress are those related to profitability, leverage and operational efficiency. The study also confirms that financial ratios can predict financial distress for non-financial sector Kenyan firms listed in the Nairobi Stock Exchange. According to Robert (2014) best predictor ratios were Net Income to total Assets, Total Liabilities to Total Equity, and Total Liability to Total Assets and Current Assets to Sales. Profitability, liquidity, leverage and operational efficiency were therefore seen as crucial the determination of the financial health of a company and even though profitability ratios are the most significant, it is of much more importance to have a combination of ratios since it gives a more accurate model.

Kemboi (2013) conducted a study with the objective of using the Altman model to predict corporate financial distress in Uchumi supermarkets in Kenya. According to the researcher, the global crisis of 2008 made the study of financial distress a significant global issue. Data was sourced from secondary data which was obtained from financial reports, journals, publications and websites and other resourceful information available at the Uchumi supermarket secretariat for 5years from 2001 to 2006 while the research design was a descriptive one. This study applied the MDA model by Altman (2006) to predict financial distress in an organization. The five leading Uchumi supermarkets in Kenya from 2001 to 2006 made the population of the study. The finding of the study was that there was a decline in the working capital of Uchumi supermarket from the year 2001 to 2005 which was a clear indication that the company had started experiencing financial difficulties evidenced by reduction in the working capital. Kemboi (2013) concluded that the z-score model is a very practical tool in the prediction of financial distress in companies and can be effectively used in the credit industry and that the exploration of the Altman z-score and other formulas should be done to develop a predictive collection of tools which will help in prediction of both bankruptcy and financial distress.

Akbar (2013) did a comparative study of bankruptcy prediction models of Fulmer and Toffler in firms accepted in Tehran Stock exchange. Financial ratios were considered to be one of the tools used to measure the financial capabilities of the companies. Data was collected from basic financial statements from the stock exchange. The firms accepted in Tehran stock exchange between 2005 and 2010 made up the statistical population. Excel software was used to analyze the data. The data was categorized first two models, that is, Toffler and Fulmer. The results of Toffler model showed that 27 firms out of 90 firms under investigation were introduced as bankrupted and the rest were not bankrupted. Also the results of Fulmer's model showed that 63 firms out of 90 firms under investigation were introduced as bankrupted and the rest were not bankrupted. Akbar (2013) found out that the Fulmer model acted more conservatively compared to the Toffler model and that it is important to use different models to predict bankruptcy since it helps identify the status of organizations and avoid bankruptcy by adequate investigation of financial statements.

2.7 Research Gaps

A number of studies have been done concerning financial distress, its impacts and the models that can be used for its prediction however, from this research, it is evident that most of the previous researches have been done between the years 2010 and 2014 as seen by Abudo (2011), Abuga (2013), Robert (2014), Riku (2010) and Natasha & Marina (2011), John, Jens & Jan (2010) to mention a few. It is undoubtedly important for research to reflect the most recent happenings and therefore a more recent research is required to give an update on statistical models and their applicability. Most of the studies done on financial distress prediction, according to the literature in this paper have majored on the Multiple Discriminant Analysis (MDA) models but have concentrated on the Altman model, leaving out other models within MDA like the Fulmer model, Steven, Jayaraman, Shankar and Ally (2011), Abudo (2011), Robert (2014) and Kemboi (2013) all applied Altman model. Riku (2010) came up with an index with a combination of Altman model, Ohlson model, Merton distance to default and Campbell default score. Riku (2010) also utilized the Static trade-off theory, pecking order theory and the Organization theory of capitalization while Abudo (2011) applied the Modigliani and Miller capital structure irrelevancy theory and the financial life cycle theory. There is need to explore more theories in this particular field and the entropy theory and cash management theory serve as a bridge to this gap. Studies on financial distress prediction have been addressed in different countries for example in this research paper, Natasha and Marina (2011) carried out their research in Croatia, Akbar (2013) in Iran, Charalambakis (2014) in Greece and Amalendu & Ruchira (2011) in India.

2.8 Conceptual Framework

Relationship between the logistic regression model and financial distress

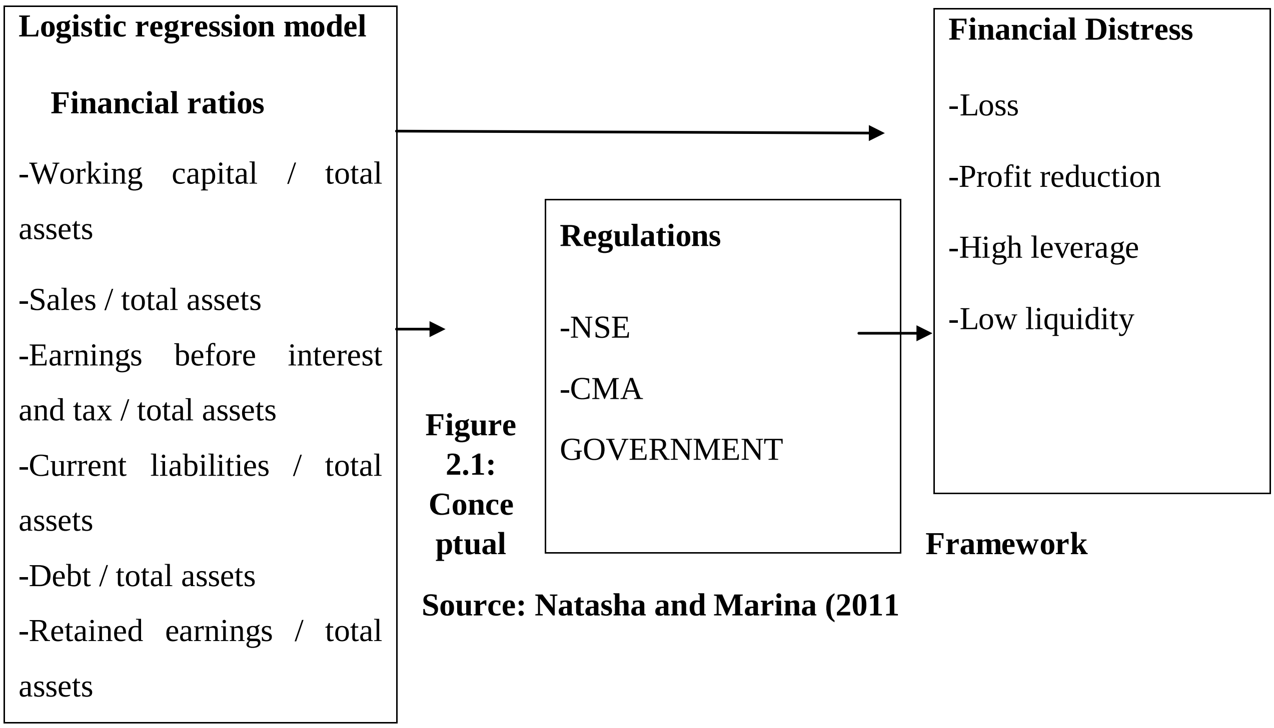

Figure 2.1: Conceptual Framework

Source: Natasha and Marina (2011

In the study, the independent variable is characterized by the financial ratios which is also characterized by working capital/ total assets, sales/ total assets, earnings before interest and tax/ total assets, current liabilities/ total assets, debt/ total assets and retained earnings/ total assets. These ratios will be moderated by the regulations of the government, the Nairobi Securities Exchange and the Capital Markets Authority all of which impact business entities in terms of policies which may change from time to time.

According to Aziz and Dar (2006), the entropy theory states that a careful look at the changes in the balance sheet of a firm is one way of identifying its financial distress position the dependent variable is financial distress which is characterized by low liquidity, high leverage, profit reduction and an experience of loss. If the financial statements of a firm reflects significant changes in the assets and liabilities on the balance sheet, it means that it is more likely that it will have difficulties maintaining an equilibrium state in order to balance liquidity and leverage levels and if these changes are likely to become uncontrollable in future, one can foresee financial distress in these firms.

Outecheva (2007) looks at financial distress in terms of leverage and concludes that a combination of very low volume of liquidity, negative cash flow and high levels of leverage leads to financial distress among many corporate firms. As soon as firms have reached a certain level of leverage but do not strategically conform to their business plans, financial distress can occur even if the economic times are favorable. Equity values become vulnerable when there is high leverage in the firms accompanied by increasing volatility. This leads to a situation where each possible decline in the value of the enterprise may rapidly impair equity.

