TEST OF RELEVANCE OF ALTMAN Z-SCORE MODEL IN PREDICTING BANK FAILURE IN KENYA

BY

LUMULA BONVENTURE TUMBU

D61/63283/2011

A RESEARCH PROJECT SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE IN MASTER OF BUSINESS ADMINISTRATION OF THE UNIVERSITY OF NAIROBI

NOVEMBER, 2021

DECLARATION

I declare that this research project is my original work and has never been submitted to any other University for assessment or award of a degree.

05 July 2021

Signature ………………… Date…………………..

This project has been submitted with my authority as the university supervisor.

Signature………………… Date……6/7/2021……………..

JOSEPH LUMUMBA BARASA
LECTURER, UNIVERSITY OF NAIROBI
DEPT OF FINANCE AND ACCOUNTING

ACKNOWLEDGMENTS

My deepest appreciation to my Supervisor Mr Joseph Barasa for his constructive criticism and guidance during the entire process of preparing this report. I also express my gratitude to the Management and Staff of the University of Nairobi, School of Business for their great support throughout my studies. To my friends and fellow classmates with whom I shared this journey, I truly acknowledge and appreciate your contribution in various ways towards the completion of this work; your input remains invaluable to me. Lastly, and in a very special and personal way, I would like to appreciate my family for the financial, emotional, and moral support throughout this journey. May the Almighty God bless you abundantly and make his light shine upon you.

DEDICATION

I dedicate this research to my beloved wife Maryanne and children Jason, Janai and Zawadi for the care and support they have accorded me throughout this journey. I am forever grateful and indebted to you.

TABLE OF CONTENTS

DECLARATION .... **ii**

ACKNOWLEDGMENTS .... **iii**

DEDICATION .... **iv**

TABLE OF CONTENTS .... **v**

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

LIST OF ABBREVIATIONS .... **x**

ABSTRACT .... **xi**

CHAPTER ONE **1**

INTRODUCTION **1**

1.1Background of the Study 1

1.1.1 Altman Model 2

1.1.2 Bank Failure 3

1.1.3 Banking Industry in Kenya 5

1.2 Research Problem 6

1.3 Research Objective 9

1.4 Value of the Study 9

CHAPTER TWO **10**

LITERATURE REVIEW 10

2.1 Introduction.. 10

2.2 Theoretical Review 10

2.2.1 Entropy Theory 10

2.2.2 Credit Risk Theory.. 12

2.2.3 Cash Management Theory 14

2.2.4 Gambler's Ruin Theory 14

2.3 Altman's Z – Score Model... 16

2.4 Causes of Bank Failure 18

2.5 Empirical Studies.. 20

2.6 Conceptual Framework.. 26

2.7 Summary of the Literature Review.. 27

CHAPTER THREE 28

RESEARCH METHODOLOGY 28

3.1 Introduction.. 28

3.2 Research Design.. 28

3.3 Target Population 29

3.4 Data collection 29

3.5 Data Analysis 29

CHAPTER FOUR 32

DATA ANALYSIS AND FINDINGS 32

4.1 Introduction 32

4.4 Descriptive Statistics Analysis 33

4.3 Trend Analysis of Z-scores 35

4.4 Companies Categorization According to Z-scores 37

4.5 Correlations 39

4.6 Regression Results 40

CHAPTER FIVE 43

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS 43

5.1 Introduction 43

5.2 Summary of Findings and Discussions 43

5.3 Conclusions and Recommendations 46

5.4 Limitations of the Study 49

5.5 Suggestions for Further Studies 50

REFERENCES 52

APPENDICES 57

Appendix 1: List of Banks in Kenya 57

Appendix 2: Data Collection Sheet 58

Appendix 3: List of Failed Banks 67

LIST OF TABLES

Table 4.1: Descriptive Statistics Results for the Independent Variables 33

Table 4.2: Descriptive Statistics Results for the Z-Scores.. 34

Table 4.3: Trend Analysis of Z-scores of Kenyan Banks from 2014-2019...................... 36

Table 4.4: Companies Categorization According to Z-scores 39

Table 4.5: Correlations.. 39

Table 4.6: Coefficients[a] 40

Table 4.7: ANOVA[a] 41

Table 4.8: Model Summary 42

LIST OF ABBREVIATIONS

BFP	Business Failure Prediction
CAPM	Capital Asset Pricing Model
CBK	Central Bank of Kenya
CBR	Case-Based Reasoning
EBIDTA	Earnings before Interest Depreciation Tax and Amortization
LA	Logistic Analysis
MDA	Multiple Discriminate Analysis
NSE	Nairobi Securities Exchange
SPSS	Statistical Package for Social Sciences
Z-SCORE	Altman's Z-Score Model

ABSTRACT

Owing to the important role played by commercial banks in an economy, understanding the determinants of their survival and viability is important. This study therefore sought to test the relevance of Altman Z-Score model in predicting failure within the Kenyan banking industry. Such a study would enable formulation of a proactive response to distress signs meant to mitigate against business failure. The study adopted a diagnostic research design and covered all banks in Kenya. It further utilized an online survey and collected secondary data published by these banks. The study adopted Altman's (1968) model for failed and non-failed Bank and examined relevant ratios for two failed banks in Kenya i.e., Dubai Bank, and Imperial Bank against 41 non-failed banks. The above ratios were analyzed further with the help of the Statistical package for Social Sciences (SPSS) and generally found to be useful in predicting firm's failure. However, the type of ratios that best discriminate between failing and successful companies differ. It was established that Liquidity, Earned surplus leverage, Earning power, Solvency, Sales generating capability ratios were significant in predicting failure. The study therefore concluded that the Altman Z-score model was reliable in predicting financial distress in Kenyan banks. According to the results, most of Kenyan banks are financially distressed mainly due to insufficient retained earnings. The study thus recommends that the banks should enhance their sales generating capacity. Finally, due to the critical role played by corporate governance and other qualitative aspects, it is important to undertake studies on the effects of such aspects on business failures in the Kenyan banking industry.

CHAPTER ONE

INTRODUCTION

1.1Background of the Study

There is urgent need to forecast business failures due to the adverse financial and non-financial outcomes associated with business failure. A model to correctly forecast business failure can come in handy for business stakeholders such as shareholders, managers, suppliers, government, customers, and employees. Forecasting business failure is an important yet also challenging venture. It forms the basis of numerous academic studies in the recent decades. The most used approaches for predicting business failure risk are, data mining, classic statistical, and machine learning. Case Based- Reasoning (CBR) is an early machine learning technique that may be used for classification, diagnosis domain, and improved some inadequacies of statistical models. A weighting and attributes extraction approach may enable CBR to recover cases that are most similar effectively and correctly (Adeyemi, 2011).

Previous research shows that business failures result from poor or bad management practices (Ahn et al., 2010). The poor or bad management practices maybe in form of fraud, inexperienced management approaches, failure to anticipate the rapid advancements in technology amongst many other variables. Financial failure occurs as insolvency or bankruptcy. Insolvency occurs when a firm cannot meet its present responsibilities as and when they occur, and thus current assets are lower in value than current liabilities. On the other hand, bankruptcy is the state in which the overall liabilities are more than assets fair value. Possibly, business failure is best avoided through examination of the various explanations advanced on the concept. Numerous articles and books focused on the identification of business failure reasons as a preventive solution.

A study by (Altman, 2010) adopted financial ratios to forecast bankruptcy incidence and he accurately predicted 94% a year prior to bankruptcy occurrence, and 72% in two (2) years prior to bankruptcy actually taking place. Altman identified different significant ratios about predicting bankruptcy including, retained earnings (RE) against total assets (TA), working capital (WC) against total assets (TA), taxes, and earnings before interest (EBI) against total assets (TA), equity market value (EMV) against total liabilities (TL) book value, and sales against total assets (TA).

1.1.1 Altman Model

Altman is credited for developing the Z-Score formula which he published in 1968. The Z-Score formula is applied in bankruptcy prediction, and it is a multivariate formula for measuring a company's financial performance in addition to being a powerful diagnostic method for forecasting a firm's probability of declaring bankruptcy within two (2) years.

The z-score (discriminant score) is a uni-dimensional measure that conveys the potential of a company to go bankrupt. According to Altman, the greater the possibility of a company to go bankrupt, the lower the value of the z-score. In a prediction or classification context, when a company's z-score goes under the a-priori selected cut-off point, such a company is categorized as failing and on the contrary as non-failing (Adeyemi, 2011). The scores of multivariate discriminant analysis (MDA) comprise of various delimiting factors, due to its reliance on four main restrictive assumptions. According to Hair, (2012), firstly the independent variables (for instance ratios) are in the form of multivariate normal distribution. Secondly, the dataset comprises two a-priori selected mutually independent groups. Thirdly, the population variances for the two groups are equal and lastly, the only requirement is for the researcher to choose the optimal a-priori cut-off point.

Studies on the Z-Score effectiveness indicate that the Altman's model reliability ranges between 70%-80%. The Altman equation is reported to have effectively distinguished bankrupt and no-bankrupt companies. The bankrupt companies (94%) were found to have Z scores below 2.7 prior to their bankruptcy. On the other hand, the non-bankrupt companies (97%) were reported to have Z-scores that were above 2.7. the present study was inspired by the urge to apply an alternative business failure forecasting approach in Kenya and the Z-Score model has been identified to be appropriate (Altman & Hotchkiss, 2010).

1.1.2 Bank Failure

One is constrained to remember any bank failures in Kenya. Indeed, the first bank failure that is documented is that of Rural Urban Credit Finance Company Ltd in December 1984. Rural Urban Credit and Finance, the first bank to lend to the Matatu Industry (the informal sector public transport industry in Kenya), failed due to interference by the directors in the day-to-day operations, and a high incidence of bad loans (Central Bank of Kenya 2014). Rural Urban's failure was closely followed in August 1986, by that of Continental Bank and Continental Credit Finance Bank, which were related and Capital Finance Bank in December of the same year. Both Continental Bank and Continental Credit Finance Bank failed because of poor lending practices and lending to unsatisfactory asset quality while Capital Finance Bank was closed due to ineffective board of directors and management (Central Bank of Kenya 2016). These institutions were liquidated according to the *Banking Act 1968*, which required that a failed bank be moved directly into liquidation (Banking Act, 2008).

The next wave of bank failure occurred in 1989 when Business Finance, Home Savings and Mortgages, Estate Finance, Union Bank, Nationwide Finance, and Jimba Credit were closed, and all their assets and liabilities taken over by Consolidated Bank of Kenya. The reasons given for their closures were interference by directors and shareholders, dominant influence of the board, poor asset quality, under capitalization, unsecured insider loans, ineffective boards of directors, liquidity problems and insolvency, to mention only a few (Central Bank of Kenya, 2016). The next wave of bank failure occurred between April and October 1993 soon after the first multiparty general elections following the repeal of the infamous section 2(a) of the (*Constitution of Kenya, 1969)*. By this time, the *Banking Act 1968* had changed so that a failed bank could either be liquidated or placed under a manager, who would take full charge of the institution to the exclusion of the Board of

Directors (Banking Act, 2008). In this wave, Nairobi Finance, Middle Africa Bank, Trade Bank, Trade Finance, Diners Finance, Central Finance, Allied Credit, United Trustees Finance, Inter Africa Credit, Exchange Bank, International Finance, Pan African Bank, Pan African Finance, and Post Bank Credit were closed for similar reasons as those mentioned above (Central Bank of Kenya, 2014).

In April 1994, Thabiti Finance, Export Bank of Africa and United Bank Ltd were placed under the CBK's management (Central Bank of Kenya, 1994). The reasons cited for placing United Bank under management were, serious under-capitalization, failure to comply with the minimum requirements for cash and liquidity ratio, over fixed assets investment and ineffective board of directors and management (Central Bank of Kenya, 2014). United Bank Ltd, which was owned by the family of The Late Hezekiah Oyugi and had only one branch based in Kisumu, would later be sold to a group of investors, and emerge as Chase Bank (Kenya) Ltd. Banks continued to collapse even after 1995. Some of those that have since gone under are Trust Bank and Trust Finance, Euro Bank, Kenya Finance Bank, Daima Bank, Meridian Biao Bank, Heritage Bank, Ari Bank Corporation, Prudential Bank, Reliance Bank, Fortune Finance and Prudential Building Society to mention a few. Some others like Charterhouse Bank are still under the Central Bank's management (Central Bank of Kenya, 2016).

1.1.3 Banking Industry in Kenya

Commercial banking in the Country began at the beginning of the 20th Century, following the European imperial colonialists partitioning of the African continent. National Bank of

India was the first to start operating in Kenya as it opened a branch in Mombasa in 1896. Their spread into the interior of the country continued in 1904 when they opened a branch in Nairobi.

Presently, Kenya has 43 commercial banks licensed to operate, and a single mortgage finance company. Of the 43 commercial banks, 32 have local ownership while 11 have foreign ownership (Habib Bank, Citibank, and Barclays Bank). Kenyan commercial banks take deposits from people and generate profits through offering the deposits as loans to people and business at an interest rate (Central Bank of Kenya, 2016).