CHAPTER THREE
RESEARCH METHODOLOGY

3.1 Research Design

According to Shukla (2010) a research design is a blueprint or a framework used for conducting research. It gives a detailed plan on how research will be conducted. This study will adopt a correlational research design, which is a type of design which is concerned with establishing whether there is the existence of a relationship between two or more variables (Leedy and Ormrod, 2010). It can be used in any research study that does not wish (or is unable) to manipulate the independent variable(s) under investigation. The researcher was to examine and extract information from documents that contain participants' data which were then analyzed to make deductions. This method ensured that the data was collected with precision which defined its reliability; accuracy which defined validity and with minimal error.

3.2 Target population

According to (Mugenda and Mugenda, 2003 a population as an entire group of individuals, events or objects having a common observable characteristic. This means that it is an aggregate of all that conforms to a given specification. For the purpose of this study the population included all the firms that were listed at the Nairobi Securities Exchange in 2008 which were 66 in number collected from the CMA website. This period was selected since it was a time when Kenya faced financial crisis. According to the Kenya National Bureau of Standards (KNBS, 2009) Economic Survey report, the economic growth in Kenya was restrained by the 2008 global financial crisis and high fuel and food prices and though the crisis was experienced only in the first quarter of 2008, its spill-over effects were manifest throughout 2008 resulting to substantial declines in growths of most of the sectors of the economy leading to a slump in economic growth from 7.1% in 2007 to 1.7% in 2008. In order to provide an in- depth analysis of the predictive ability of the hazard model, out- of-sample forecast tests was done using data for the period prior to the financial crisis, which is, 2004-2006 and then the estimated coefficients were used to predict financial distress throughout the financial crisis. That is, 2007- 2009 which was the in- sample forecast. Data were collected from Capital Markets Authority (CMA) since the data were publicly available and reliable as such were drawn from audited financial statements. This enabled the researcher to use descriptive observation of the data collected in order to achieve the objectives of the study.

3.3 Sampling Design and Size

Sampling is the process of selecting a number of individuals for a study in such a way that they represent the large group from which they were selected. (Mugenda and Mugenda, 2003). Purposive sampling was used since according to Mugenda & Mugenda, (2003), this type of sampling allows a researcher to use cases that have the required information with respect to the objectives of the study. The study sample comprised of companies whose profitability declined in 2008 due to the financial crisis of 2007. Therefore, only the companies which made losses or experienced a 25% reduction in profits in year 2008 compared to year 2007 were chosen and forecasts were done for the years between 2004 and 2009. This was useful in determining whether the model would have helped to prevent distress had it been used before it actually occurred. This, therefore, meant that the sample comprised of only the distressed firms and for purposes of this study, the event of profit reduction by 25% and over and/ or loss making was treated as a clear signal of financial distress. The sample size was 11 listed firms whose profitability declined or made losses for the period under review.

3.4 Data Collection Method

Secondary data were used in this study. These were obtained from published financial reports of listed companies whose profits declined in 2008. This, according to KNBS (2009) is the period where Kenya faced financial crisis. Data were collected for the period between 2004 and 2009 that is, the pre – recession period and during distress which were obtained from the Capital Markets Authority. In addition, data were gathered using data collection sheets. The financial reports included the income statements and the statements of financial position.

3.5 Data Analysis

To analyze the collected data, the researcher employed the logistic regression model brought forward by Ohlson (1980) and the accounting ratios were those employed by Natasha and Marina (2011) on comparing financial distress prediction models before and during recession. The five main categories of ratios (liquidity ratios, profitability ratios, leverage ratios, operational or activity ratios, and solvency ratios) were significant in prediction of financial distress. Despite the fact that many studies reported high predictive power for their ratios, a unique perfect combination of financial ratios hasn't been found.

The study utilized the following regression model;

$$\mathbf{Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \varepsilon}$$

Where

Y	represents	financial distress
β_0	represents	Constant
X_1	represents	Working capital/total assets
X_2	represents	Sales/total assets
X_3	represents	EBIT/total assets
X_4	represents	Current liabilities/total assets
X_5	represents	Debt/total assets
X_6	represents	Retained earnings/total assets
ε	represents	Error term
β_1 to β_6	represent	Regression coefficients of predictor variables

Hypotheses in the study was tested using multiple regressions and the significance level at 0.05

CHAPTER FOUR
RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents the findings emanating from the analysis of the secondary data relating to financial distress and factors leading to its prediction. The results capture both descriptive and inferential statistics and are in tandem with the study variables which include working capital/total assets ratio, sales/total assets ratio, earnings before interest and tax/total assets ratio, current liabilities/total assets ratio, debt/total assets ratio, retained earnings/total assets ratio, and financial distress. The findings seek to test the hypothesis that the foregoing financial ratios influence financial distress among listed firms in Kenya.

4.2 Descriptive Statistics

In this section the results of descriptive analysis are presented alongside pertinent interpretations and discussions. The descriptive statistics employed include measures of central tendencies represented by mean, median and mode, and also measures of variation or dispersion as characterized by the standard deviation. The choice of these statistics was founded on the fact that the data collected and consequently analyzed were continuous. The descriptive statistics in respect of financial ratios and financial distress for the 11 surveyed firms are presented and explained.

4.2.1 Working Capital to Total Assets Ratio

The study analyzed the ratio of working capital against total assets for firms listed on the Nairobi Securities exchange for the period between 2004 and 2009. The averages of the financial ratios indicators over the foregoing duration is presented in Table 4.1. The study as shown in Table 4.1 indicated that highest average working capital/total assets ratio (mean = 0.257) was recorded by Eveready E.A. Limited followed closely by Crown Berger (mean = 0.238). Expectedly, the former company posted the highest median working capital/total assets ratio (median = 0.295) followed by Crown Berger (median = 0.245). On the other hand, Pan-Africa Insurance had the least working capital/total assets ratio (mean = 0.030). However, in terms of median working capital/total assets ratio, TPS Serena posted the least (median = 0.045). Most of the 11 firms surveyed posted mean working capital/total assets ratio of less than 0.2 (mean < 0.2). In terms of stability, Express Kenya was found to experience the largest fluctuation in its working capital/total assets ratio (std dev = 0.234). On the other hand, Williamson Tea was established to be the most stable (std dev = 0.015).

Interpretatively, Eveready E.A. Ltd which recorded the highest financial ratio implied that in comparison to the other listed firms its working capital was far much higher than its total assets. The high working capital/total assets ratio was a manifest of relatively poor performance of the firm; a factor that is likely to have contributed to its ultimate delisting from the NSE. For every 100 units of its total assets, 25.7 units were part of the working capital. On the extreme end where Pan-Africa Insurance recorded a mean of 0.030 in working capital/total assets ratio, it meant that in every 100 units of the company's total assets, only 3 units constituted the working capital. The foregoing is a clear manifest of good financial performance of the firm. It is highly probable that the Eveready E.A. Ltd was more prone to financial distress than all the other surveyed firms whereas the Pan-Africa Insurance was the least likely to suffer from financial distress.

Table 4.1: Descriptive Statistics for Working Capital to Total Assets Ratio

	Mean	Median	Mode	Std. Dev.
A. Baumann	.163	.165	.01[a]	.124
Crown Berger	.238	.245	.180[a]	.035
E.A Portland Cement	.188	.190	.13	.054
Eveready E.A Ltd	.257	.295	.30	.131
Express Kenya	.040	.105	-.28[a]	.234
Kapchorua	.113	.120	.12	.020
Kengen	.047	.045	.03[a]	.035
Marshalls E. A	.067	.115	.13	.106
Pan- Africa Insurance	.030	.055	.06	.048
Tps Serena	.070	.045	.01[a]	.072
Williamson Tea	.112	.115	.12	.015

Source: Researchers own work

4.2.2 Sales to Total Assets Ratio

The study further examined the ratio of total sales made by listed firms against their total assets. This ratio was aimed at determining the companies that recorded highest growth in sales in respect of their total assets. The firms which returned higher ratio implied that they had encouraging growth rate given that sales are parameters of an organization's growth. The results to this effect are as shown in Table 4.2. According to the descriptive results shown in Table 4.2, the largest sales to total assets ratio on average was posted by Eveready E.A. Ltd (mean = 1.767). The median ratio recorded by the firm was found to be (median = 2.000). It was also revealed that Kengen posted the least average sales/total assets ratio (mean = 0.122). The foregoing findings implied that at Eveready E.A. Ltd, for every unit of total assets, there was 1.767 units of sales realized. This meant that the average annual sales turnover for the company was far much higher than the total assets held by the firm. In a normal firm, the foregoing results do not reflect a positive image of the company from financial perspective granted that, ordinarily, total assets which include plant and equipment, inventory among others are expected to be far much more than the sales turnover.

On the other hand, at Kengen, for every unit of total assets, the firm realized 0.122 unit sales. The results underpinned the huge asset base of the company. Though sales are a manifest of the firm's performance, the total assets guarantee, to a large extent, the financial performance and position of the company. Therefore, Kengen was more likely to have posted better financial performance than all the other listed firms (including Eveready E.A. Ltd) that posited a decline in profitability in 2008. It is clear that a decline in profitability does not translate to loss and hence the foregoing interpretation of financial performance holds.

It was also observed that Eveready E.A Ltd recorded the largest standard deviation (std dev = 0.940) in reference to sales/total assets ratio between 2004 and 2009. The results were indicative of significance fluctuation or variation in the sales made by the company and/or total assets held by the firm over the stated duration of time. In the same breadth, Williamson Tea posted the least variation in respect of sales to total assets ratio (std dev = 0.042). These results underpinned the stability of the firm in relation to both its average sales turnover and total assets.

Table 4.2: Sales to Total Assets Ratio

	Mean	Median	Mode	Std. Dev.
A. Baumann	.410	.410	.28	.218
Crown Berger	1.227	1.190	1.100[a]	.132
E.A Portland Cement	.685	.685	.56[a]	.075
Eveready E.A Ltd	1.767	2.000	.00[a]	.940
Express Kenya	1.322	1.020	.61[a]	.864
Kapchorua	.542	.550	.55	.073
Kengen	.122	.130	.14	.071
Marshalls E. A	.993	1.115	.41[a]	.353
Pan- Africa Insurance	.367	.360	.30[a]	.064
Tps Serena	.630	.560	.50[a]	.146
Williamson Tea	.323	.325	.26[a]	.042

Source: Researchers own work

4.2.3 EBIT to Total Assets Ratio

The study also evaluated the ratio of earnings before interest and tax (EBIT) to total assets owned by listed companied that recorded declined profitability in 2008. The average results for years 2004 to 2009 are presented in Table 4.3. The study as shown in Table 4.3 revealed that there were some listed firms that recorded negative EBIT/total assets ratios. As previously observed, Eveready E.A. Ltd yet again posted the largest ratio with a mean = 0.133. This meant in every unit of total assets, there was 0.133 unit of earnings before interest and tax. The relatively large ratio could have been attributed to minimal total assets held by the company. Moreover, both A. Baumann and Marshalls E.A. posted negative EBIT/total assets ratios, that is, (mean = -0.082) and (mean = -0.003) respectively. Moreover, the former company recorded the largest standard deviation (std dev = 0.344) among the 11 surveyed firms. This was interpreted to mean that the foregoing ratio in respect of this firm fluctuated significantly.

In regard to EBIT/total assets ratio, A.Baumann returned the lowest mean (-0.082) which meant that the firm had the least earnings before interest and tax in relation to total assets. In the same breadth, the same firm had the largest variation in reference to the foregoing financial ratio (std dev = 0.344). On the other hand, Crown Berger had the least variation in respect of EBIT/total assets ratio (std dev = 0.019). The results indicated that Crown Berger was the most stable regarding the aforestated financial ratio while A. Baumann was the most unstable firm out of the 11 listed companies considered in the survey.

Table 4.3: EBIT to Total Assets Ratio

	Mean	Median	Mode	Std. Dev.
A. Baumann	-.082	-.055	-.64[a]	.344
Crown Berger	.065	.065	.040[a]	.019
E.A Portland Cement	.092	.110	-.05[a]	.075
Eveready E.A Ltd	.133	.095	.00[a]	.134
Express Kenya	.062	.065	.02	.072
Kapchorua	.012	.021	-.11[a]	.069
Kengen	.035	.035	.03	.021
Marshalls E. A	-.003	.035	-.14[a]	.086
Pan- Africa Insurance	.038	.030	.03	.035
Tps Serena	.085	.085	.05[a]	.024
Williamson Tea	.018	.040	.04	.042

Source: Researchers own work

4.2.4 Current Liabilities to Total Assets Ratio

Moreover, the study analyzed the ratio of current liabilities to total assets of 11 listed firms that posted a decline in profitability in 2008. The descriptive results to this effect are as shown in Table 4.4. The study as shown in Table 4.4 found that the Pan-Africa Insurance posted the largest current liabilities/total assets ratio (mean = 0.753; median = 0.750) between 2004 and 2009. On the same vein, Kengen posted the least ratio (mean = 0.057; median = 0.070). According to the foregoing descriptive results, it is apparent that Pan-Africa Insurance had relatively more current liabilities in comparison to the other surveyed firms. Similarly, Kengen had the least current liabilities, at least, in respect of its total assets. With the assumption that it was easy to convert the available assets to cash, it is imperative to infer that Kengen was the best financially performing entity among the 11 studied due to the fact that its current liabilities were significantly less in relation to the total assets. Williamson Tea also had very low ratio of current assets to total assets (mean = 0.082; median = 0.075). Both Kengen and Williamson Tea were the most likely in that order to pay their creditors and employees among other current liabilities.

The study also established that Eveready E.A. Ltd had the largest fluctuation of its current liabilities to total assets ratio (std dev = 0.209). The findings implied that the company could not reliably address its current liabilities. On the other hand, East Africa Portland Cement was found to have the most stable current liabilities to total assets ratio (std dev = 0.015). The foregoing implied that the firm could reliably pay up its current liabilities with minimal fluctuations. Williamson Tea was also found to exhibit insignificant variation in respect to the aforementioned financial ratio (std dev = 0.021).

Table 4.4: Current Liabilities to Total Assets Ratio

	Mean	**Median**	**Mode**	**Std. Dev.**
A. Baumann	.355	.300	.14[a]	.193
Crown Berger	.445	.425	.390[a]	.057
E.A Portland Cement	.138	.135	.13	.015
Eveready E.A Ltd	.417	.495	.54	.209
Express Kenya	.445	.410	.31[a]	.118
Kapchorua	.117	.110	.07	.046
Kengen	.057	.070	.07	.029
Marshalls E. A	.532	.505	.43[a]	.118
Pan- Africa Insurance	.753	.750	.72	.033
Tps Serena	.182	.165	.11[a]	.070
Williamson Tea	.082	.075	.07	.021

Source: Researchers own work

4.2.5 Debt to Total Assets Ratio

In addition, the study examined the ratio of debt to total assets for companies listed on the NSE and which recorded a decline in profitability. The pertinent results are as illustrated in Table 4.5. The results shown in Table 4.5 indicated that between 2004 and 2009, the most indebted firms included Pan-Africa Insurance, TPS Serena and Marshalls E.A. respectively. The ratios of debt to total assets recorded by the three firms over the said period of time were (mean = 0.763), **(**mean = 0.713), and (mean = 0.710) respectively. Interpretatively, for every 1000 units of total assets for each of the foregoing firms, 763 units, 713 units, and 710 units constituted debt in Pan-Africa Insurance, TPS Serena and Marshalls E.A. respectively. The findings further underpinned the high leverage of the aforestated firms. The results could also have been attributed to the foregoing firms giving out high amounts of dividends to their shareholders while retaining little amounts of their earnings (profits).

On the other hand, Williamson Tea, Kapchorua and Kengen were the least leveraged with the three firms exhibiting increasing leverage respectively. The listed companies returned (mean = 0.288), (mean = 0.353), and (mean = 0.362) debt to total assets ratios respectively. This implied that the aforementioned firms did not depend so much on debt; rather they relied more on other constituents of capital structure which include equity and retained earnings. This could have emanated from the preference of the companies to plough back most of their profits as opposed to giving out highly-valued dividends to their shareholders. Optionally, the firms are also likely to have posted more profits and return on assets vis-à-vis the total assets in comparison to the other surveyed listed entities.

t is evident that most of the surveyed firms (7 out of 11) had debt to total assets ratios exceeding 0.5. This meant that more than 50% of their total assets constituted debt. This could have been occasioned by the policies of these companies on leverage, dividends and associated financial issues including funding infrastructural projects for development. Granted that the surveyed firms recorded a decline in profitability in 2008, then the high leverage could have implied that the reduced profits translated to reduced retained earnings and hence increasing the chances of these firms to leverage in order to remain afloat in the market. It is also evident that the variation of debt to total assets ratios was largely minimal across most of the listed firms studied. This implied that the issue of high leverage was persistent and was as such likely to be founded on the individual company's policies. Indeed, it is only TPS Serena that recorded significant variation in its debt to total assets ratio (std dev = 0.631) over the period between 2004 and 2009. This could have been occasioned by changing debt policies made and adopted by the company especially in the wake of posting a decline in profitability.