1.2 Research Problem

Due to important role played by commercial banks in an economy, understanding the determinants of their survival and viability is important. The main purpose of any bank is profit generation and wealth maximization. However, distressful situations affect a bank's performance and its stability and over time the implications in the business community are adverse. For instance, extensive distress periods leading to liquidation particularly for commercial banks operating in Least Developed Economies since they have limited resources to endure poor performance over extended periods. Incidences of failures of commercial banks elevate genuine concerns to investors, both foreign and local, in any nation. Therefore, this study expected that the Altman Z-Score model can assist different stakeholders within the financial industry in Kenya to proactively respond to distress signs witnessed by the banks so as to elude total failure.

What is the degree to which commercial banks can depend on a discriminant predictive model in the accurate indication of their financial status? Alexakis (2008) analyzed if Altman's Z-Score accurately predicts failing companies. The author established that Altman's Z-Score effectively predicted failures within the range of five years and below and portfolio managers could use it to select stock. Moreover, company management can use it to make merger decisions or additional strategic moves at the corporate level. Samarakoon and Hasan (2013) examined Altman Z-score's ability to forecast corporate distress in Sri Lanka's emerging market. The authors established that the model comprised of a remarkable accuracy degree in forecasting failure through financial ratios calculated from financial statements before the year of distress. The Z-score reported an 81% general success rate.

Shaefer (2012) observed some inadequacies of the Z-Score model. The author asserted that the Z-Score model is not accurate, and it needs to be computed and interpreted carefully. To begin with, Z-Score is not exempt to wrong accounting practices. Shaefer (2012) further asserts that the Z-Score is not very useful to newly established companies or those that generate minimal earnings since such companies, despite their financial health score lowly. Additionally, the Z-Score hardly addresses direct cash flow issues instead, it hints at the issues by using net working capital to asset ratio. Lastly, Shaefer (2012) asserts that Z-Score can move from one quarter to the next upon company's recording of single write offs and these may alter the score, an indication that a company under no risk may face possible bankruptcy.

A research gap on failure facing Kenyan commercial banks based on the few numbers of local research on the matter. Kogi (2013) carried out a study that came up with a discriminant model that incorporates the stability of financial ratios to forecast corporate failure. The author sought to determine important financial ratios that had significant forecasting ability. Kogi (2013) found out that its corporate failure could be predicted by an accuracy of 70% in a period of three years prior to the actual incidence through the stability-based discriminant model. Keige (2011) had previously formulated a business failure prediction model of Kenyan companies and achieved 90% prediction accuracy two years prior to an actual occurrence of failure. Nganga (2016) explored and exposed the likely indicators of looming failures and established Kenyan insurance companies' prediction model. The author developed a model for failure prediction for both general and composite insurance companies.

Kamau (2013) used multiple discriminant analysis approach and multiple discriminant analysis to establish a failure prediction model. The model generated an 85% general correct categorization accuracy a year before occurrence of failure resulting in the confirmation that cash flows are useable in giving precise and clear information concerning an organization. Kamau (2013) study paid specific attention on Kenyan Commercial banks unlike other studies that focused on. Kamau (2013) study aimed to improve knowledge related to a diverse environment. Therefore, the study sought answers to the question: does the Altman Z-score Model demonstrate relevance in predicting bank failure in Kenya?

1.3 Research Objective

The objective of the study was to assess whether the Altman's financial distress prediction model was useful in predicting business failure in Kenya's banking Sector.

1.4 Value of the Study

The study may be of value towards investors, regulatory bodies, future researchers, managers, and owners of firms listed or planning to list on the NSE.

The study may provide input onto the finance theory by offering empirical proof on the predictability of business failure. A large proportion of the studies undertaken focused on other areas of the financial sector as well as the manufacturing segment. Therefore, the current study enhances liquidity theories knowledge in the banking sector.

Another value of the study is it may offer insights to financial experts on the application of various liquidity motives to reduce chances of business failures. Thus, the study may shed light on managers of such firms implement policies on liquidity management and company operations.

Numerous companies collapsed following poor liquidity management practices, therefore, for the firms listed in the NSE, this study may help in re-emphasis of efficient and effective liquidity management practices for profitability enhancement and firm's growth. This study will help policy makers and investors understand whether it is possible to establish an early warning system of probable business failure to enable them take preventive or mitigating measures.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

The chapter presents an analytical evaluation of past literature with respect to business failure predictability which offered the study's theoretical background. The chapter also analyzed relevant models and theories for optimal cash balances and liquidity. Moreover, the determinants of business failure predictability were reviewed and discussed. Lastly, the chapter incorporated empirical studies by other scholars.

2.2 Theoretical Review

Theoretical arguments form the basis of business failure models construction since such theories can predict firms' financial distress by assessing present conditions of distress within such firms. The theories include, credit risk theory, entropy theory, gamblers' ruin theory, and cash management theory (Robinson and Maguire, 2011).

2.2.1 Entropy Theory

The Entropy theory is alternatively referred to the Balance Sheet Decomposition Measure Theory and was coined by Claude Shannon in 1948 (Claude, 1948). The Entropy theory asserts that one means of identifying business failure is carefully looking at changes that occur in company's balance sheets (Aziz & Dar, 2016). Entropy theory applies the Univariate Analysis (UA) and Multiple Discriminant Analysis (MDA) to examine changes on balance sheet structure. Univariate Analysis refers to application of ratios that are accounting-based or market measures for evaluation of distress risk (Natalia, 2014). Therefore, Monti & Moriano, (2010) companies' financial ratios are compared at a point in time and distinction made using a single ratio using a cut-off value that categorizes a company being distressed or not distressed.

MDA (MA also known as Multivariate Statistic) refers to statistical analysis whereby many variables are simultaneously analyzed (Slotemaker, 2008). The MDA is to get rid of the weaknesses present in a UA. Firstly, single ratios computed using UA fail to capture time differences of financial ratios. Thus, accounting ratios are deemed to possess a predictive ability each at a time and it is not possible to undertake an analysis such as the extent of ratio changes over time. Secondly, the results of single ratios may be inconsistent upon the application of different ratio classifications for a given firm. Thirdly, most accounting variables are significantly correlated, thus interpreting a single ratio alone becomes incorrect. Single ratios cannot capture multidimensional interrelationships occurring within a firm.

Lastly, because a sample's failure probability differs from that of a population, specific cut-off point values obtained for a sample maybe invalid for a given population (Natalia, 2014). Consequently, when a company's financial statements indicate a substantial shift in assets and liabilities composition within the balance-sheet, it is likely that such a company may not maintain its equilibrium state. When the changes have the possibility of becoming uncontrollable in future, financial distress can be foreseen in such firms

(Aziz & Dar, 2016). This theory was relevant in explaining the usefulness of ratios obtained from the Bank's balance sheet compared between successive periods in predicting failure and some of the weaknesses such ratios possess. This approach however suffers from the challenge that information from the balance sheet is mainly historical and may have limitations in accurately predicting the future of business that has become quite dynamic especially with the current disruptions caused by technological advancement.

2.2.2 Credit Risk Theory

Credit risk theory was introduced by Melton in 1974. The credit risk theory is based on the presumption that default occurs through an organization's assets evolution exhibited through a process of diffusion with constant parameters ((Longstaff and Schwartz, 1995). Credit refers to the offering of services and good to an individual or company on defined terms and conditions of making payments at a future date inclusive of or exclusive of interest. Credit risk arises when the individuals or entities in the credit contract fail to honor their obligations as they fall due thus exposing the creditor to credit risk that may eventually result in default (Natalia, 2014). Therefore, credit risk refers to an investor's risk of loss either financial or of a non-financial form as a result of failure by a borrower to honor their dues as per the contractual terms.

Theories of credit risk that are closely linked to Basel I and Basel II accords; usually refer to a financial firm. The recommended Basel II framework comprises of three pillars: minimum capital option that are currently set at 8%, based on a purposely demarcated capital ratio. The second pillar is the supervisory evaluation of a company's internal review processes well as capital adequacy. The third pillar focuses on the effective application of public disclosure for the strengthening of market discipline to complement supervisory efforts. The present Basel II Accord applies the capital ratio concept that is computed through division of a bank's capital volume with a measure of the risk it faces (also known as the risk-weighted assets).

Westgaard and Wijst (2011) describe credit risk as the likelihood of a counterparty/borrower defaulting on an amount belonging to a bank. Credit risk comprises of counterparties and explanations for the possibility of defaulting on their repayment obligations. Ensuing Basel II guidelines, the past few years have witnessed various attempts to develop internal review models for credit risk measurement. Some of the models have received more recognition than other such as Credit Metrics by JP Morgan, KMV model by Moody's, Credit Portfolio view by McKinsey, and CSFP's Credit Risk+. More notably, with exceptions of one or two of the models, the basis of the models and risk predictions that have received significant recognition has been either micro or macro-economic theories of corporate finance. Collectively the models can be termed as theories of credit risk. This theory was relevant in explaining ways in which regulators and other key players in the sector ensure that Banks have cushioned themselves against particular risks that can lead to failure. The theory however focuses mainly on credit risk though lately other emerging risks like information technology vulnerability of a Bank have the potential of leading to business failure.

2.2.3 Cash Management Theory

Cash management theory (Huseyin, 1991) focuses on managing cash flows into and out of a company, as well as firm cash flows and cash balances retained at a given period due to financing shortages or excess cash from investments. Every company's temporary corporate cash balances management is a major concern since accurately predicting cash flows, particularly inflows, is challenging because there is no perfect likelihood of cash inflows and outflows (Aziz & Dar, 2016).

In some periods, cash outflows are more than cash inflows since tax, seasonal inventory or dividends payments build up. During other times, cash inflows exceed cash sales and thus debtors end up promptly realizing large amounts (Pandey, 2015). A cash inflow or cash outflow imbalance implies a failure of the firm’s cash management function. Perseverance of this type of imbalance can cause financial distress for such a firm and thus, business failure (Aziz & Dar, 2016). The theory was relevant in explaining the key nature of proper cashflow management in sustaining a business. It however ignores the importance of other fundamental aspects like competitiveness and technological advancement that impact the sustenance of a business.

2.2.4 Gambler’s Ruin Theory

Feller (1968) established the gambler ruin theory based on the probability theory, which states that a gambler's loss or win is determined by chance. The gambler normally begins with an arbitrary and positive sum of money and continues to gain or lose a dollar through probability (p) for each period. The game continues until the gambler's bankroll is depleted (Espen, 2009). The company can be compared to a gambler who continues to operate despite the risk of losing money until its net worth hits zero (also bankruptcy). Regarding firms' financial distress, the gambler would be the firm that carries on with operations until the point where its net worth becomes zero, and thus going bankrupt. The assumption of the theory is that a firm possesses some volume of cash that would continuously and randomly enter or exit the firm depending on its operations. In each period, such firms would encounter either negative or positive cash flows.

Within various periods, there is a single likely composite probability that there will be negative cash flows that may force a company to announce bankruptcy for running out of cash. Therefore, under the gambler ruin approach, a firm is solvent to the extent that its overall net worth is more than zero. The net worth is computed from the liquidation amount of shareholders' equity. With a presumed cash amount in a defined period, there exists a net positive that a company's cash flow shall be constantly negative through numerous periods eventually resulting in bankruptcy (Aziz & Dar, 2016). The theory was relevant in explaining the importance of shareholder's equity in determining the health status of a firm. The main weakness of the gambler ruin theory is its assumption that a company begins with a given cash amount. Additionally, there exists two major challenges with the gambler ruin theory in the prediction of business failure that a firm has no admittance to subsidizing from the protections markets and that incomes are results of free preliminaries with administrative activity having no impact on the outcomes (Espen, 2009).

2.3 Altman's Z – Score Model

Altman (1968) led the application of MDA in corporate failure prediction. MDA merges multivariate independent variables information such as ratios into one score used to categorize an observation into either a-priori or mutually independent groups (Hair, 2012). Therefore, MDA is superior to UA since it considers a complete firm variable profile and the variables interaction. The Altman's Z-Score model, which is based on the MDA, is perhaps the most well-known model for failure prediction. The Z-Score model was developed in 1968 using a sample of 66 manufacturing enterprises divided into two groups of 33 companies each. The bankruptcy group included businesses that filed for bankruptcy under Chapter 10 of the United States Bankruptcy Act of 1946 through 1965. Using a discriminant function in the form of the following, the Z-Score model predicted a firm's financial well-being.

The Z-score formula: $Z' = 0.012X1+0.014X2+0.033X3+0.006X4+0.999X5$

Whereby Z = Score

$X1 = (CA - CL)$ / the TA

$X2 = RE / TA$

$X3 = EBIT / TA$

X4 = BVE / TL

X5 = S/TA

The above Z score formula was used to identify discrimination zones through ratios calculated from a defined sample.