Table 4.5: Debt to Total Assets Ratio

	Mean	Median	Mode	Std. Dev.
A. Baumann	.665	.725	1.00	.331
Crown Berger	.507	.495	.440[a]	.050
E.A Portland Cement	.632	.630	.50[a]	.097
Eveready E.A Ltd	.495	.580	.00[a]	.248
Express Kenya	.608	.630	.67	.085
Kapchorua	.353	.350	.32	.034
Kengen	.362	.400	.00[a]	.192
Marshalls E. A	.710	.705	.63[a]	.060
Pan- Africa Insurance	.763	.755	.72[a]	.035
Tps Serena	.713	.465	.42[a]	.631
Williamson Tea	.288	.280	.27	.024

Source: Researchers own work

4.2.6 Retained Earnings to Total Assets Ratio

The study further analyzed the retained earnings to total assets ratio in respect of the 11 listed firms that recorded a decline in profits in 2008. The results of descriptive analysis over the period between 2004 and 2009 are as shown in Table 4.6. The results shown in Table 4.6 indicate that only 2 out of the 11 surveyed listed firms had retained earnings constituting more than 50% of their total assets. These firms are Kapchorua (mean = 0.543), and Williamson Tea (mean = 0.598). Interpretatively, the two firms had 54.3% and 59.8% of their total assets respectively consisting of profits ploughed back to the business. The foregoing could have been alluded to both firms recording relatively high profits such that a small percentage of the profits could effectively address all the current liabilities and dividends to shareholders. Optionally, the policies of the two firms could have informed investment and expenditure decisions. In this case, the policies advocated for a larger proportion of profits realized at the end of a financial year to be reinvested to the business. It is also evident as shown in Table 4.6 that both Kapchrua (std dev = 0.046) and Williamson Tea (std dev = 0.030) indicated consistency in respect of the ratio of retained earnings to total assets where the variation of the aforesaid financial ratio over the period ranging from 2004 to 2009 was found to be largely insignificant.

On the other hand, Marshalls E.A. exhibited the lowest ratio of retained earnings to total assets (mean = 0.042) over the surveyed period (2004 to 2009). The results implied that only 4.2% of the company's total assets was made up of retained earnings. That is, the retained earnings constituted a very marginal part of the capital structure. This could have been attributed to the firm posting minimal profits where it was practically not possible to have much of the said profits being ploughed back for reinvestment. Alternatively, this firm's policy could have advocated for debt and equity as the primary constituents of its capital structure. The firm was also found to be highly consistent in respect of its retained earnings to total assets ratio (std dev = 0.047) over the period from 2004 to 2009. Therefore, just like the case of Kapchorua and Williamson Tea, Marshalls E.A. could not be inferred to be affected by the 2008's decline in profitability in regard to its capital structure and investment decisions. The fact that both Kapchorua (median = 0.545) and Williamson Tea (median = 0.595) returned the highest median values which were above the 50% mark, while Marshalls E.A. returned the lowest (median = 0.032) all of which were very close to the median ratios further supported the part played by the retained earnings in reference to their total assets.

Table 4.6: Retained Earnings to Total Assets Ratio

	Mean	Median	Mode	Std. Dev.
A. Baumann	.392	.455	.08[a]	.245
Crown Berger	.402	.400	.400	.039
E.A Portland Cement	.135	.120	.01[a]	.105
Eveready E.A Ltd	.117	.120	.12[a]	.072
Express Kenya	.147	.115	.08	.094
Kapchorua	.543	.545	.49[a]	.046
Kengen	.415	.510	.56	.220
Marshalls E. A	.042	.032	.00	.047
Pan- Africa Insurance	.110	.135	.15	.056
Tps Serena	.188	.185	.13[a]	.044
Williamson Tea	.598	.595	.58	.030

Source: Researchers own work

4.2.7 Financial Distress

Financial distress was characterized by the level of liquidity, leverage and profit or loss among listed firms which posted a decline in profitability in 2008. As such the composite score for the four parameters was employed to constitute financial distress. It is apparent that any firm that returned a financial loss, reduction in profits, high leverage, and low liquidity was in some level of financial distress. The pertinent results of descriptive statistics are as shown in Table 4.7. According to the results shown in Table 4.7, East Africa Portland Cement exhibited, on average, the highest level of financial distress over the period between 2004 and 2009 (mean = 1.073). The results implied that the foregoing firm was more likely to have posted reduced profits, increased losses, increased leverage, and/or reduced liquidity over the aforestated period of time. On the other hand, over the same period of time, Express Kenya was found to have the lowest level of financial distress (mean = 0.401). In this regard, the firm was found to be the one out of the 11 surveyed firms that posted increased profits, reduced losses, reduced leverage or/and increased liquidity over the indicated period of time.

It was further revealed that between 2004 and 2009, Crown Berger (std dev = 0.048), Express Kenya (std dev =0.053), and Marshalls E.A. (std dev = 0.08) were the most consistent listed firms in respect of financial distress over the stated period. The foregoing implied that there was quite insignificant variation in financial distress among the three firms. However, Kengen (std dev = 0.374), A. Baumann (std dev = 0.367), and Eveready E.A. Ltd (std dev = 0.316) indicated the largest fluctuations in respect of financial distress. This implied that their profitability, liquidity and/or leverage were highly inconsistent over the 6 years period ending 2009.

Table 4.7: Financial Distress

	Mean	Median	Mode	Std. Dev.
A. Baumann	.673	.610	.24[a]	.367
Crown Berger	.700	.715	.72	.048
E.A Portland Cement	1.073	1.005	.93[a]	.171
Eveready E.A Ltd	.640	.757	.00[a]	.316
Express Kenya	.401	.423	.33[a]	.053
Kapchorua	.842	.825	.66[a]	.166
Kengen	.709	.792	.00[a]	.374
Marshalls E. A	.591	.627	.46[a]	.078
Pan- Africa Insurance	.740	.768	.54[a]	.155
Tps Serena	.766	.695	.56[a]	.217
Williamson Tea	.961	.923	.80[a]	.160

Source: Researchers own work

4.3 Inferential Statistics

The study examined the relationship between financial ratios and financial distress among listed companies in Kenya. The foregoing was achieved by correlating the aforesaid ratios against financial distress by use of Spearman rank correlation coefficient. Moreover, the extent to which the financial ratios affected financial distress was also analyzed using multiple regression.

4.3.1 Relationship between Financial Ratios and Financial Distress

The results of Spearman rank correlation analysis are as illustrated in Table 4.8. The significance of the relationships was tested at 0.05. The correlation analysis sought to rank the strengths of relationships between individual financial ratios and financial distress among listed firms that posted a decline in profitability in 2008. The results of the Spearman rank correlation analysis shown in Table 4.8 indicated that the relationship between working capital/total assets and financial distress was positive, moderately strong and statistically significant ($r = 0.389$; $p < 0.05$) at 0.05 level of significance. The results were interpreted to mean that an increase in the ratio of working capital to total assets of the surveyed firms was likely to moderately increase the financial distress of the said firms. As such, in order to reduce the financial distress, it was imperative to reduce the aforementioned financial ratio.

The relationship between sales/total assets and financial distress was found to be negative, weak and statistically not significant ($r = -0.085$; $p > 0.05$). This meant that the ratio of sales to total assets hardly influenced financial distress, and when it did, its increase reduced financial distress of the listed firms.

Moreover, the study established that the relationship between EBIT/total assets and financial distress was positive, weak and statistically significant ($r = 0.295$; $p < 0.05$). Interpretatively, increasing the ratio of earnings before interest and tax to total assets was likely to slightly increase financial distress. However, the increase though slight, was found to be considerable. In the same breadth, the relationship between current liabilities/total assets and financial distress was revealed to be positive, moderately strong and statistically significant ($r = 0.396$; $p < 0.05$). This meant that an increase in current liabilities to total assets ratio was likely to moderately and substantially increase financial distress among the surveyed firms. Therefore, it was apparent that reducing current liabilities was likely to occasion significant reduction in financial distress of the aforestated entities.