According to the sample, each firm that had a Z-score that was more than 2.99 became part of the non-bankruptcy category, and those that had a Z-Score lower than 1.81 became part of the bankrupt category. Z-Scores within the 1.81-2.99 range fell in the grey zone. The importance of each ratio is described below;

WC/TA a ratio that reliably tests corporate distress. Firms having a negative working capital hive a high likelihood of experiencing challenges in fulfilling its temporary obligations since there current assets present are inadequate to fulfill them. On the contrary, a company that has significantly positive working capital hardly experiences trouble in meeting its obligations.

RE/TA reflects a company's leverage by calculating the volume of losses or earnings reinvested. Companies with a low RE/TA fund capital expenditures using borrowed funds rather than retained earnings. Companies with a high RE/TA suggest a history of profitability as well as the ability to weather a difficult year of loss.

EBIT/TA represents a form of ROA. EBIT/TA is an efficient way of evaluating a company’s capability to extract profits before deducting factors such as tax and interest.

ME/TL represents the extent to which a firm’s market value would decline before assets are exceeded by liabilities in its financial statements upon a firm becoming insolvent. The EE/TL ratio includes a market value aspect to the model whose basis is not on pure fundamentals. Therefore, a long-lasting market capitalization may be perceived as a market’s confidence in a company’s steady financial position thus developing the market efficiency dimension. S/TA informs investors of management’s effectiveness in handling competition and a firm’s efficiency in using its assets for sales generation. Failure to increase market share results in a falling or low S/TA.

2.4 Causes of Bank Failure

According to Runyora (2012) the determinants of business success are proper financial leverage, cash floor, business planning, demand, and good company image among firms. A company is deemed to be in distress if its EBITDA is lower that interest expense. Financial leverage is defined as the replacement of fixed-cost debt for owner's equity with the goal of boosting returns on equity. Financial leverage improves financial health when business prospects are high, but it has a negative impact on financial performance when business prospects are poor. As a result, increasing a company's debt to equity ratio makes the company less solvent and exposes it to greater financial risk than a debt-free corporation.

Capital adequacy concerns a company’s capital sufficiency to finance future operations. When a firm has inadequate capital, it must then successfully offer new equity or organize new debt. The volume of debt a company can absorb successfully and repay from ongoing operations is usually known as its debt capacity (Thynne, 2006). For most newly formed and small businesses, debt capacity is usually the single and most crucial business failure reason. The problem comes about when the sales revenue of a firm is not adequate to meet production costs. Important to note is that debt capacity is the case of having enough cash to settle owings when they fall due instead of simply making sufficient revenues through a year to take care of costs (Patrick, 2014).

Most new undertakings have a strategy set up to present to a bank prior to getting monetary help or advances. The work and time put into such plans is significant for progress since lacking preparation or data shaping the premise of an arrangement might prompt firm challenges. For instance, when a firm plan to make sales of 2,000 units every month within its first year based on limited market research, and manages to sell only 500 units per month, such a firm will serious dangers of failure (Chiritou, 2012).

Declining sales are a sign of challenges with a product, its price, or an aspect of marketing mix. Sometimes, declining sales are a result of competitors offering better products or services and thus the business can work on this by first recognizing the problem (Moyer, 2006). Other reasons for declining sales are changing tastes and preferences, fashion, and technology and businesses need to be aware of such trends. Sales decline may also be caused by factors beyond the firm's control such as changes in a country's climate. When an economy experiences a downturn, people may have limited disposable incomes to spend on a company's products or services (Sipika and Smith, 2012).

Numerous reasons may also cause an increase in production costs, for instance, wage rises, increases in materials prices such as gas or oil, new legislation, or standards requirements and more. In most cases, companies can plan for the aforementioned changes and put them into consideration, however, when costs unexpectedly rise, a company is caught unawares and tipped into possible bankruptcy (Kip, 2012). Projecting a high-profile company's image through renting extravagant office space, fancy logos and website may not highly facilitate business success. Instead, such high overheads may drive a firm out of business quickly since a golden rule of business success is keeping overheads low particularly when starting up (Argenti, 2013).

Moreover, flexibility in adapting new ideas and trends plays a critical role in business continuity (Eidleman, 2003). Uncontrolled business growth may lead a firm to fail if inappropriately managed since obesity is an issue in business just as with peoples' wellbeing. Proper and adequate planning should be implemented for business growth. Additionally, successful business growth needs the factors of professional management teams, proper and adequate systems, and controls as well as flexible organizations (Eidleman, 2003).

2.5 Empirical Studies

Numerous empirical studies have been undertaken to assess business failure predictability in various economic sectors. A summary of some of the studies is presented in this section.

Many and varied techniques have been adopted to Business Failure Prediction (BFP) since the 1960's. Even though the field began earlier, the initial mathematical and statistical BFP models were published through the 1960's. In 1966, Beaver presented the univariate model, and in 1968 Altman developed the MDA models that was later developed in 1972 by Deakin. In 1980, Ohslon adopted conditional Logistic Analysis (LA) to overcome the challenges associated with MDA, in his novel study on the prediction of business survival.

Beaver (2006) used t-tests in the evaluation of the predictive abilities of different financial ratios by use of a pair-combined sample. Altman (1968) applied five financial ratios in the prediction of a company's going concern. The study by Altman was highly accurate in predicting the companies most likely to become bankrupt and the study has since remained relevant 45 years later (Keener, 2013). The recommended MDA model offered a linear ratios combination that effectively distinguished between segments of failing and non-failing firms. The MDA model combined ratios into one determinant score referred to as the 'Z-score' whereby a low score indicated poor financial well-being.

The Altman study was based on 66 manufacturing firms with the same number of survivors and failures, as well as 22 ratios from five segments including, profitability, liquidity, solvency, leverage, and activity. Altman's Z-Score pass mark was three, companies that surpassed three were considered to be relatively safe and companies with a score that was below 1.8 were considered to be potential failures.

The Ohslon (1980) paper is also considered to be a landmark paper that discusses the topic on use of financial ratios in predicting financial failure. Specifically, Ohlson (1980) adopted logistic regression across an extensive sample that excluded pair-matching, and he determined that the four most statistically important factors for failure probability identification were company size, financial structures measures, performance measures, and current liquidity measures. Ohlson's formulated the basis for extensive future research on financial ratios predictive power (Keener, 2013).

Lennox (1999) assessed the bankruptcy reasons among a section of UK listed companies in years between 1987 and 1994. Lennox (1999) established that some key bankruptcy determinants were leverage, profitability, cash flow, industry sector, organization size and cycle of the economy. Lennox (1999) further argued the well-defined probit and logit models would be much more accurate in the identification of failing companies compared to discriminant analysis (Keener, 2013).

In the past decade, more studies have been developed and evaluated for bankruptcy prediction. For instance, Barniv and McDonald (1999) discusses various alternate approaches to the logit and probit models for prediction of company failure, including EGB2, burrit, and lomit, models. Other scholars tried to apply text or information mining for bankruptcy prediction (Shiri et al., 2010; Divsalar et al., 2012; Olson et al., 2012; Kwak et al., 2012b). Other scholars applied the semi-parametric techniques for bankruptcy prediction (Hwang et al., 2007; Cheng et al., 2010).

There have been studies that examined the effect of adding extra variables to predict bankruptcy. For instance, Elam (1975) specifically looked at the impact of lease data on financial ratios predictive power. Elam's review applied an aggregate of 28 monetary proportions that are usually applied in monetary reading material and writing. Elam in the end set up that capital rented information expansion to budget summaries had no expanding impact on monetary proportions prescient power (Keener, 2013).

Gentry et al., (1985) established that outflows elements of financial statements, such as investments and dividends were better financial failure predictors compared to inflow elements of financial statements. Therefore, Gentry et al., (1985) suggested that elements of funds flow that are cash-based provided better results in financial failure prediction. Moreover, addition of cash components pointedly enhanced predictive performance (Gentry et al., as cited by Keener, 2013).

Gilbert et al., (1990) suggested that diverse variables can be used to differentiate bankrupt and non-bankrupt firms. Moreover, numerous researchers (Gilbert et al., 1990; Giacomino and Mielke, 1993) confirmed Gentry et al., (1985) findings that cash flow elements enhanced the explanatory power to bankruptcy prediction (Keener, 2013). Baldwin and Glezen (1992) contrasted quarterly data power of prediction with previous empirical studies' outcomes acquired through yearly financial data. The results by Baldwin and Glezen (1992) confirmed quarterly financial data could establish bankruptcy prediction models more timely without losing the accuracy sometimes associated with annual financial data application (Keener, 2013).

Morris (1997) looked at the actual usefulness of bankruptcy prediction models. The scholar determined that ultimately, many prediction models reflected listed companies that had large losses, low profits, and debt burdens had a higher risk compared to firms that were more profitable and had lower debt. Additionally, Morris (1997) pointed out that firm's failure usually occurs due to bad luck or unfortunate series of events of a company. The author suggested the difficulty in a model distinguishing between companies likely to go bankrupt and those that are just undergoing financial distress (Keener, 2013).

Other than the aforementioned quantitative models, a section of scholars postulated qualitative models that depend on the thought that utilizing monetary parameters as the super hierarchical exhibition pointers are restricted. Subjective models are established on non-bookkeeping factors such as the A-score model by Argenti (1976). The A-score model conceptualizes that the failure process adheres to a predictable sequence summarized into three main segments mistakes made, defects, and failure symptoms. All the three main segments are weighted for failure probability determination (Sharma & Mahajan, 1980)

Kiragu (1993) undertook a study on corporate failure prediction using accounting information that was price adjusted. The review zeroed in on an example of 10 fizzled and non-bombed organizations. Monetary proportions were registered from monetary measurements changed on value level. The discriminant model set up demonstrated 9 proportions which had significant degrees of prescient capacity of corporate disappointment. The proportions included, fixed charge inclusion, time revenue inclusion, fast proportion, current proportion, value to add up to resources proportion, financial liabilities changes, working cash-flow to add up to obligation, all out obligation to add up to resources, and profit from speculations to add up to resources.

Kiragu (1993) found that the most important ratios were liquidity and debt service ratios. The findings complemented the finance theory of firm's risk. To avoid issues pertaining to insolvency, firms must maintain adequate liquidity. Moreover, the firms should make sufficient earnings to handle relevant fixed finance charges. The findings by Kiragu (1993) differed with those by Altman (1968) and Kimura (1980) who established that liquidity ratios did not significantly predict bankruptcy, instead, profitability and efficiency ratios were found to be the most important.

Keige (1991) study used the discriminate analysis to predict business failure. The author established that ratios could forecast company failure. Then again, the proportions that would best separate among upset and effective organizations contrasted from one area to another. In Kenya inclusion for fixed charge, current proportion, return on procuring to add up to resources, and return on total assets could be effectively used to anticipate for an as long as 2 years preceding its event. Keige (1991) determined that stakeholders need to focus on leverage, liquidity, and activity ratios.

Many more studies attempted to predict bankruptcy across other sectors, however, very few papers examined banking industry bankruptcy prediction. An incremental contribution of the current study was its focus on bankruptcy prediction for a defined industry segment, which is the Kenya's banking industry.

2.6 Conceptual Framework

The study's conceptual model was developed by the researcher with the aim of identifying the answers in the study. The dependent variable for the study was relevance of Altman Z-Score Model in predicting bank failure while the independent variables: liquidity, earned surplus leverage, earning power, solvency, and sales generation capability. The framework supposes that the presence or absence of the indicated independent variables will determine the relevance of Altman Z-Score Model in predicting bank failure.

- Current Assets-Current Liabilities)/Total Assets
- Retained Earnings/Total Assets
- Earnings before Interest and Taxes/Total Assets
- Book Value of Equity/ Total Liabilities

→

Altman Z-Score Model relevance in the prediction of Bank Failure in Kenya

Independent Variables **Dependent Variable**

2.7 Summary of the Literature Review

The foregoing literature review shows that investors should monitor their investments in addition to regularly assessing their firms Z-score. A declining Z-Score indicates looming trouble and offers an easier conclusion compared to mass of ratios. Thus, the Z-Score is useable for only gauging relative financial wellbeing but also for business failure prediction. Undeniably, the Z-Score model is relevant in quickly checking a company's financial health and in cases where a problem is identified, a more detailed analysis needs to be conducted.

Most studies undertaken at both the local and foreign economies concur that the Altman Z-Score model has been systematically tested and extensively accepted for business failure prediction. Therefore, the Z-Score model is an important tool applied in turnaround management to diagnose and evaluate the overall financial performance of organizations and the viability of restructuring and turnaround efforts.

Due its reliability in testing organizational financial health, the model is extensively used by law courts, banking industry, turnaround industries and credit risk management industries globally as corporate health benchmark. The literature reviews further revealed that the basis of most of the information available to the public about prediction models is academic publications. Moreover, the primary beneficiaries of the information are public accounting firms, commercial banks, and other institutional organizations.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

The chapter discussed the research design applied, the target population and sample size used, instruments, techniques, and procedures for data collection, and data analysis methods applied.