It was further revealed that the relationship between the debt/total assets and financial distress was negative, weak and statistically not significant ($r = -0.052$; $p > 0.05$). The results implied that the ratio of debt to total assets was likely to have very marginal influence on financial distress which was also not substantial. It further implied that the aforesaid financial ratio was not worth consideration in respect of financial distress. It was also found that there existed a positive, moderately strong and statistically significant relationship between retained earnings/total assets and financial distress ($r = 0.395$; $p < 0.05$). The results implied that increasing the ratio of retained earnings to total assets was likely to moderately increase financial distress amongst the surveyed listed firms. It was imperative to conclude that having large amounts of retained earnings could possibly increase financial distress

Table 4.8: Correlation Matrix for Financial Ratios and Financial Distress

			1	2	3	4	5	6	7
Spearman's rho	**WC/TA**	Correlation Coefficient	1.000						
		Sig. (2-tailed)	.						
	S/TA	Correlation Coefficient	.523**	1.000					
		Sig. (2-tailed)	.000	.					
	EBIT/TA	Correlation Coefficient	.275*	.465**	1.000				
		Sig. (2-tailed)	.025	.000	.				
	CL/TA	Correlation Coefficient	.021	.478**	.063	1.000			
		Sig. (2-tailed)	.865	.000	.613	.			
	D/TA	Correlation Coefficient	.034	.296*	.114	.737**	1.000		
		Sig. (2-tailed)	.788	.016	.363	.000	.		
	RE/TA	Correlation Coefficient	.155	-.236	.048	.538**	.661**	1.000	
		Sig. (2-tailed)	.213	.056	.704	.000	.000	.	
	FD	Correlation Coefficient	.389**	-.085	.295*	.396**	-.052	.395**	1.000
		Sig. (2-tailed)	.001	.498	.016	.001	.677	.001	.

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Key:

CL/TA (4) represents 'Current Liabilities to Total Assets Ratio'

D/TA (5) represents 'Debt to Total Assets Ratio'

EBIT/TA (3) represents 'Earnings before Interest and Tax to Total Assets Ratio'

FD (7) represents 'Financial Distress'

RE/TA (6) represents 'Retained Earnings to Total Assets Ratio'

S/TA (2) represents 'Sales to Total Assets Ratio'

WC/TA (1) represents 'Working Capital to Total Assets Ratio'

The results of this study were in congruence with the observations made in a previous study conducted by Charalambakis (2014) among Greek firms. Similarly to this study, Charalambakis found that a model that combines the three financial ratios (that is, sales to total assets, EBITDA to total assets, and current liabilities to total assets) with three market–based variables exhibits the highest predictive ability.

4.3.2 Effect of Financial Ratios on Financial Distress

The study examined the extent to which the each of the financial ratios affected financial distress among listed firms. The first part as shown in Table 4.9, illustrates the general correlation between all the financial ratios combined against financial distress as denoted by R, and also the coefficient of determination (R^2) which shows the proportion of financial distress that could be explained by or attributed to the studied financial ratios. The significance of the regression model is further tested by use of analysis of variance (ANOVA), the results of which are as shown in Table 4.10. Moreover, as illustrated in Table 4.11, the extent to which the financial ratios affected financial distress ($\boldsymbol{\beta_n}$) is examined. The results of the t-statistics indicated in the same table (Table 4.11) facilitates testing of the null hypotheses.

The study as shown in Table 4.9 revealed that the general correlation between all the studied financial ratios (working capital/total assets, sales/total assets, EBIT/total assets, current liabilities/total assets, debt/total assets, and retained earnings/total assets) and financial distress was positive and strong (R = 0.716). In addition, according to the results of coefficient of determination ($R^2 = 0.463$), it was found that 46.3% of financial distress could be explained by the studied financial ratios. The remaining proportion (53.7%) of financial distress could be attributed to other factors that were not part of this study. The results underpinned the importance of financial ratios in respect of financial distress among listed firms.

Table 4.9: Regression Weights for Overall Model

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.716[a]	.512	.463	.19593

a. Predictors: (Constant), Working Capital/Total Assets, Sales/Total Assets, EBIT/Total Assets, Current Liabilities/Total Assets, Debt/Total Assets, Retained Earnings/Total Assets

The results as shown in Table 4.9, significantly departed from the findings of a past study conducted by Ming- Chang (2014) among firms listed in the Taiwan Stock Exchange. Unlike the current study that found that only 46.3% of financial distress could be predicted by the studied financial ratios, the former study observed that the Cox Proportional Hazard Model could accurately predict 87.93% of financial distress among the aforestated firms. Similarly, to the present study, Abudo (2011) carried out a study to determine how financial distress can be predicted in the banking industry. Abudo's study examined the prediction accuracy of the Altman model in examining the failure of listed commercial banks in Kenya. This largely mirrored the present study that analyzed the prediction accuracy of discrete hazard model in examining financial distress of firms listed on the NSE.

The significance of the regression model was tested using the analysis of variance whose results are as shown in Table 4.10. The results shown in Table 4.10 indicated that the following regression model was significant ($F = 10.327$; $p < 0.05$).

$$\mathbf{Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \varepsilon}$$

Therefore, the model was suitable in analyzing the influence of financial ratios on financial distress among the surveyed listed firms.

Table 4.10: Significant Test Results

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.379	6	.396	10.327	.000[a]
	Residual	2.265	59	.038		
	Total	4.644	65			

a. Predictors: (Constant), Working Capital/Total Assets, Sales/Total Assets, EBIT/Total Assets, Current Liabilities/Total Assets, Debt/Total Assets, Retained Earnings/Total Assets

a. Dependent Variable: Financial Distress

Table 4.11: Results for Overall Model

	Unstandardized Coefficients		Standardized Coefficients		
Model	**B**	**Std. Error**	**Beta**	**t**	**Sig.**
1 (Constant)	.339	.095		3.568	.001
Working Capital/Total Assets	.568	.215	.257	2.647	.010
Sales/Total Assets	-.021	.049	-.048	-.429	.669
EBIT/Total Assets	.519	.214	.242	2.426	.018
Current Liabilities/Total Assets	-.282	.143	-.247	-1.974	.053
Debt/Total Assets	.471	.107	.477	4.401	.000
Retained Earnings/Total Assets	.543	.142	.435	3.813	.000

a. Dependent Variable: Financial Distress

The results of multiple regression analysis shown in Table 4.11 were used to substitute and interpret the following regression model.

$$\mathbf{Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \varepsilon}$$

Where

Y	represents	financial distress
β_0	represents	Constant
X_1	represents	Working capital/total assets
X_2	represents	Sales/total assets
X_3	represents	EBIT/total assets
X_4	represents	Current liabilities/total assets
X_5	represents	Debt/total assets
X_6	represents	Retained earnings/total assets
ε	represents	Error term
β_1 to β_6	represent	Regression coefficients of predictor variables

The regression model is substituted as follows

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \varepsilon$$

$$Y = 0.339 + 0.568X_1 - 0.021X_2 + 0.519X_3 - 0.282X_4 + 0.471X_5 + 0.543X_6$$

The model was interpreted to mean that one unit change in financial distress was subject to 0.568 unit, -0.021 unit, 0.519 unit, -0.282 unit, 0.471 unit, and 0.543 unit changes in working capital to total assets ratio, sales/total assets, EBIT/total assets, current liabilities/total assets, debt/total assets, and retained earnings/total assets ratios respectively while holding other factors (0.339) that were not part of the study constant. According to the results, it is apparent that working capital to total sales ratio had the greatest effect on financial distress ($\beta_1 = 0.568$) while sales to total assets ratio had the least effect ($\beta_2 = -0.021$).The above results indicate that the model could generally significantly predict financial distress among listed firms. This is underscored by the significant effect of all the studied financial ratios (except sales to total assets ratio) on financial distress as shown in Table 4.11. The foregoing results supported earlier findings by Amalendu and Ruchira (2011) where it was found that financial ratios have predictive power with regards to whether a company will fail or not. Moreover, the study's findings were in agreement with Robert's (2014) observations that that financial ratios can predict financial distress for non-financial sector Kenyan firms listed in the Nairobi Stock Exchange.