3.2 Research Design

The study adopted a diagnostic research design which attempts to determine the relationship between a subject matter and another item (Kothari, 2004). The main concern of the study was business failure predictability. The researcher was able to determine the existing association between the independent and dependent variables using the diagnostic study methodology. Over a five-year period, panel data was used to identify the correlations that existed between the study variables (2010-2015 i.e., a five-year period going back from the period of failure of Dubai/Imperial and Chase Banks). Baltagi (2001) asserted that panel data methodology derives benefits such as the assumption that the nature of diverse companies is heterogeneous thus presence of unrelated elements. Panel data methodology also considers data variability hence providing higher degree of freedom and efficiency.

3.3 Target Population

The study covered all banks; hence it was a census study. The study's population comprised of all the 43 Kenyan banks according to the Kenya Bankers Association report. Commercial banks were preferred due to their proper organization and also because of their regular filing of returns to the Central Bank of Kenya. Several measures were adopted to establish firm size including number of employees in the firm, cash flow margin, return on assets, cash to current liabilities and debt-to-equity ratio.

3.4 Data collection

The study utilized an online survey to collect secondary data because banks financial reports are published on their websites. The researcher scrutinized the banks' balance sheets to identify predictability components while income statements offered data on the profits for the period under scrutiny to assess the predictability for the business failure for banks. The Cash flow statement and relevant notes and indicators for the predictability of business failure for the period was also considered.

3.5 Data Analysis

The study adopted Altman's (1968) model for failed and non-failed Bank. The Altman (1968) model was relevant in the primary classification and development of predictions of problems involving dependent variable that between the one of two possibilities, i.e., bankrupt, or non-bankrupt. The model used for testing analyzed two (2) failed banks, Dubai Bank, and Imperial Bank against 41 non-failed banks.

The data was used to calculate ratios for every company every year. Data analysis involved the use of the following ratios; for liquidity, working capital against total assets; for leverage/earned surplus, retained earnings against total assets; for earning power, earnings before interest and taxes against total assets. Moreover, for solvency, market value equity against total liabilities book value; and for sales generation capability ratio, sales against total assets was applied. The ratios were chosen because they had previously been used to predict business failure in prior studies, particularly the overall appropriateness and irrationality in the development of a discriminant function. As a result, the aforementioned ratios have proven to be quite useful in financial analysis and assessing a company's financial health.

The Z-score symbolizes a linear combination of an estimated four to five ordinary and coefficient weighted business ratios whose estimation is achieved by identifying a set of bankruptcy declared firms. The identified firms were thereafter matched against a set of surviving firms based on their asset size and industry of operation. In total, five measures were weighted objectively and summed up so as to achieve a general score that was used to classify firms into a single a-priori groups (the distressed group and the non-distressed group).

The Z score formula used in the identification of discrimination zones comprising ratios calculated from the sample set is shown below.

The Z-score formula: $Z' = 0.717T1 + 0.847T2 + 3.107T3 + 0.420T4 + 0.998T5$

$T1 = (CA - CL) / TA$

$T2 = RE/TA$

$T3 = EBIT / TA$

$T4 = BE / TL$

$T5 = I + NII /TA$

Z' Score Bankruptcy Model:

$$Z' = 0.717T1 + 0.847T2 + 3.107T3 + 0.420T4 + 0.998T5$$

Zones of Discrimination:

$Z' > 2.9$ - “Safe” Zone $1.23 < Z' < 2. 9$ - “Grey” Zone

$Z' < 1.23$ - “Distress” Zone

As such, a firm that presents a Z-score of above 2.9 is considered to be in the “Safe” zone and thus having a strong balance sheet and good performance with low risk of getting into bankruptcy. A firm with a Z-score of between 1.23 and 2.9 would be categorized as being in the “Grey” zone and thus with a potential of deteriorating into the “Distress” zone in the absence of mitigating steps from management, while a firm presenting a Z-score of less than 1.23 would be categorized as being in the “Distress” zone and thus having a very high risk of getting into bankruptcy.

CHAPTER FOUR

DATA ANALYSIS AND FINDINGS

4.1 Introduction

The chapter presented findings on data analysis and their interpretation based on the study's objectives of assessing whether Altman's model for predicting financial distress may be useful in business failure prediction among the banking Sector in Kenya based on the multivariate discriminant analysis method. Similarly, the results of the prediction regarding the dual features variable of the failed and non-failed indicators were categorized and calculated in the following table. Non-text approaches, such as tables, were also used throughout the chapter to present data. The Statistical Package for Social Sciences was used to perform quantitative data analysis (SPSS). Data was analyzed and categorized based on predictor variables in accordance with the applied data.

To calculate the Z-score, the following ratios were weighted by coefficients; for liquidity, WC/TA; for leverage/earned surplus, RE/TA; for earning power, EBIT/TA. Moreover, for solvency, EMV/TL book value; and for sales generation capability ratio, S/TA. The ratios were chosen based on their use elsewhere in studies on prediction of business failure, their rationality and overall suitability to develop a discriminant function. The above ratios show considerable merit in undertaking financial analysis as well as gauging of the financial health of companies.

4.4 Descriptive Statistics Analysis

The mean and standard deviations (SD) for the independent variables were computed and the results presented in Table 4.2 below.

According to the findings presented in table 4.1, the variables descriptive statistics are indicated by the mean scores and SD values. The highest mean of the Liquidity was 0.406 in year 2019 with SD of 0.320. The mean value of Earned surplus leverage was highest in year 2018 with a score of 48.647 and SD of 315.251. The findings also indicate that the mean value of earning power was highest in years 2015 and 2015 with scores of 0.079 and SDs of 0.051 and 0.049, respectively. Moreover, the mean value of Solvency was highest in year 2019 with a score of 1.555 and SD of 7.841. Additionally, the mean value of Sales generating capability was highest in years 2016 and 2014 with scores of 0.122 and SDs of 0.056 and 0.041, respectively.

Table 4.1: Descriptive Statistics Results for the Independent Variables

Liquidity	**Mean**	**Std. Deviation**
2019	0.406	0.320
2018	0.352	0.220
2017	0.302	0.184
2016	0.280	0.165
2015	0.287	0.153
2014	0.326	0.167
Earned surplus leverage	**Mean**	**Std. Deviation**
2019	0.093	0.237

2018	48.647	315.251
2017	48.497	315.114
2016	48.467	314.959
2015	48.414	314.808
2014	48.349	314.658
Earning power	**Mean**	**Std. Deviation**
2019	0.025	0.064
2018	0.048	0.072
2017	0.050	0.084
2016	0.077	0.055
2015	0.079	0.051
2014	0.079	0.049
Solvency	**Mean**	**Std. Deviation**
2019	1.555	7.841
2018	0.243	0.591
2017	0.308	0.526
2016	0.287	0.546
2015	0.273	0.557
2014	0.289	0.578
Sales generating capability	**Mean**	**Std. Deviation**
2019	0.082	0.116
2018	0.079	0.056
2017	0.099	0.051
2016	0.122	0.056
2015	0.119	0.050
2014	0.122	0.041

The ratios of the model's mean and standard deviations were determined, and the findings are displayed in Table 4.2.

Table 4.2: Descriptive Statistics Results for the Z-Scores

Year	Mean	Std. Deviation
2019	1.042	3.238
2018	0.042	0.306
2017	-0.023	0.290
2016	0.054	0.258
2015	0.030	0.246

2014	0.036	0.259

The findings presented in table 4.2 illustrate the variables descriptive statistics results for the Z-scores covering years 2014 to 2019. The mean value for 2019 is 1.042 with SD of 3.238. The mean value for 2018 is 0.042 with SD of 0.306. The mean value of year 2017 is -.023 with SD of 0.290. The findings also indicate that the mean value of year 2016 is 0.054 with SD of 0.258. Moreover, the mean value of year 2015 is 0.030 with SD of 0.246. Lastly, the mean value of year 2014 is 0.036 with a SD of 0.259.

4.3 Trend Analysis of Z-scores

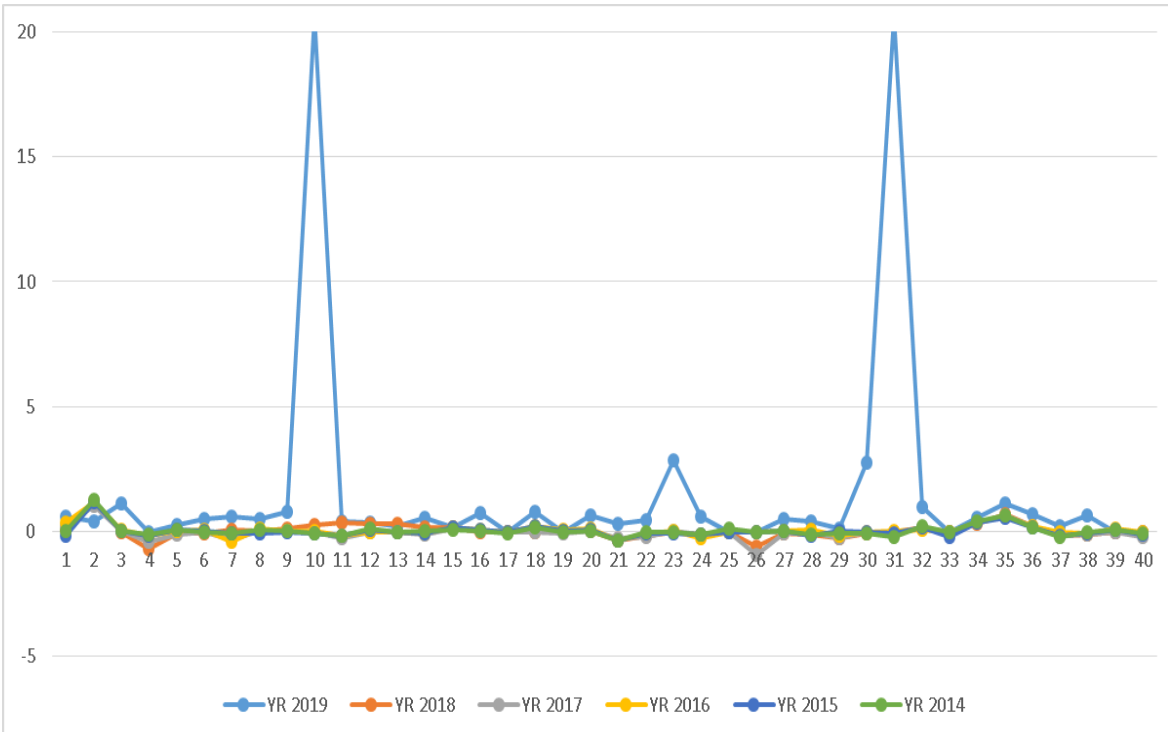
From the below trend analysis table, it is evident that the coefficients of Z-scores indicate that the status of a company's financial health is not rigid it keeps on varying now and then. All companies, whose *Z*”-score was below 1.23 were grouped into the distress zone category of companies. Companies whose Z-score ranged between 1.23 and 2.9 were put in the grey zone category and those whose *Z*”-score was above 2.9 were put in the category of companies falling within the safe zone. The implication for the different zones are as follows, within the distress zone a firm is highly likely to undergo bankruptcy, within the grey zone a firm’s state of bankruptcy is uncertain, while in the safe zone, a firm has a low likelihood of becoming bankrupt. Based on the findings presented in the tables below, most of the commercial banks have been operating in the distress zone.