4.4 Test of Hypothesis

The results of the T-statistics as shown in Table 4.11 were used to test the null hypotheses in relation to specific financial ratios while the results of F-statistics were used to test the significance of the overall model as follows:

4.4.1 Financial ratios and financial distress prediction

The study sought to examine the effect of financial ratios on financial distress. It was hypothesized (Hypothesis HO_1) that there are no financial ratios which significantly contribute to the prediction of financial distress. The alternative hypothesis (HA_1) was that there are financial ratios which significantly contribute to the prediction of financial distress. Results of T-statistics as shown in Table 4.11 indicated that several financial ratios returned ($p < 0.05$)

Table 4.11: Results for Overall Model

	Unstandardized Coefficients		**Standardized Coefficients**		
Model	**B**	**Std. Error**	**Beta**	**t**	**Sig.**
1 (Constant)	.339	.095		3.568	.001
Working Capital/Total Assets	.568	.215	.257	2.647	.010
Sales/Total Assets	-.021	.049	-.048	-.429	.669
EBIT/Total Assets	.519	.214	.242	2.426	.018
Current Liabilities/Total Assets	-.282	.143	-.247	-1.974	.053
Debt/Total Assets	.471	.107	.477	4.401	.000
Retained Earnings/Total Assets	.543	.142	.435	3.813	.000

It was interpreted that here are financial ratios which significantly contribute to the prediction of financial distress. The null hypothesis (H_{01}) was rejected. The hypothesis was rejected because it was found that there were several financial ratios which indeed significantly predicted financial distress among listed firms. This was in tandem with part of the findings made in a study conducted by Charalambakis (2014) where ratio of retained earnings to total assets was found to be a strong predictor of financial distress.

4.4.2 Predictive ability of the model and financial distress

The study sought to establish whether the logistic regression model has significant predictive ability to make accurate forecasts of financial distress. The alternative hypothesis (HA_2) was that the model has significant predictive ability to make accurate forecasts of financial distress.

For this objective the results of F-statistics as shown in Table 4.10 indicated that ($F = 10.327$; $p < 0.05$)

Table 4.10: Significant Test Results

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.379	6	.396	10.327	.000[a]
	Residual	2.265	59	.038		
	Total	4.644	65			

The interpretation was that the model has significant predictive ability to make accurate forecasts of financial distress. The null hypothesis was therefore rejected. The rejection of the hypothesis was premised on the fact that the model was found to significantly predict financial distress. These results supported the findings of a study carried out by Ming- Chang (2014) where Cox proportional hazard model was found to have an 87.9% overall prediction accuracy of financial distress. The key difference between the former and the present studies was the application of varying models (Cox proportional hazard model and discrete hazard model respectively).

4.4.3 Predictive accuracy of the model before financial crisis

The study sought to establish whether the logistic regression model has significant predictive accuracy in predicting financial distress before financial crisis. The alternative hypothesis (HA_2) was that the model has no significant accuracy in predicting financial distress before financial crisis.

Results of F-statistics as shown in Table 4.12 indicated that ($F = 11.505$; $p < 0.05$)

Table 4.12: Significant Test Results for 2004 – 2006

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.280	6	.380	11.505	.000[a]
	Residual	.859	26	.033		
	Total	3.139	32			

Predictors: (Constant), Working Capital/Total Assets, Sales/Total Assets, EBIT/Total Assets, Current Liabilities/Total Assets, Debt/Total Assets, Retained Earnings/Total Assets

The hypothesis was rejected since according to the regression results, the model was able to predict financial distress of the firms under study prior to the financial crisis of 2007. The results underscores the importance of the model in forestalling negative financial ramifications during normal economic period.

4.4.4 Predictive accuracy of the model during financial crisis

The study sought to establish whether the logistic regression model has significant predictive accuracy in predicting financial distress during financial crisis. The alternative hypothesis (HA_2) was that the model has no significant accuracy in predicting financial distress during financial crisis.

Results of F-statistics as shown in Table 4.13 indicated that ($F = 4.089$; $p < 0.05$)

Table 4.13: Significant Test Results for 2007 – 2009

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.720	6	.120	4.089	.005[a]
	Residual	.764	26	.029		
	Total	1.484	32			

a. Predictors: (Constant), Working Capital/Total Assets, Sales/Total Assets, EBIT/Total Assets, Current Liabilities/Total Assets, Debt/Total Assets, Retained Earnings/Total Assets

b. Dependent Variable: Financial Distress

The interpretation was that the model has significant predictive accuracy in predicting financial distress during financial crisis. The null hypothesis (HO_4) was therefore rejected. The study results indicated the suitability and applicability of the model when there is a financial crisis as was experienced in Kenya between 2007 and 2009. As earlier observed, it was imperative to infer that the application of the model inn predicting financial distress of listed firms was not prone to whether or not the prevailing financial situation was a crisis.

4.4.5 Comparison of predictive accuracy of the model before and during financial crisis

The study sought to establish whether there is a difference in the predictive accuracy of the model in predicting financial distress before and during financial crisis. The alternative hypothesis (HA_5) was that there is significant difference in the predictive accuracy of the model in predicting financial distress before and during financial distress. The results of F-statistics as shown in both Table 4.12 and Table 4.13 were ($F = 11.505$; $p < 0.05$) and ($F = 4.089$; $p < 0.05$) respectively. This was interpreted to mean that there is no significant difference in the predictive accuracy of the model in predicting financial distress before and during financial distress.The null hypothesis (H_{05}) therefore failed to be rejected. The above conclusion implied that the model was not subject to the prevailing financial climate; rather its application is constant. The foregoing underpinned the suitability of the model in accurately predicting financial distress among listed entities in Kenya and beyond.

CHAPTER FIVE
SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter presents a summary of key findings emanating from the analyzed data and in respect of the study objectives. The chapter also covers the conclusions drawn from the summarized findings. Moreover, it outlines the recommendations suggested from the conclusions drawn. The last part presents the areas recommended for further studies.

5.2 Summary of Findings

The study summarizes the major findings, both descriptive and inferential, obtained from the analysis of the data collected in respect of listed firms that recorded a decline in profits during the financial crisis of 2008.

The first objective of the study was to determine the financial ratios which contribute significantly to the prediction of financial distress.The results of the multiple regression analysis indicated that one unit change in financial distress was subject to 0.568 unit, -0.021 unit, 0.519 unit, -0.282 unit, 0.471 unit, and 0.543 unit changes in working capital to total assets ratio, sales/total assets, EBIT/total assets, current liabilities/total assets, debt/total assets, and retained earnings/total assets ratios respectively while holding other factors (0.339) that were not part of the study constant. Therefore it was found that working capital had the greatest and most significant effect on financial distress while sales had the least effect.

The second objective of the study was to evaluate the predictive ability of the model in making accurate forecasts of financial distress.The findings of the F statistic indicated that the model has significant predictive ability to make accurate forecasts of financial distress. Therefore the model was suitable in analyzing the influence of financial ratios on financial distress among the surveyed listed firms.

The third objective of the study was to determine the predictive accuracy of the model in predicting financial distress before financial crisis. The results of the F statistic for 2004-2006 indicated that the model has significant predictive accuracy in predicting financial distress before financial crisis because the p value was less than 0.05.The results underscores the importance of the model in forestalling negative financial ramifications during normal economic period

The fourth objective was to determine the predictive accuracy of the model in predicting financial distress during financial crisis. The findings from the F statistic indicated that the model has significant predictive accuracy in predicting financial distress during financial crisis as was experienced in Kenya in 2007 since it returned a p value which was less than 0.05

The fifth objective was to compare the predictive accuracy of the model in predicting financial distress before and during financial crisis. The comparison of the results of the statistic for 2004- 2006 and 2007- 2009 indicated that there is no significant difference in the predictive accuracy of the model in the two periods. This implied that the performance of the model was not subject to the prevailing financial climate.

5.3 Conclusions of the Study

The study concluded that, in order to reduce the financial distress, it was imperative to reduce the working capital to total assets ratio of the surveyed firms. It was concluded that the ratio of sales to total assets marginally related to financial distress. The increase of the ratio of earnings before interest and tax to total assets though slight, was concluded to be considerable. It was inferred that reducing current liabilities was likely to occasion significant reduction in financial distress of the afforestated entities. Moreover, the study concluded that the ratio of debt to total assets was not worth consideration in respect of financial distress. It was concluded that having large amounts of retained earnings could possibly increase financial distress. The study concluded that the studied financial ratios played a crucial role in determination of financial distress among listed firms. It was further inferred that that while working capital to total sales ratio had the greatest effect on financial distress sales to total assets ratio played the least role in determination.