Table 4.3: Trend Analysis of Z-scores of Kenyan Banks from 2014-2019

(Z Score)	2019	2018	2017	2016	2015	2014
UBA	0.587	0.094	0.213	0.355	-0.152	0.027
Trans-National Bank	0.424	1.204	1.047	1.176	1.186	1.259
Standard Chartered Bank	1.105	0.000	0.013	0.057	0.016	0.021
Spire	0.000	-0.670	-0.398	-0.190	-0.170	-0.124
Sidian	0.261	-0.090	-0.130	0.005	0.096	0.095
Victoria Commercial Bank	0.522	-0.064	-0.024	0.066	0.047	-0.034
SBM Bank Kenya Limited	0.615	0.081	-0.303	-0.418	-0.078	-0.069
Paramount Bank	0.497	0.009	0.018	0.120	-0.062	0.059
Prime Bank	0.804	0.134	0.011	0.048	-0.014	0.006
NIC Bank Kenya	20.639	0.268	-0.029	0.007	-0.066	-0.093
National Bank of Kenya	0.419	0.339	-0.247	-0.173	-0.151	-0.161
Middle East Bank	0.338	0.311	-0.004	-0.031	0.097	0.104
Mayfair Bank	0.228	0.327	-0.013	0.000	0.000	0.000
Kenya Commercial Bank	0.567	0.175	-0.102	-0.066	-0.069	0.007
M Oriental Bank	0.173	0.170	0.116	0.169	0.164	0.069
I&M Bank Kenya	0.768	-0.029	0.029	0.089	0.064	0.014
Imperial Bank	0.000	0.000	0.000	0.000	0.000	-0.076
Habib Bank Ltd	0.814	0.000	0.000	0.220	0.213	0.169
Gulf African Bank	0.000	0.014	-0.060	0.080	0.045	-0.027
GT Bank Kenya	0.634	0.045	0.044	0.117	0.093	0.007
First Community Bank	0.337	-0.369	-0.277	-0.362	-0.361	-0.381
Family Bank	0.456	-0.173	-0.232	-0.059	-0.076	-0.005
Equity Bank	2.869	-0.016	0.023	0.032	-0.054	-0.035
Ecobank (Kenya)	0.614	-0.113	-0.106	-0.274	-0.121	-0.121
Dubai Bank	0.000	0.000	0.000	0.000	0.000	0.102
DIB Bank Kenya	-0.009	-0.581	-0.947	0.000	0.000	0.000
Development Bank of Kenya	0.525	-0.048	-0.089	0.010	0.046	0.024
Credit Bank	0.386	-0.105	-0.038	0.068	-0.163	-0.139
Consolidated Bank	0.133	-0.277	-0.255	-0.180	0.007	-0.091
Co-operative Bank of Kenya	2.782	-0.052	-0.042	-0.006	-0.044	-0.090
Commercial Bank of Africa	0.000	-0.032	-0.027	0.020	-0.069	-0.237
Citibank N.A. Kenya	0.997	0.170	0.101	0.057	0.165	0.200
Chase Bank	0.000	0.000	0.000	0.000	-0.211	-0.032
Barclays Bank of Kenya	0.544	0.327	0.342	0.353	0.360	0.417
Bank of India (Kenya)	1.107	0.705	0.652	0.612	0.556	0.628
Bank of Baroda (Kenya)	0.704	0.215	0.229	0.226	0.178	0.166
Bank of Africa (Kenya)	0.197	-0.158	-0.146	-0.009	-0.186	-0.228

Stanbic Bank Kenya	0.662	-0.134	-0.103	-0.064	-0.063	-0.005
Giro Commercial Bank	0.000	0.000	0.000	0.141	0.093	0.087
Jamii Bora Bank	0.000	0.000	-0.199	-0.030	-0.122	-0.076

Figure 4.1: Trend Analysis of Z-scores of Kenyan Banks from 2014-2019



4.4 Companies Categorization According to Z-scores

(Z Score)	2019	2018	2017	2016	2015	2014
UBA	0.587	0.094	0.213	0.355	-0.152	0.027
Trans-National Bank	0.424	1.204	1.047	1.176	1.186	1.259
Standard Chartered Bank	1.105	0.000	0.013	0.057	0.016	0.021
Spire	0.000	-0.670	-0.398	-0.190	-0.170	-0.124
Sidian	0.261	-0.090	-0.130	0.005	0.096	0.095
Victoria Commercial Bank	0.522	-0.064	-0.024	0.066	0.047	-0.034

SBM Bank Kenya Limited	0.615	0.081	-0.303	-0.418	-0.078	-0.069
Paramount Bank	0.497	0.009	0.018	0.120	-0.062	0.059
Prime Bank	0.804	0.134	0.011	0.048	-0.014	0.006
NIC Bank Kenya	20.639	0.268	-0.029	0.007	-0.066	-0.093
National Bank of Kenya	0.419	0.339	-0.247	-0.173	-0.151	-0.161
Middle East Bank	0.338	0.311	-0.004	-0.031	0.097	0.104
Mayfair Bank	0.228	0.327	-0.013	0.000	0.000	0.000
Kenya Commercial Bank	0.567	0.175	-0.102	-0.066	-0.069	0.007
M Oriental Bank	0.173	0.170	0.116	0.169	0.164	0.069
I&M Bank Kenya	0.768	-0.029	0.029	0.089	0.064	0.014
Imperial Bank	0.000	0.000	0.000	0.000	0.000	-0.076
Habib Bank Ltd	0.814	0.000	0.000	0.220	0.213	0.169
Gulf African Bank	0.000	0.014	-0.060	0.080	0.045	-0.027
GT Bank Kenya	0.634	0.045	0.044	0.117	0.093	0.007
First Community Bank	0.337	-0.369	-0.277	-0.362	-0.361	-0.381
Family Bank	0.456	-0.173	-0.232	-0.059	-0.076	-0.005
Equity Bank	2.869	-0.016	0.023	0.032	-0.054	-0.035
Ecobank (Kenya)	0.614	-0.113	-0.106	-0.274	-0.121	-0.121
Dubai Bank	0.000	0.000	0.000	0.000	0.000	0.102
DIB Bank Kenya	-0.009	-0.581	-0.947	0.000	0.000	0.000
Development Bank of Kenya	0.525	-0.048	-0.089	0.010	0.046	0.024
Credit Bank	0.386	-0.105	-0.038	0.068	-0.163	-0.139
Consolidated Bank	0.133	-0.277	-0.255	-0.180	0.007	-0.091
Co-operative Bank of Kenya	2.782	-0.052	-0.042	-0.006	-0.044	-0.090
Commercial Bank of Africa	0.000	-0.032	-0.027	0.020	-0.069	-0.237
Citibank N.A. Kenya	0.997	0.170	0.101	0.057	0.165	0.200
Chase Bank	0.000	0.000	0.000	0.000	-0.211	-0.032
Barclays Bank of Kenya	0.544	0.327	0.342	0.353	0.360	0.417
Bank of India (Kenya)	1.107	0.705	0.652	0.612	0.556	0.628
Bank of Baroda (Kenya)	0.704	0.215	0.229	0.226	0.178	0.166
Bank of Africa (Kenya)	0.197	-0.158	-0.146	-0.009	-0.186	-0.228
Stanbic Bank Kenya	0.662	-0.134	-0.103	-0.064	-0.063	-0.005
Giro Commercial Bank	0.000	0.000	0.000	0.141	0.093	0.087
Jamii Bora Bank	0.000	0.000	-0.199	-0.030	-0.122	-0.076

The categorization established that the status of a company's financial health is not rigid it keeps on varying now and then. All companies, whose *Z*”-score was below 1.23 were grouped into the distress zone category of companies. Companies whose Z-score ranged between 1.23 and 2.9 were put in the grey zone category and those whose Z”-score was above 2.9 were put in the category of companies falling within the safe zone. The implication for the different zones are as follows, within the distress zone a firm is highly likely to undergo bankruptcy, within the grey zone a firm’s state of bankruptcy is uncertain, while in the safe zone, a firm has a low probability of becoming bankrupt. Based on the findings presented in the tables below, most of the commercial banks have been operating in the distress zone.

Table 4.4: Companies Categorization According to Z-scores

4.5 Correlations

The researcher carried out correlation analysis of the variables making up the model. Table 4.5 below presents the findings.

Table 4.5: Correlations

		Liquidity	ESP	EP	Solvency	SGC	Z score
Liquidity	Pearson Correlation	1					
	Sig. (2-tailed)						
	N	40					
ESP	Pearson Correlation	-.457**	1				
	Sig. (2-tailed)	.003					
	N	40	40				
EP	Pearson Correlation	-.294	.133	1			
	Sig. (2-tailed)	.065	.412				
	N	40	40	40			
Solvency	Pearson Correlation	.004	-.156	-.022	1		
	Sig. (2-tailed)	.981	.338	.891			
	N	40	40	40	40		
SGC	Pearson Correlation	-.003	-.484**	.383*	.159	1	
	Sig. (2-tailed)	.987	.002	.015	.326		
	N	40	40	40	40		
Z score	Pearson Correlation	-.009	-.151	.161	.702**	.180	1
	Sig. (2-tailed)	.957	.354	.322	.000	.267	
	N	40	40	40	40	40	40

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

According to the findings, there is a weak negative and insignificant correlation between Z values and; liquidity (r=-0.009; p-value = 0.957 at 5% significance level); earned surplus average (r=-0.151; p-value = 0.354 at 5% significance level); Furthermore, there is a weak positive and insignificant correlation between Z values and earning power (r=-0.161; p-value = 0.322 at 5% significance level). The findings go on to indicate that there is a strong positive and significant correlation between Z values and solvency (r=-0.702; p-value = 0.000 at 5% significance level). The findings finally indicate that there is a weak positive and insignificant correlation between Z values and sales generating capability (r=-0.180; p-value = 0.267 at 5% significance level).

4.6 Regression Results

Table 4.6: Coefficients[a]

Model		**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**
		B	**Std. Error**	**Beta**		
	(Constant)	-.220	.348		-.633	.531
	Liquidity	.036	.648	.008	.055	.956
1	Earned surplus leverage	-.299	.512	-.096	-.583	.564
	Earning power	2.881	1.880	.215	1.532	.135
	Solvency	.422	.072	.701	5.845	.000
	Sales generating capability	-1.094	2.881	-.061	-.380	.706

a. Dependent Variable: Z score

Table 4.6 shows the results of the regression model formed from the independent and dependent variables, as well as the results of the regression model generated from the independent and dependent variables;

Z=-.220 + 0.036 Liquidity -0.299Earned surplus leverage + 2.881 Earning power + 0.422 Solvency – 1.094 Sales generating capability.

The results show that the 0.036 Liquidity coefficient is positive and insignificant at the 0.05 significance level. Furthermore, at the 0.05 significance level, the coefficient of -0.299 Earned excess leverage is negative and negligible. Furthermore, at the 0.05 significance level, the coefficient of 2.881 earning power is positive and insignificant. At the 0.05 significance level, the coefficient of 0.422 Solvency is positive and significant. Finally, at the 0.05 significance level, the coefficient of -1.094 Sales producing capability is negative and negligible.

Table 4.7: ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	12.195	5	2.439	7.674	.000[b]
	Residual	10.805	34	.318		
	Total	23.000	39			

a. Dependent Variable: Z score
b. Predictors: (Constant), Liquidity, Earned surplus leverage, Earning power, Solvency, Sales generating capability

The study calculated Analysis of Variance (ANOVA) to establish the model's variance and also determine the reliability of the regression model using the F statistic. The model was considered reliable when the p-value is lower than 0.05. The findings presented in table 4.7 show that the model was reliable at a 5% level of significance (p-value is 0.000, F calculated value 7.674 > F critical value 2.49). The implication of this result is that the study variables can correctly predict the Z-score.

Table 4.8: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.728[a]	.530	.461	.56375

a. Predictors: (Constant), Liquidity, Earned surplus leverage, Earning power, Solvency, Sales generating capability

The study findings in table 4.8 present the regression model findings. According to the findings, R squared is (.530) which indicates that 53.0% of the changes in Z can be explained by the independent variables (Liquidity, Earned surplus leverage, Earning power, Solvency, Sales generating capability).

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter seeks to provide the study findings summary, conclusion, and recommendations.

5.2 Summary of Findings and Discussions

The study's goals were to see if a discriminant model known as the Altman Z-score might forecast financial hardship in Kenyan commercial banks. The goal of the research was to find crucial financial ratios that may be used to predict the future. The following ratios were found to be statistically significant. Liquidity, earned surplus leverage, earning power, Solvency, and Sales generating capabilities are all terms used to describe a company's ability to generate revenue. In general, ratios are beneficial in predicting a company's failure; nevertheless, the types of ratios that best distinguish between failed and successful businesses vary. According to the data presented, Altman's model appears to operate fairly well in Kenya.

The study found out that the highest mean of the Liquidity was 0.406 in year 2019 with SD of 0.320. The mean value of Earned surplus leverage was highest in year 2018 with a score of 48.647 and SD of 315.251. The findings also indicate that the mean value of earning power was highest in years 2015 and 2015 with scores of 0.079 and SDs of 0.051

and 0.049, respectively. Moreover, the mean value of Solvency was highest in year 2019 with a score of 1.555 and SD of 7.841. Additionally, the mean value of Sales generating capability was highest in years 2016 and 2014 with scores of 0.122 and SDs of 0.056 and 0.041, respectively.

The study also found out that the descriptive statistics of the variables in which the Z-scores mean value for 2019 is 1.042 with SD of 3.238. The mean value for 2018 is 0.042 with SD of 0.306. The mean value of year 2017 is -.023 with SD of 0.290. The findings also indicate that the mean value of year 2016 is 0.054 with SD of 0.258. Moreover, the mean value of year 2015 is 0.030 with SD of 0.246. Lastly, the mean value of year 2014 is 0.036 with a SD of 0.259.

The trend analysis showed that the coefficients of Z-scores of most of the commercial banks have been operating within the distress limits with all the sampled failed banks having exhibited distress signs ahead of their failure. Since this is the case, this shows that the model works in the Kenyan market scenario. The companies' categorization according to Z-scores also established that the status of commercial banks financial health was that most of the commercial banks have been operating in the distress zone.

The correlations of the variables of the model indicated that there is a weak negative and insignificant correlation between Z values and; liquidity (r=-0.009; p-value = 0.957 at 5% significance level); earned surplus average (r=-0.151; p-value = 0.354 at 5% significance level). Furthermore, there is a weak positive and insignificant correlation between Z values and; earning power (r=-0.161; p-value = 0.322 at 5% significance level); sales generating capability (r=-0.180; p-value = 0.267 at 5% significance level). The findings go on to indicate that there is a strong positive and significant correlation between Z values and solvency (r=-0.702; p-value = 0.000 at 5% significance level).

The regression model was as follows; Z=-.220 + 0.036 Liquidity - 0.299 Earned surplus leverage + 2.881 Earning power + 0.422 Solvency – 1.094 Sales generating capability.

The results show that the 0.036 Liquidity coefficient is positive and insignificant at the 0.05 significance level. Furthermore, at the 0.05 significance level, the coefficient of -0.299 Earned excess leverage is negative and negligible. At the 0.05 significance level, the coefficient of 2.881 earning power is positive and insignificant. At the 0.05 significance level, the coefficient of 0.422 Solvency is positive and significant. Finally, at the 0.05 significance level, the coefficient of -1.094 Sales producing capability is negative and negligible.

The ANOVA results indicated that the model was reliable at a 5% level of significance (p-value is 0.000, F calculated value 7.674 > F critical value 2.49). The implication of this result is that the study variables can correctly predict the Z-score.

The study finally found out that the R squared is (.530) which indicates that 53.0% of the changes in Z can be explained by the independent variables (Liquidity, Earned surplus leverage, Earning power, Solvency, Sales generating capability).

5.3 Conclusions and Recommendations

The Altman model is reliable in predicting financial crisis in Kenyan commercial banks, according to the study. Kenyan commercial banks, according to the model, are financially troubled due to a lack of retained earnings. Financial hardship occurs when a company's cash inflows from operations are insufficient to cover the company's day-to-day operational financial needs. As a result, the company will be unable to satisfy its financial obligations in a timely manner.

This study recommends that the commercial banks should enhance their sales generating capacity. The recommendation is based on the rationale that retained earnings represent the total amount of money shareholders deserve even though such monies can only be received during a dividend payout as determined by the firm’s board of directors.

Moreover, the board of directors use the retained earnings statement to determine the much they should invest in the organization or redistribute to the firm’s shareholders. Since the board of directors are responsible to shareholders, they must make decisions in the shareholders interest, therefore, they may use the money for investment purposes in pursuit of the growth of the firm or convert the retained earnings to dividends which are then paid out to shareholders as their return on investment.

Potential investors also carefully analyze the retained earnings statements of the firms they hope to invest in. Potential investors not only analyze the most recent statements of retained earnings but also the periodic statements of the firm’s retained earnings. From this assessment, investors usually get a sense of the amount of money to reasonably expect to be generated from their investments.

Creditors on the other hand are keen on various organization performance measures that include retained earnings in order to make crediting decisions. High levels of retained earnings shows that the firm is profitable and may have fewer challenges related to debt repayment. Low or no retained earnings show that a firm may have issues in making loan repayments hence creditors may opt not to offer credit facilities to such firms or may alternatively opt to charge them higher interest rates.

Accumulated losses over a period may adversely affect shareholders' equity. In the shareholder's equity section on an organization's statement of financial position, retained earnings are highlighted by the balance remaining from net income or profits, and it is usually set aside for use in activities such as paying dividends, debt reduction or reinvestment in the firm for growth purposes.

In case of a net loss, such a loss is netted off from the retained profits. Therefore, a negative shareholder's equity implies that a firm has suffered losses over a series of years/periods to the extent that the current retained earnings and funds received upon the issuance of stock have been totally wiped off the firm's balance sheet.

Moreover, large dividend payments that may have exceeded shareholders' equity or exhausted retained earnings would indicate a deficit balance. Additionally, combined financial losses in the years after a substantial dividend payment may result in a negative balance too.

Another reason for a negative shareholders’ equity is the borrowing and use of such funds to cover cumulative deficits instead of using new share issues for equity funding. Normally, shareholder’s equity balance would be positive from a stock issue. As indicated earlier, all financial losses that may reduce shareholders’ equity indicate a deficit balance and all debts incurred appear like liabilities. Therefore, a firm may cover such losses using borrowed funds, however, shareholder’s equity is likely to still appear as a negative balance on the firm’s balance sheet.

A company's negative shareholders' equity is a major warning indicator that it is in financial trouble. Furthermore, a negative shareholders' equity could indicate that a company has spent all of its retained earnings and stock issuance capital on reinvestment activities such as the purchase of expensive plant and equipment. Therefore, negative shareholders’ equity would signal to investors to introspect and evaluate the reasons attributable to the negative balance.

The current study highlighted a financial distress prediction model for Kenyan commercial banks using stability of financial ratios. Similar models could be developed through other ratio stability measures such as the financial ratios coefficient of variation and the standard error of estimate.

The current study also highlights a need to undertake a study that accounts for the nature of finance ratios distribution. More specifically, a model maybe developed that accounts for the absence of a normal distribution but the presence of a positive skew for ratios. This implies that variables may not always be linear in real life. Therefore, the assumption of linearity in the current model maybe lowered and efforts pursued to establish a non-linear model for instance probit and logit models.

A faulty prediction could be explained by other factors including data reliability, data smothering by managers particularly for firms that eventually failed. A firm's top management bears the ultimate responsibility of bringing their organizations on track or building them up to financial soundness since it benefits the firm, its stakeholders and ultimately the country of operation (Altman, 2014).

5.4 Limitations of the Study

This study has a number of limitations that should be noted. To begin with, the findings are limited due to the small sample under review; consequently, if a bigger sample size is used, the results may vary. It is critical to calculate a good variation of ratios during the in-depth review of financial accounts. Only a few of the ratios are notable, and only a few are independent in the sense that they cannot be logically deduced from other ratios without referring to the original data.

It was impossible to compute some ratios from the information available. For instance, X_4(Retained Earnings / Total Assets) was incomputable from the sample due to a lack of data like matching of non-failed and failed firms was difficult to undertake on a stratified basis.

The limited public availability of information on private owned companies resulted in extended time taken to gather the necessary data. The study also focused on how applicable the Altman’s model is in the prediction of Kenyan commercial banks financial distress. Qualitative aspects including a firm’s strategy, technology enhancements, age in operation, and management quality need to be considered when interpreting the results.

This study could not escape the drawbacks and defects and that are usually inherent in all human endeavors such as financial challenges and constraints.

5.5 Suggestions for Further Studies

The current study only looked at five ratios, but there may be a desire to look into more. For example, sales statement-based ratios such as retention ratios or combined ratios could be used (Calandro Junior, et al 2013).

In future studies, actuarial liabilities may be worth addressing to isolate the aspect of shareholder's equity in respect to life funds. Studies on prediction models based on different bank lines, such as long and short-term banks, may be required. Similar research has been carried out in the past (Browne et al, 2013 and 2013).

There have also been studies related to corporate governance undertaken elsewhere, whereby weights and indices are applied to given corporate governance parameters (Esmeralda et al, 2015). Due to the critical role played by corporate governance, it is important to consider undertaking studies on the effects of corporate governance on business failures in the banking industry. Other studies could focus on the circumstances under which firms' management might prefer to promptly predict bankruptcy or financial distress to avoid collapsing or undergoing insolvency.

Other areas that may need exploration are interventions model for enabling managers to restore productivity and confidence in times of insolvency or bankruptcy within the banking industries.

REFERENCES

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.

Ahn, B. S., Cho S. S., & Kim, C.Y. (2010). *The integrated methodology of rough set theory and artificial neural network for business failure prediction.* Expert Systems with Applications, 18, 65-74.

Alexakis, P. (2008). *Altman Z-score model and prediction of business failures.* International Journal of Monetary Economics and Finance, Vol. 1. No.4.

Altman, E.I., & Hotchkiss, E. (Eds.). (2010). *corporate financial distress and bankruptcy:* predict and avoid bankruptcy, analyze, and invest in distressed debt (3rd ed.). Hoboken, NJ: Wiley.

Altman, E. I. (2014). Financial Ratios, Discriminant Analysis, and the Prediction of Corporate Bankruptcy. *The Journal of Finance, 23(4).*

Argenti (2013). *The Magnitude and Causes of Corporate Failures in Kenya- 1970 to 1984*. (MBA Thesis, University of Nairobi).

Aziz, M. & Dar, H. (2016). *Predicting Corporate Financial Distress: Whither Do We Stand?* Corporate governance, 6(1), 18-33.

Barniv and McDonald (2009). *Managing Strategic Change*. EW York: John Wiley & Sons, 1983.

Beaver, W. (2006). Financial Ratios as predictors of Failure. *Journal of Accounting Research (supplement).*

Central Bank of Kenya. (1994). *Annual Report - Central Bank of Kenya.* Retrieved from https://www.centralbank.go.ke/reports/cbk-reports-and-financial-statements/.

Central Bank of Kenya. (2014). *Annual Report - Central Bank of Kenya*. Retrieved from https://www.centralbank.go.ke/reports/cbk-reports-and-financial-statements/.

Central Bank of Kenya. (2016). *Prudential guidelines for institutions licensed under the Banking Act", Central Bank of Kenya*. pp. 27-48. Retrieved from: https://www.centralbank.go.ke/reports/cbk-reports-and-financial-statements/.

Christopoulos, A., Vergos, K., & Mylonakis, J. (2008). How Stock Prices React to Managerial Decisions and Other Profit Signaling Events in the Hellenic Mobile Telecom Market. *Journal of Money, Investment and Banking, (2), 37-47*.

Claude, S.E. (October, 1948). *A Mathematical Theory of Communication.* Bell System Technical Journal. 27 (4): 623–656. doi:10.1002/j.1538-7305.1948.tb00917.x.

Espen, S. (2009). *Assessment of Credit Risk in Norwegian Business Sector*. (Doctoral Dissertation. Master's Thesis, The University of Bergen, Bergen, Norway).

Eidleman, G. J. (1995). *Z scores - a guide to failure prediction.* (Business failure) (Auditing). The CPA Journal Online, February.

Hair, I. (2012). *Competition under Financial Distress*. The Journal of Industrial Economics, 54(3), 309-324.

Kamau Metho (2013), *Cash flow ratios as a predictor of corporate failure*. (Unpublished MBA research work. UON).

Keener, (2013). *The New Manufacturing Challenge.* Techniques for Continuous Improvement, Free Press, New York.

Kiege, P.N (2011). *Business failure prediction using discriminant analysis.* (Unpublished MBA project. University of Nairobi).

Kip, A.F. (2012) *A methodology for predicting company failure in the construction industry*. (PhD thesis, Loughborough University of Technology, Loughborough).

Kogi, S.K (2013). *An analysis of discriminant corporate failure prediction model based on stability of financial ratios.* (Unpublished MBA project. University of Nairobi).

Longstaff, P. & Schwartz, E. (1995). A simple approach to valuing risky fixed and floating rate debt. *Journal of Finance, Vol.5, pp789-819.*

Maaka (2013). *A Practical Guide to Behavioral Research*. USA: Merrill Publishing Company.

Maina, (2011). Prediction of Firms Failures. *Journal of Finance*.

Monti, E.N. & Moriano, G, R. (2010). A Statistical Analysis to Predict Financial Distress. *Journal Service & Management, 45(2), 20-25.*

Moyer, R. Charles., (2006). *Forecasting Financial Failure.* A Re-Examination, Financial Management, spring, pp.11-17.

Mugenda, O.M. & Mugenda, A. G. (2003). *Quantitative and Qualitative Approaches. African Centre for Technology Studies (ACTS).* Research Methods.

Natalia, O. (2014). *Corporate Financial Distress: An Empirical Analysis of Distress Risk*. (Doctoral Dissertation No. 3430, University of St. Gallen, St. Gallen, Switzerland).

Nganga I. K. (2016). *Failure prediction of Insurance companies in Kenya.* (Unpublished MBA research work UON).

Nyabwanga. (2013), *Financial Management*. 7th edition. New Delhi, India.

Pandey, I.M. (2015). Financial Management (10th Ed). New Delphi, India, Vikas Publishing.

Patrick, S. & Ooghe, H. (2014). *35 years of studies on business failure: an overview of the classic statistical methodologies and their related problems.* The British Accounting Review, 38(1), 63-93.

Robinson, R.A. & Maguire, G. (2011). Top common causes of construction contractor failures. *Journal of Construction Accounting and Taxation, Jan/Feb 2003.*

Runyora, N.M., (2012). Commercial Banking Crises in Kenya: Causes and Remedies. *African Journal of Accounting, Economic, Finance and Banking Research, (N), pp. 12-33*.

Samarakoon, P. & Hasan, T. (2013). Altman's Z-Score model of predicting corporate distress: Evidence from the emerging Sri Lankan Stock Market. *Journal of the Academy of Finance, Vol.1.*

Schaefer, T.F. (2012). The Information Content of Current cost Income Relative to Dividends and Historical Cost Income. *Journal of Accounting Research, Autumn.*

Sipika, C. & Smith, D. (2012). *From Disaster to Crisis – the Failed Turnaround of Pan-American Airlines*. Liverpool Business School, Liverpool, UK.

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

Thynne K. (2006), "Test of the Generalizability of Altman's Bankruptcy. Prediction Model," *Journal of Business Research, 53-61, 10, 2006.*

Wernerfelt, & Cynthia A. (2011). *Montgomery Briger; Tobin and the Importance of focus in firm performance*. The American Economic Review; Vol. 78 (1); March 1988; pp. 246-250.