It was also concluded that the logistic regression model could generally significantly predict financial distress among listed firms. The study results indicated the suitability and applicability of the model when there is a financial crisis as was experienced in Kenya between 2007- 2009.The model was also able to predict financial distress of the firms under study prior to the financial crisis of 2007.

The findings of the study concluded that the logistic regression model was not subject to the prevailing financial climate, rather its application is constant. The model is therefore suitable in accurately predicting financial distress among listed firms in Kenya and beyond

5.4 Recommendations of the Study

The study made several recommendations in tandem with the conclusions drawn from the study and pertinent to the study objectives. It is advisable for all listed companies to reduce their working capital particularly in respect of their total assets as one way of bolstering their financial performance, and therefore mitigating against financial distress. It is equally important to stabilize the proportion of the working capital against total assets owned by the listed firms. This is important in increasing the precision of forecasting financial performance of the said entities.

The study recommends that the listed firms ought to ensure that they have a large asset base. This is founded on the reasoning that increased sales and overall financial performance of the firms is largely dependent on total assets held by the said firms. Moreover, it is recommended that the listed firms should effectively address the factors that are likely to occasion the fluctuation of sales in respect of total assets of the firms. The study further advocates for increased stability of earnings before interest and tax (EBIT) in respect of total assets held by the listed firms. In order to enhance their financial performance and shun financial distress, the listed firms are recommended to reduce their current liabilities. Moreover, they should seek means of addressing current liabilities in line with contractual agreement with suppliers, employees, and other creditors. Failure to effect the foregoing recommendation is likely to result in potential financial distress.

The study recommends that all listed entities should have debt policies that are alive to the dynamics occasioned by both micro and macroeconomic factors. In this regard, in spite of the obvious benefits associated with leverage, it is advisable for listed firms to effectively address their debts in order to have control over their financial activities. It is also recommended that the listed firms should plough back to business a significant proportion of their profits while using the remainder to pay dividends to shareholders. The retained earnings should be balanced alongside equity and debt in reference to the capital structure of the listed entities. Moreover, it is recommended that the listed firms should ensure that they have high liquidity, are appropriately leveraged and have a positive trajectory of profitability in order to effectively mitigate financial distress.

5.5 Suggestions for Further Research

The following areas are suggested for further research: The influence of the logistic regression model on financial distress prediction of firms listed on the NSE immediately after 2008 economic crunch; The other area of research would be testing of bankruptcy prediction models to the firms which are not listed in the Nairobi Stock Exchange and are relatively smaller in terms of turnover. This study could also be applied to listed firms but this time incorporating other measurable aspects like inflation rate impacts, number of years in business, nature of the auditing process and board composition.

REFERENCES

Abuga, N. J. (2013). Causes of financial distress: a survey of firms funded by Industrial and commercial Development Corporation in Kenya. *MBA, JKUAT.*

Adeyemi, B. (2011). *Bank Failure in Nigeria:* A Consequence of Capital Inadequacy, Lack of Transparency and Non-Performing Loans. Banks and Bank System, 6(1), 99–109.

Rahimipoor, A. (2013). A comparative study of bankruptcy prediction models of Fulmer and Toffler in firms accepted in Tehran Stock Exchange. *Journal of Novel Applied Sciences*, *2*(10), 522-527.

Arieff, A. (2010). *Global economic crisis: Impact on sub-Saharan Africa and global policy responses*. DIANE Publishing.

Altman, E. I. (1993). Corporate Financial Distress and Bankruptcy. *A complete guide to Predicting and Avoiding Distress and Profiting from Bankruptcy*. Second Edition. USA, John Riley and Sons Inc.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The journal of finance*, *23*(4), 589-609.

Alves, K., Kalatzis, A., & Matias, A. B. *Survival Analysis of Private Banks in Brazil* (No. 21500002). Eco Mod.

Bhunia, A., & Sarkar, R. (2011). A study of financial distress based on MDA. *Journal of Management Research*, *3*(2).

Amoa-Gyarteng, K. (2014). Analyzing a listed firm in Ghana for early warning signs of bankruptcy and financial statement fraud: An empirical investigation of AngloGold Ashanti. *European Journal of Business and Management*, *6*(5), 10-17.

Baharin, I. & Sentosa, I. (2013). Capital Structure and the Post Performance Factors of Malaysian PN 17 Firms. *International Journal of Business and Management Invention*, *2*(3), 50–56.

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of accounting research*, 71-111.

Bilanas, A. F., & Harris, F. (2004). A methodology predicting failure in the construction Industry. *Journal of Construction Management and Economics*, *13*(3), 189-196.

Boser, B. E., Guyon, I. M., & Vapnik, V. N. (1992, July). A training algorithm for optimal margin classifiers. In *Proceedings of the fifth annual workshop on Computational learning theory* (pp. 144-152). ACM.

Carson, M. J. (1995). Financial Distress in the Life Insurance Industry: An Empirical Examination. *Illinois University*.

Cirmizi, E., Klapper, L. & Uttamchandani, M. (2012). The Challenges of Bankruptcy Reform. *The World Bank Research Observer*, 27(2), 185-203.

Charalambakis, E. C. (2014). On corporate financial distress prediction: what can we learn from private firms in a small open economy? *Working Paper No. 188, Bank of Greece, Athens, Greece.*

Cooper& Schindler (2001), "*Business Research Methods*", 7th Ed. Irwin/ McGraw- Hill, New York.*Corporate governance, 6(*1), 18-33.

Cox, D. R. (1972), "Regression models and life-tables", Journal of Royal Statistical Society B, Vol. 34, pp. 187-220.

Demyanyk, Y. & Hasan, I. (2010). Financial crises and bank failures: A review of prediction methods. *Omega*, *38*(5), 315-324.

Erkens, D. H., Hung, M., & Matos, P. (2012). Corporate governance in the 2007–2008 financial crisis: Evidence from financial institutions worldwide. *Journal of Corporate Finance*, *18*(2), 389-411.

Fulmer, J. G., Moon, J. E., & Gavin, T. A. (1984). A (1984). Bankruptcy Classification Model for Small Firms. *Journal of Commercial Bank Lending, Julius*, 25-37.

Gass, S. I., & Assad, A. A. (2005). *An annotated timeline of operations research: An informal history* (Vol. 75). Springer Science & Business Media.

Gitman, L. J. (2009) *Principles of Managerial Finance,* 12.Edition, Person Prentice Hall.

Gharaibeh, M. A., Sartawi, I. I. S. M., & Daradkah, D. (2013). The Applicability of corporate failure models to emerging economies: Evidence from Jordan. *Interdisciplinary Journal of Contemporary Research in Business*, *5*(4), 313-325.

Hair, J. F., Tatham, R. L., Anderson, R. E. & Black, W. (2006). Multivariate data analysis, *Prentice Hall, New Jersey, USA.*

Ghodrati, H., & Moghaddam, A. M. (2012). A Study of the Accuracy of Bankruptcy Prediction Models: Altman, Shirata, Ohlson, Zmijewsky, CA Score, Fulmer, Springate, Farajzadeh Genetic, and McKee Genetic Models for the Companies of the Stock Exchange of Tehran. *American Journal of Scientific Research*, *59*, 55-67.International Monetary Fund, *World Economic Outlook Update*, July 8, 2009.

Jahur, M. S., & Quadir, S. N. (2012). Financial distress in small and medium enterprises (SMES) of Bangladesh: Determinants and remedial measures. *Economia. Seria Management*, *15*(1), 46-61

.Jamshed, P. (2012). *Theories of Financial Analysis.* Hub pages. John Wiley & Sons. Journal of Accounting Research, 18(1):109-131

John Y. C, Jens H & Jan S. (2010).*Predicting financial distress and performance of distressed stocks.*

Jones, Stewart, and David A. Hensher, 2008, Advances in Credit Risk Modelling and Corporate Bankruptcy Prediction (Cambridge University Press, Cambridge).

Kemboi, E. K. (2013) *the validity of Altman's failure prediction model in predicting corporate financial distress in Uchumi supermarket in Kenya*. School of business UON, Kenya National Bureau of Standards, *Economic survey, 2009*

Koksal, M.H., & Ozgul, E. (2007). *The relationship between marketing strategies and performance in an economic crisis*. Marketing intelligence and planning, 25(4), 326-342.

Kothari, C.R (2008) *Research Methods*: Methods and Techniques.2nd edition. New Delhi: New Age International.