APPENDICES

Appendix 1: List of Banks in Kenya

1. African Banking Corporation Limited
2. Bank of Africa Kenya Limited
3. Bank of Baroda (K) Limited
4. Bank of India
5. Barclays Bank of Kenya Limited
6. Charterhouse Bank Limited (under statutory management)
7. Chase Bank (K) Limited (in receivership)
8. Citibank N.A Kenya
9. Commercial Bank of Africa Limited
10. Consolidated Bank of Kenya Limited
11. Co-operative Bank of Kenya Limited
12. Credit Bank Limited
13. Development Bank of Kenya Limited
14. Diamond Trust Bank Kenya Limited
15. Ecobank Kenya Limited
16. Equatorial Commercial Bank Limited
17. Equity Bank Kenya Limited
18. Family Bank Limited
19. Fidelity Commercial Bank Limited
20. First Community Bank Limited
21. Guaranty Trust Bank (K) Ltd
22. Giro Commercial Bank Limited
23. Guardian Bank Limited
24. Gulf African Bank Limited
25. Habib Bank A.G Zurich
26. Habib Bank Limited
27. Imperial Bank Limited (in receivership)
28. I & M Bank Limited
29. Jamii Bora Bank Limited
30. KCB Bank Kenya Limited
31. Middle East Bank (K) Limited
32. National Bank of Kenya Limited
33. NIC Bank Limited
34. Oriental Commercial Bank Limited
35. Paramount Bank Limited
36. Prime Bank Limited
37. Postbank Ltd
38. Sidian Bank Limited
39. Stanbic Bank Limited
40. Standard Chartered Bank Kenya Limited
41. Trans-National Bank Limited
42. UBA Kenya Bank Limited
43. Victoria Commercial Bank Limited

Source: Central Bank of Kenya website (2019)

Appendix 2: Data Collection Sheet

1. UBA	2019	2018	2017	2016	2015	2014
T1=Liquidity	0.758	0.735	0.417	0.365	0.584	0.746
T2= EPS	-0.087	-0.858	-0.668	-0.620	-0.858	-0.763
T3= EP	0.007	0.044	0.045	0.064	0.001	-0.026
T4=Solvency	0.091	0.165	0.498	0.620	0.168	0.315
T5= SGC	0.059	0.088	0.131	0.159	0.083	0.087
Z Score	0.587	0.094	0.213	0.355	-0.152	0.027
Category	Distress	Distress	Distress	Distress	Distress	Distress
2. Trans-National	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.330	0.287	0.299	0.308	0.305	0.349
T2= EPS	0.065	-0.981	-0.985	-0.987	-0.988	-0.988
T3= EP	-0.006	0.078	0.079	0.083	0.070	0.068
T4=Solvency	0.133	3.306	2.829	3.046	3.182	3.347
T5= SGC	0.096	0.199	0.234	0.254	0.251	0.229
Z Score	0.424	1.204	1.047	1.176	1.186	1.259
Category	Distress	Distress	Distress	Distress	Distress	Grey
3. SCB	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	1.440	0.435	0.451	0.413	0.387	0.352
T2= EPS	0.036	-0.875	-0.875	-0.859	-0.858	-0.870
T3= EP	0.005	0.073	0.075	0.085	0.080	0.089
T4=Solvency	0.011	0.189	0.185	0.213	0.212	0.222
T5= SGC	0.021	0.123	0.120	0.135	0.128	0.136
Z Score	1.105	0.000	0.013	0.057	0.016	0.021
Category	Distress	Distress	Distress	Distress	Distress	Distress
4. Spire	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.000	0.377	0.296	0.302	0.291	0.270
T2= EPS	0.000	-1.181	-0.911	-0.886	-0.887	-0.944
T3= EP	0.000	0.000	-0.003	0.048	0.055	0.095
T4=Solvency	0.000	-0.100	0.119	0.152	0.167	0.075
T5= SGC	0.000	0.104	0.120	0.131	0.131	0.154
Z Score	0.000	-0.670	-0.398	-0.190	-0.170	-0.124
Category	Distress	Distress	Distress	Distress	Distress	Distress
5. Sidian	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.420	0.373	0.297	0.269	0.280	0.285
T2= EPS	0.002	-0.847	-0.828	-0.819	-0.803	-0.852
T3= EP	0.002	0.050	0.041	0.075	0.095	0.109

T4=Solvency	0.091	0.190	0.217	0.227	0.251	0.182
T5= SGC	-0.088	0.125	0.138	0.177	0.176	0.198
Z Score	0.261	-0.090	-0.130	0.005	0.096	0.095
Category	Distress	Distress	Distress	Distress	Distress	Distress
6. VCB	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.344	0.311	0.226	0.270	0.308	0.288
T2= EPS	0.114	-0.825	-0.794	-0.784	-0.833	-0.848
T3= EP	0.019	0.081	0.083	0.094	0.101	0.090
T4=Solvency	0.028	0.226	0.275	0.292	0.213	0.200
T5= SGC	0.110	0.106	0.112	0.121	0.129	0.114
Z Score	0.522	-0.064	-0.024	0.066	0.047	-0.034
Category	Distress	Distress	Distress	Distress	Distress	Distress
7. SBM	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.772	0.748	0.402	0.317	0.254	0.306
T2= EPS	-0.016	-0.902	-0.913	-1.092	-0.908	-0.906
T3= EP	0.016	0.056	0.014	0.042	0.098	0.096
T4=Solvency	0.033	0.109	0.159	-0.070	0.131	0.116
T5= SGC	0.010	0.088	0.072	0.180	0.151	0.133
Z Score	0.615	0.081	-0.303	-0.418	-0.078	-0.069
Category	Distress	Distress	Distress	Distress	Distress	Distress
8. Paramount	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.440	0.391	0.348	0.345	0.262	0.531
T2= EPS	0.075	-0.841	-0.826	-0.835	-0.862	-0.874
T3= EP	0.008	0.078	0.082	0.111	0.092	0.080
T4=Solvency	0.115	0.206	0.226	0.211	0.171	0.153
T5= SGC	0.045	0.113	0.117	0.145	0.123	0.107
Z Score	0.497	0.009	0.018	0.120	-0.062	0.059
Category	Distress	Distress	Distress	Distress	Distress	Distress
9. Prime	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.771	0.545	0.400	0.337	0.320	0.341
T2= EPS	0.116	-0.804	-0.854	-0.851	-0.872	-0.878
T3= EP	0.023	0.066	0.079	0.101	0.098	0.101
T4=Solvency	0.079	0.305	0.219	0.199	0.155	0.164
T5= SGC	0.050	0.090	0.109	0.131	0.125	0.124
Z Score	0.804	0.134	0.011	0.048	-0.014	0.006
Category	Distress	Distress	Distress	Distress	Distress	Distress
10. NIC	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.000	0.374	0.369	0.262	0.241	0.251

T2= EPS	0.490	0.000	-0.857	-0.843	-0.863	-0.863
T3= EP	0.163	0.000	0.081	0.099	0.092	0.084
T4=Solvency	45.841	0.000	0.177	0.230	0.203	0.204
T5= SGC	0.169	0.000	0.107	0.130	0.121	0.112
Z Score	20.639	0.268	-0.029	0.007	-0.066	-0.093
Category	Safe	Distress	Distress	Distress	Distress	Distress
11. NBK	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.461	0.473	0.415	0.396	0.379	0.400
T2= EPS	-0.049	0.000	-0.968	-0.950	-0.922	-0.916
T3= EP	0.001	0.000	0.043	0.061	0.063	0.055
T4=Solvency	0.123	0.000	0.068	0.064	0.095	0.109
T5= SGC	0.074	0.000	0.112	0.133	0.122	0.112
Z Score	0.419	0.339	-0.247	-0.173	-0.151	-0.161
Category	Distress	Distress	Distress	Distress	Distress	Distress
12. MEB	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.242	0.433	0.366	0.237	0.281	0.358
T2= EPS	0.076	0.000	-0.777	-0.776	-0.780	-0.795
T3= EP	0.007	0.000	0.051	0.064	0.094	0.088
T4=Solvency	0.069	0.000	0.294	0.295	0.286	0.262
T5= SGC	0.050	0.000	0.110	0.134	0.144	0.136
Z Score	0.338	0.311	-0.004	-0.031	0.097	0.104
Category	Distress	Distress	Distress	Distress	Distress	Distress
13. Mayfair	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.456	0.546	0.761	0.000	0.000	0.000
T2= EPS	-0.146	0.000	-0.671	0.000	0.000	0.000
T3= EP	-0.042	0.000	-0.073	0.000	0.000	0.000
T4=Solvency	0.302	0.000	0.491	0.000	0.000	0.000
T5= SGC	0.029	0.000	0.029	0.000	0.000	0.000
Z Score	0.228	0.327	-0.013	0.000	0.000	0.000
Category	Distress	Distress	Distress	Distress	Distress	Distress
14. KCB	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.371	0.244	0.236	0.244	0.253	0.257
T2= EPS	0.104	0.000	-0.870	-0.876	-0.880	-0.847
T3= EP	0.041	0.000	0.081	0.090	0.087	0.093
T4=Solvency	0.004	0.000	0.191	0.191	0.209	0.237
T5= SGC	0.084	0.000	0.133	0.142	0.136	0.151
Z Score	0.567	0.175	-0.102	-0.066	-0.069	0.007
Category	Distress	Distress	Distress	Distress	Distress	Distress

15. M Oriental	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.000	0.237	0.259	0.275	0.316	0.338
T2= EPS	-0.007	0.000	-0.737	-0.728	-0.761	-0.823
T3= EP	0.005	0.000	0.082	0.090	0.094	0.091
T4=Solvency	0.266	0.000	0.401	0.419	0.358	0.255
T5= SGC	0.051	0.000	0.131	0.135	0.138	0.133
Z Score	0.173	0.170	0.116	0.169	0.164	0.069
Category	Distress	Distress	Distress	Distress	Distress	Distress
16. I&M	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.463	0.469	0.276	0.291	0.264	0.295
T2= EPS	0.240	-0.851	-0.838	-0.850	-0.841	-0.861
T3= EP	0.013	0.089	0.101	0.115	0.114	0.104
T4=Solvency	0.419	0.201	0.235	0.236	0.215	0.189
T5= SGC	0.015	0.114	0.129	0.144	0.143	0.129
Z Score	0.768	-0.029	0.029	0.089	0.064	0.014
Category	Distress	Distress	Distress	Distress	Distress	Distress
17. Imperial	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.000	0.000	0.000	0.000	0.000	0.242
T2= EPS	0.000	0.000	0.000	0.000	0.000	-0.884
T3= EP	0.000	0.000	0.000	0.000	0.000	0.095
T4=Solvency	0.000	0.000	0.000	0.000	0.000	0.152
T5= SGC	0.000	0.000	0.000	0.000	0.000	0.141
Z Score	0.000	0.000	0.000	0.000	0.000	-0.076
Category	Distress	Distress	Distress	Distress	Distress	Distress
18. Habib Bank Ltd	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.779	0.757	0.000	0.664	0.577	0.501
T2= EPS	0.108	0.122	0.000	-0.829	-0.819	-0.805
T3= EP	0.016	0.017	0.000	0.077	0.086	0.087
T4=Solvency	0.161	0.019	0.000	0.244	0.266	0.259
T5= SGC	0.048	0.050	0.000	0.104	0.115	0.112
Z Score	0.814	0.000	0.000	0.220	0.213	0.169
Category	Distress	Distress	Distress	Distress	Distress	Distress
19. GAB	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.000	-0.213	-0.177	-0.124	-0.047	-0.179
T2= EPS	0.000	2018.000	2017.000	2016.000	2015.000	2014.000
T3= EP	0.000	0.400	0.344	0.341	0.321	0.312
T4=Solvency	0.000	-0.850	-0.854	-0.854	-0.864	-0.881
T5= SGC	0.000	0.080	0.073	0.107	0.106	0.098

Z Score	0.000	0.014	-0.060	0.080	0.045	-0.027
Category	Distress	Distress	Distress	Distress	Distress	Distress
20. GT	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.493	0.326	0.367	0.430	0.439	0.495
T2= EPS	0.032	-0.800	-0.810	-0.816	-0.829	-0.859
T3= EP	0.062	0.055	0.055	0.069	0.067	0.056
T4=Solvency	0.005	0.501	0.453	0.394	0.368	0.277
T5= SGC	0.060	0.106	0.104	0.119	0.117	0.090
Z Score	0.634	0.045	0.044	0.117	0.093	0.007
Category	Distress	Distress	Distress	Distress	Distress	Distress
21. FCB	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.351	0.388	0.351	0.189	0.180	0.264
T2= EPS	-0.022	-0.957	-0.919	-0.902	-0.896	-0.907
T3= EP	0.010	0.016	0.037	0.033	0.034	0.019
T4=Solvency	0.023	0.077	0.109	0.116	0.124	0.110
T5= SGC	0.064	0.081	0.088	0.115	0.110	0.092
Z Score	0.337	-0.369	-0.277	-0.362	-0.361	-0.381
Category	Distress	Distress	Distress	Distress	Distress	Distress
22. Family	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.331	0.216	0.229	0.154	0.230	0.307
T2= EPS	0.063	-0.840	-0.843	-0.827	-0.860	-0.835
T3= EP	0.017	0.052	0.032	0.081	0.083	0.077
T4=Solvency	0.019	0.206	0.202	0.222	0.172	0.207
T5= SGC	0.104	0.135	0.133	0.189	0.158	0.157
Z Score	0.456	-0.173	-0.232	-0.059	-0.076	-0.005
Category	Distress	Distress	Distress	Distress	Distress	Distress
23. Equity	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.521	0.384	0.381	0.350	0.233	0.220
T2= EPS	0.767	-0.873	-0.854	-0.865	-0.860	-0.856
T3= EP	0.154	0.080	0.084	0.094	0.092	0.095
T4=Solvency	2.872	0.160	0.180	0.160	0.161	0.168
T5= SGC	0.160	0.133	0.138	0.154	0.154	0.167
Z Score	2.869	-0.016	0.023	0.032	-0.054	-0.035
Category	Distress	Distress	Distress	Distress	Distress	Distress
24. Ecobank	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.661	0.627	0.565	0.356	0.346	0.398
T2= EPS	-0.027	-0.897	-0.892	-0.852	-0.827	-0.803
T3= EP	0.017	0.023	0.034	0.013	0.050	0.031

T4=Solvency	0.097	0.133	0.137	0.184	0.169	0.205
T5= SGC	0.069	0.069	0.082	0.076	0.105	0.091
Z Score	0.614	-0.113	-0.106	-0.274	-0.121	-0.121
Category	Distress	Distress	Distress	Distress	Distress	Distress
25. Dubai	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.000	0.000	0.000	0.000	0.000	0.122
T2= EPS	0.000	0.000	0.000	0.000	0.000	-0.710
T3= EP	0.000	0.000	0.000	0.000	0.000	0.090
T4=Solvency	0.000	0.000	0.000	0.000	0.000	0.422
T5= SGC	0.000	0.000	0.000	0.000	0.000	0.160
Z-Score	0.000	0.000	0.000	0.000	0.000	0.102
Category	Distress	Distress	Distress	Distress	Distress	Distress
26. DIB	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.271	0.291	0.334	0.000	0.000	0.000
T2= EPS	-0.279	-0.776	-0.714	0.000	0.000	0.000
T3= EP	-0.084	-0.138	-0.318	0.000	0.000	0.000
T4=Solvency	0.645	0.589	0.946	0.000	0.000	0.000
T5= SGC	0.025	0.050	0.008	0.000	0.000	0.000
Z Score	-0.009	-0.581	-0.947	0.000	0.000	0.000
Category	Distress	Distress	Distress	Distress	Distress	Distress
27. DBK	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.094	0.364	0.362	0.392	0.449	0.428
T2= EPS	0.105	-0.884	-0.901	-0.894	-0.897	-0.897
T3= EP	0.074	0.078	0.073	0.091	0.093	0.092
T4=Solvency	0.091	0.231	0.219	0.215	0.202	0.195
T5= SGC	0.101	0.101	0.096	0.114	0.112	0.110
Z Score	0.525	-0.048	-0.089	0.010	0.046	0.024
Category	Distress	Distress	Distress	Distress	Distress	Distress
28. Credit	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.281	0.215	0.266	0.281	0.245	0.306
T2= EPS	0.007	-0.852	-0.821	-0.801	-0.869	-0.875
T3= EP	0.014	0.076	0.073	0.089	0.063	0.060
T4=Solvency	0.142	0.192	0.226	0.253	0.156	0.149
T5= SGC	0.076	0.146	0.145	0.164	0.138	0.134
Z Score	0.386	-0.105	-0.038	0.068	-0.163	-0.139
Category	Distress	Distress	Distress	Distress	Distress	Distress
29. Consolidated	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.270	0.251	0.265	0.242	0.251	0.291

T2= EPS	-0.216	-0.995	-0.974	-0.946	-0.923	-0.928
T3= EP	-0.045	0.060	0.060	0.073	0.111	0.087
T4=Solvency	0.377	0.077	0.086	0.112	0.129	0.116
T5= SGC	0.103	0.168	0.158	0.174	0.209	0.167
Z Score	0.133	-0.277	-0.255	-0.180	0.007	-0.091
Category	Distress	Distress	Distress	Distress	Distress	Distress
30. Co-operative	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.410	0.313	0.260	0.250	0.297	0.270
T2= EPS	0.919	-0.865	-0.846	-0.852	-0.873	-0.867
T3= EP	0.258	0.077	0.084	0.095	0.087	0.077
T4=Solvency	0.556	0.201	0.217	0.207	0.170	0.176
T5= SGC	0.676	0.131	0.136	0.153	0.140	0.140
Z Score	2.782	-0.052	-0.042	-0.006	-0.044	-0.090
Category	Distress	Distress	Distress	Distress	Distress	Distress
31. CBA	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.000	0.391	0.443	0.413	0.354	0.268
T2= EPS	0.490	-0.891	-0.911	-0.910	-0.914	-0.922
T3= EP	0.163	0.082	0.079	0.098	0.090	0.067
T4=Solvency	45.841	0.170	0.159	0.150	0.129	0.113
T5= SGC	0.169	0.118	0.114	0.128	0.118	0.096
Z Score	20.639	-0.032	-0.027	0.020	-0.069	-0.237
Category	Safe	Distress	Distress	Distress	Distress	Distress
32. Citibank	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.793	0.473	0.464	0.481	0.471	0.560
T2= EPS	0.148	-0.782	-0.806	-0.821	-0.791	-0.778
T3= EP	0.058	0.081	0.076	0.068	0.084	0.071
T4=Solvency	0.059	0.292	0.258	0.235	0.282	0.301
T5= SGC	0.097	0.120	0.107	0.098	0.116	0.111
Z Score	0.997	0.170	0.101	0.057	0.165	0.200
Category	Distress	Distress	Distress	Distress	Distress	Distress
33. Chase	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.000	0.000	0.000	0.000	0.232	0.350
T2= EPS	0.000	0.000	0.000	0.000	-0.933	-0.910
T3= EP	0.000	0.000	0.000	0.000	0.081	0.096
T4=Solvency	0.000	0.000	0.000	0.000	0.084	0.115
T5= SGC	0.000	0.000	0.000	0.000	0.127	0.143
Z Score	0.000	0.000	0.000	0.000	-0.211	-0.032
Category	Distress	Distress	Distress	Distress	Distress	Distress

34. BBK	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.398	0.378	0.317	0.268	0.276	0.367
T2= EPS	0.096	-0.884	-0.857	-0.855	-0.854	-0.856
T3= EP	0.028	0.065	0.068	0.078	0.078	0.075
T4=Solvency	0.008	1.154	1.191	1.194	1.197	1.203
T5= SGC	0.088	0.118	0.129	0.142	0.142	0.140
Z Score	0.544	0.327	0.342	0.353	0.360	0.417
Category	Distress	Distress	Distress	Distress	Distress	Distress
35. BOI	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	1.030	0.685	0.617	0.576	0.570	0.622
T2= EPS	0.221	-0.801	-0.812	-0.821	-0.835	-0.828
T3= EP	0.037	0.085	0.087	0.087	0.082	0.088
T4=Solvency	0.021	1.266	1.258	1.249	1.205	1.215
T5= SGC	0.056	0.096	0.097	0.098	0.094	0.101
Z Score	1.107	0.705	0.652	0.612	0.556	0.628
Category	Distress	Distress	Distress	Distress	Distress	Distress
36. BOB	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.784	0.652	0.551	0.550	0.514	0.531
T2= EPS	0.130	-0.837	-0.831	-0.837	-0.836	-0.849
T3= EP	-0.010	0.088	0.105	0.107	0.102	0.100
T4=Solvency	0.016	0.199	0.229	0.207	0.198	0.189
T5= SGC	0.054	0.099	0.117	0.120	0.116	0.114
Z Score	0.704	0.215	0.229	0.226	0.178	0.166
Category	Distress	Distress	Distress	Distress	Distress	Distress
37. BOA	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.487	0.393	0.306	0.265	0.293	0.255
T2= EPS	-0.094	-0.930	-0.909	-0.900	-0.899	-0.902
T3= EP	-0.067	0.057	0.068	0.107	0.065	0.061
T4=Solvency	0.161	0.159	0.185	0.177	0.140	0.146
T5= SGC	0.067	0.104	0.116	0.159	0.107	0.103
Z Score	0.197	-0.158	-0.146	-0.009	-0.186	-0.228
Category	Distress	Distress	Distress	Distress	Distress	Distress
38. Stanbic	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.584	0.359	0.383	0.334	0.394	0.450
T2= EPS	0.103	-0.882	-0.867	-0.860	-0.870	-0.858
T3= EP	0.026	0.063	0.060	0.075	0.068	0.067
T4=Solvency	0.013	0.140	0.160	0.173	0.166	0.184
T5= SGC	0.071	0.101	0.103	0.119	0.110	0.114

Z Score	0.662	-0.134	-0.103	-0.064	-0.063	-0.005
Category	Distress	Distress	Distress	Distress	Distress	Distress
39. GCB	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.000	0.000	0.000	0.417	0.389	0.466
T2= EPS	0.000	0.000	0.000	-0.819	-0.828	-0.846
T3= EP	0.000	0.000	0.000	0.099	0.096	0.087
T4=Solvency	0.000	0.000	0.000	0.232	0.218	0.191
T5= SGC	0.000	0.000	0.000	0.131	0.126	0.117
Z Score	0.000	0.000	0.000	0.141	0.093	0.087
Category	Distress	Distress	Distress	Distress	Distress	Distress
40. Jamii Bora	**2019**	**2018**	**2017**	**2016**	**2015**	**2014**
T1=Liquidity	0.000	0.000	0.101	0.175	0.190	0.324
T2= EPS	0.000	0.000	-0.822	-0.829	-0.870	-0.833
T3= EP	0.000	0.000	0.047	0.080	0.079	0.051
T4=Solvency	0.000	0.000	0.368	0.296	0.232	0.310
T5= SGC	0.000	0.000	0.126	0.173	0.136	0.107
Z Score	0.000	0.000	-0.199	-0.030	-0.122	-0.076
Category	Distress	Distress	Distress	Distress	Distress	Distress

Key:

BBK	Barclays Bank of Kenya
BOA	Bank of Africa (Kenya)
BOB	Bank of Baroda (Kenya)
BOI	Bank of India (Kenya)
CBA	Commercial Bank of Africa
DBK	Development Bank of Kenya
EP	Earning power
EPS	Earned surplus leverage
FCB	First Community Bank
GAB	Gulf African Bank
GCB	Giro Commercial Bank
KCB	Kenya Commercial Bank
MEB	Middle East Bank
NBK	National Bank of Kenya
SBM	Standard Bank of Mauritius
SCB	Standard Chartered Bank
SGC	Sales generating capability
VCB	Victoria Commercial Bank

Appendix 3: List of Failed Banks

Bank	Year
Rural Urban Credit Finance Company Ltd	1984
Continental Bank	1986
Continental Credit Finance Bank	1986
Capital Finance Bank	1986
Business Finance	1989
Home Savings and Mortgages	1989
Estate Finance	1989
Union Bank	1989
Nationwide Finance	1989
Jimba Credit	1989
Nairobi Finance	1993
Middle Africa Bank	1993
Trade Bank	1993
Trade Finance	1993
Diners Finance	1993
Central Finance	1993
Allied Credit	1993
United Trustees Finance	1993
Inter Africa Credit	1993
Exchange Bank	1993
International Finance	1993
Post Bank Credit	1993
Pan African Bank	1994
Pan African Finance	1994
Thabiti Finance	1994
Export Bank of Africa	1994
United Bank Ltd	1994
Kenya Finance Corporation Bank	1996
Meridian Biao Bank	1996
Heritage Bank	1996
Ari Bank Corporation	1997
Bullion Bank	1998
Prudential Bank	2000
Reliance Bank	2000
Fortune Finance	2000
Trust Bank and Trust Finance	2001
Euro Bank	2003
Daima Bank	2005

Prudential Building Society	2005
Charterhouse Bank	2006
Dubai Bank	2015
Imperial bank	2015
Chase bank	2016

TEST OF RELEVANCE OF ALTMAN Z-SCORE MODEL IN PREDICTING BANK FAILURE IN KENYA

ORIGINALITY REPORT

13%	12%	3%	5%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

True Original Copy
Barasa
3/12/2021

PRIMARY SOURCES

1	erepository.uonbi.ac.ke Internet Source	4%
2	Erepository.uonbi.ac.ke Internet Source	2%
3	Mary Hilston Keener. "Predicting The Financial Failure Of Retail Companies In The United States", Journal of Business & Economics Research (JBER), 2013 Publication	<1%
4	erepository.uonbi.ac.ke:8080 Internet Source	<1%
5	ir-library.egerton.ac.ke Internet Source	<1%
6	pdfs.semanticscholar.org Internet Source	<1%
7	orsea.net Internet Source	<1%
8	ir.jkuat.ac.ke Internet Source	