Laitinen, E. K. and Luoma, M. (1991). 'Survival Analysis as a Tool for Company Failure Prediction,' Omega, 19(6). 673-678.

Leedy P.D. & Ormrod J.E. (2010) Practical Research: Planning and Design. 9th edn.Pearson Educational International, Boston

Li, H. & Sun, J. (2008). *Ranking-order case-based reasoning for financial distress prediction*. Knowledge Based Systems, 21(8), 868-878.

Martin, D. (1977): *Early warning of bank failure: a logit regression approach*. Journal of Banking and Finance 1: 249-276.

Makridakis, S. (1991). What Can We Learn from Corporate Failure? Long Range Planning, 24(4), 115-126.

Mamo, A. Q. (2011). Applicability of Altman (1968) model in predicting financial distress of commercial banks in Kenya. *PhD diss*.

Ming- Chang, L. (2014): Business bankruptcy prediction based on survival analysis approach. *International Journal of computer science &Information technology (IJCSIT)* Vol 6, No 2. April.

Macharia M. N. & Basweti K. (2017): The applicability of textual disclosures and selected bankruptcy prediction models in assessing the going concern risk of listed firms in Kenya. *International Journal of Economics, Commerce and Management* .Vol. V, Issue 8, August. ISSN 2348 0386.

Moyer, R. C. (1977), *"Forecasting financial failure: A re-examination"* Financial Management 6 (1), pp. 11–17.

Mugenda, O. & Mugenda, A. (2003). *Research Methodology: Quantitative and Qualitative Approaches.* Acts, Press, Nairobi, Kenya.

Nam, J., Chae, W., Tong S., Kim, Park, & Hoe, K. L. (2008), *Bankruptcy Prediction Using a Discrete-Time Duration Model Incorporating Temporal and Macroeconomic Dependencies*, Journal of Forecasting 27, 493–506.

Natalia, O. (2007). *Corporate Financial Distress: An Empirical Analysis of Distress Risk* (Doctoral Dissertation No. 3430, University of St. Gallen, St. Gallen, Switzerland).

Natasa, S. & Marina, J. (2011) *Comparing financial distress prediction before and during recession.* Croatian Operational Research Review (CRORR) Vol. 2, National Bureau of Economic Research (2010), Available at http://www.bank.gov.ua /ENGL/Macro/ index.htm

Ohlson, J.A. (1980). Financial ratios and the probabilistic prediction of bankruptcy,

Outecheva, S. (2007). *Corporate Financial Distress: An Empirical Analysis of Distress Risks*, PhD Dissertation at the Graduate School of Business Administration, Economics, Law and Social Science, The University of St. Gallen. Switzerland.

Pai, P. F., Lin, C. S (2005), *A hybrid ARIMA and support vector machines model in stock price forecasting*, The international journal of management science, vol. 33:497-505.

Pandey, I.M. (2005). *Financial Management (10th Ed).* New Delphi, India, Vikas Publishing

Rachlin, E. (2009), *"How to Measure a Recession".* Epoch Times, available at http://epoch-archive.com/a1/en/us/nyc/2009/04-Apr/16/C4_Your Money-20090416.pdf.

Ravi, K. P., & Ravi, V. (2007). *Bankruptcy prediction in banks and firms via statistical and intelligent techniques* – A review. European Journal of Operational Research, 180(1), 1-28.

Riku, N. (2010), *Implications of Financial Distress*: Aalto University School of Economics. Master Thesis

Ritchie, J. & Akoto, O. (2012). *Spotting the early warning signs of a company's impending financial collapse*. A White Paper from LexisNexis and State of Flux.

Otom, R. O. (2014) *Predicting financial distress using financial ratios in companies listed in Nairobi Stock Exchange.* USIU-Africa.

Sami, B. J. (2013). *Financial Distress and Bankruptcy costs*. Global Strategies for Banking and Finance (369–379). United States: IGI Global.

Shukla, P. (2010). *Essentials of Marketing Research*. Shukla & Ventus Publishing, ApS

Shumway, T. (2001), *Bankruptcy More Accurately: A Simple Hazard Model,* the Journal of Business 74, 101–124.

Slotemaker, R. (2008). *Prediction of Corporate Bankruptcy of Private Firms in the Netherlands,* a Master's Thesis, Erasmus University, Rotterdam, Netherlands

Sobehart, Jorge, Sean Keenan, and Roger Stein, 2001, Benchmarking Quantitative Default Risk Models: A Validation Methodology, Algo Research Quarterly 4, 57–71.

Springate, Gordon, L.V. (1978), *"Predicting the Possibility of Failure in a Canadian Firm".* Unpublished M.B.A. Research Project, Simon Fraser University.

Steven, L., W., C., Jayaraman M., Shankar C. & Ally M. (2011), *Effects of financial distress condition on the company performance:* A Malaysian Perspective Review of Economics & Finance Submitted on 25/Mar./2011 Article ID: 1923-7529-2011-04-85-15

Steyn, B., &Hamman, W.D. (2006). *'Company failure in South Africa: Classification and prediction by means of recursive partitioning',* South African Journal of Business Management, **37,** pp. 7-18.

Sun, J., He, K., & Li, H. (2011). *SFFS-PC-NN optimized by genetic algorithm for dynamic prediction of financial distress with longitudinal data streams.* Knowledge-Based Systems, In Press, Uncorrected Proof

Sun, J., Jia, M., & Li, H. (2011). *AdaBoost ensemble for financial distress prediction: An empirical comparison with data from Chinese listed companies.* Expert Systems with Applications, 38(8), 93059312.

Usdin, S. D. & Bloom, N. M. (2012). *Identifying Signs a Company Is in Financial Distress*. The Legal Intelligencer, 245(80). Available on http://www.flastergreenberg.com/media/article/380_Bloom_Usdin_Legal%20Intelligencer_20120425. Pdf. Retrieved on 21/11/2014.

Vuran, B. (2009). *Financial Failure Prediction Using Financial Ratios: An Empirical Application on Istanbul Stock Exchange*. Istanbul University Journal of the School of Business Administration, 3(3), 47–65.

Wanjohi, A.M. (2011). *Economic Crisis in Kenya during Recession Period between 2008 and 2009.* KENPRO Online Papers Portal. Available online at www.kenpro.org/papers

World Bank, *World Trade Indicators 2008*, p. 72

Whalen, G. A (1991*). Proportional hazards model of bank failure. An examination of its*

Usefulness as an early warning tool.

Economic Review, Federal Reserve >Bank of Cleveland, First Quarter, p. 21-31, 1991.

Yoon, J.S., Kwon, Y.S. (2010). *A practical approach to bankruptcy prediction for small businesses: substituting the unavailable financial data for credit card sales information*.
Expert systems with Applications, 37, 3624-3629.

Zhuang, Q. & Chen, L. (2014*). Dynamic Prediction of Financial Distress Based on Kalman Filtering. Discrete Dynamics in Nature and Society (July 2014*) - Hindawi Publishing Corporation. Available on http://www.hindawi.com/journals/ddns/2014/370280/. Retrieved on 21/11/2014.

Zmijewski, M. (1984). *Methodological issues related to the estimation of financial distress prediction models*. Journal of Accounting Research, 59-82.

APPENDICES

Appendix I: Companies under financial distress for the period under review

Company/ year	2008 profit/ loss	2007 profit/ loss	% change
A. Baumann	(34,436)	(14,929)	Loss
Crown Berger	77,781	140,293	-45%
E.A Portland Cement	715,889	1,112,625	-36%
Eveready East Africa	27,855	179,505	-84%
Express Kenya	38,069	241,591	-84%
Kapchorua Tea	(103,081)	2,054	Loss
Kengen	1,628,854	4,719,279	-65%
Marshalls East.Africa	(169,688)	42,321	Loss
Pan- Africa Insurance	(28,375)	(3,584)	loss
TPS Serena	330,014	617,380	-46%
Williamson Tea	53,704	153,087	-65%

Appendix II: Data collection sheet for Discreet Hazard model

Company/ Financial ratio	**Working capital/ total assets**	**Sales / total assets**	**EBIT / total assets**	**Current Liabilities/ total assets**	**Debt/total assets**	**Retained earnings/ total assets**
A. Baumann Limited						
Crown Berger						
E.A Portland Cement						
Eveready East Africa						
Express Kenya						
Kapchorua Tea						
Kengen Limited						
Marshalls East Africa						
Pan- Africa Insurance						
TPS Serena						
Williamson Tea						