THE APPLICABILITY OF ALTMAN'S FAILURE PREDICTION MODELS IN THE INSURANCE COMPANIES IN KENYA

LAWRENCE K. KIRUI

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DECLARATION

I declare that this is my original work and has not been presented for a degree in any other university.

Signature ……………………………………..   Date ……………………………

LAWRENCE K. KIRUI - D61/75184/2009

This project has been submitted for examination with my approval as the University Supervisor:

Signature ……………………………………..   Date …………………………….

JOSEPH LUMUMBA BARASA

DEPARTMENT OF ACCOUNTING AND FINANCE

DEDICATION

To

My Lovely Wife

Rhoda Olesi

(Your Encouragement was Indispensable)

My Dear Children

Sandra

Tracy

Raymond

(To Inspire You For Excellence Beyond)

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May almighty God bless you all.

ABSTRACT

There is a dire need for prediction of business failures since the results of business failure leads to heavy losses both financially and non-financially. Thus a model that could accurately predict business failure in time would be quite useful to managers, shareholders, the government, suppliers, customers, employees amongst other stakeholders. The prediction of business failure is an important and challenging issue that has served as the impetus for many academic studies over the past three decades.

The objective of the study was to determine the applicability of Altman's failure prediction models in the insurance companies in Kenya. The population of the study was composed of Insurance firms that operated in Kenya between 2000 and 2011. All the firms still in operation were used in the study and the five firms that become insolvent during the period were also used. The source of secondary data was from financial reports of these solvent and insolvent companies at the Insurance Regulatory Authority.

The research study revealed that Edward Altman's financial distress prediction model was applicable in 4 out of the 5 failed firms that were analyzed, which indicates an 80% successful prediction of the model. On the 36 non-failed firms analyzed, 24 of them proved that Edward Altman's financial distress prediction model was successful indicating a 69% validity of the model. The study concludes that Edward Altman model of predicting financial failure of companies was a useful tool for predicting failure of insurance companies in Kenya.

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LIST OF ABBREVIATION

AN	-	Artificial Neurons
CUSUM	–	Cumulative Sum Control Chart
EBIT/TA	-	Earnings before Interest and Taxes/Total Assets
EBITDA	–	Earnings before Internet Taxes, Depreciation and Amortization
GA	–	Genetic Algorithms
IAK	-	Insurance Association of Kenya
IRA	–	Insurance Regulating Authority
LPM	–	Linear Probably Model
MDA	–	Multi Disbarment Analysis
MIPS	–	Medical Insurance Providers
MVE/TL	–	Market Value of Equity/Total Liabilities
NN	–	Neural Networks
RE/TA	-	Retained Earning/Total Assets
SPSS	-	Statistical Package for Social
UDA	–	Univariate Discriminant Analysis
WC/TA	–	Working Capital /Total Assets

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

One of the most significant threats for many businesses today, despite their size and the nature of their operations, is insolvency. Corporate liabilities have default risk and there is always a chance that a corporate borrower will not meet its contractual obligations and may renege from paying the principal and interest due. Even for the typical high-grade borrower, this risk is there and even though it may be small, they are highly significant to an organization since they can increase quickly and with little warning. Further, the margins in corporate lending are very tight, and even small miscalculations of default risks can undermine the profitability of lending. But most importantly, many lenders are themselves borrowers, with high levels of leverage and unexpected realizations of default risk have destabilized, decapitalized, and destroyed many internationally active lending institutions (Charitou et al., 2002).

In the post Enron-Andersen debacle era, there has been widespread debate among various stakeholders in the quest to identify firms likely to go bankrupt and/or become financially distressed (Gerald, 2002). This is because the economic cost of business failure is large and evidence shows that the market value of the distressed firm decline substantially as well affecting suppliers of capital, creditors, management and employees. Further, the auditors will face the threat of a potential law suits if they fail to provide early warning signals about failing firms through the issuance of qualified audit opinion Boritz (1991). The factors that lead businesses to failure vary. Many economists attribute the phenomenon to high interest rates, recession-squeezed profits and heavy debt burdens. Furthermore, industry-specific characteristics, such as government regulation and the nature of operations, can contribute to a firm's financial distress (Wang and Deng, 2006). Studies of patterns of business failure in the UK, US, Canada and Australia found that small, private and newly founded companies with ineffective control procedures and poor cash flow planning are more vulnerable to financial distress than large well-established public firms. As a result, there is need for development of a model that will predict signs of corporate failure promptly and accurately.

Several statistical methods have been developed to predict corporate failures. The statistical technique such has those adopted by Beaver (1966) as noted by Appiah and Abor (2010) begs the question of dependence on a single ratio rather than taking a holistic view of possible complex factors that may indicate future bankruptcy. Zavgren (1993) argues that UDA creates inconsistent signals since different variables could give conflicting forecast. Therefore, alternatives that guarantee consistency are imperative. Altman (1968) has been reviewed by many scholars and proved to provide a better predictor of corporate failure.

In Altman's models, the highest contributor of corporate failure was the profitability ratio, earnings before interest and taxes/total assets, whilst the least was working capital/total assets. Altman (1968) argues that the profitability ratios contribution is not surprising, considering that the incidence of profitable firms' failure is almost nil.

1.1.1 Corporate Failure

Financial failure may take the form of bankruptcy or insolvency, Insolvency refers to where a firm is unable to meet its current obligations as and when they fall due this happens when the current liabilities exceed the current assets. Bankruptcy on the other hand refers to where the totals liabilities exceed the fair value of assets. Financial statements are normally used to gauge the performance of the firm and its management. The financial statements commonly used are profit and loss statement, balance sheet and cash flow statements. From the financial statements, various ratios can be calculated to assess the current performance and future prospects of the concerned firm. Some of the ratios used include current ratio, quick ratio, and working capital to total debt, total debt to total assets, profit margin to sales and return on total assets (Ahn, 2000).

Perhaps the best way to avoid failure is to examine the numerous explanations for business failure. Many writers and articles have focused on identifying reasons for failure as a remedy for prevention. Studies carried out by Altman (2003) used financial ratios to predict occurrence of bankruptcy and he was able to predict 94% occurrence correctly, one year before bankruptcy occurred and 72% two years before its actual occurrence.

Significant ratios identified by Altman with regard to bankruptcy prediction were working capital over total assets, retained earnings over total assets, earnings before interest and taxes over total assets, market value of equity over book value of total liabilities and sales over total assets.

1.1.2 Corporate Failure Prediction Models

The use of cash flow analysis towards a bankruptcy prediction of a firm has been augmented by a study carried out by Terry Ward and Benjamin Foster. These two authors compared the trends in the various components of a cash flow statement - operating cash flow, investing cash flow and financing cash flow. The authors found out that healthy companies have a tendency towards comparatively stable association amongst the three components of a cash flow: operating, investing and financing activities. Altman (1981), Multivariate discriminant analysis (MDA) is a statistical technique used to classify an observation into one of several a *priori* groupings dependent upon the observation's individual characteristics. It is used primarily to classify and/or make predictions in problems where the dependent variable appears in qualitative form, for example, male or female, bankrupt or non-bankrupt. Therefore, the first step is to establish explicit group classifications. Some analysts refer to discriminant analysis as "multiple" only when the number of groups exceeds two. After the groups are established, data are collected for the objects in the groups; MDA in its most simple form attempts to derive a linear combination of these characteristics which "best" discriminates between the groups.

The neural computing is yet another model that has generated considerable research interest and has been applied in various areas, including the prediction of corporate bankruptcy or financial distress. Neural computing is a computer system that consists of a network of interconnected units called artificial neurons (AN). Artificial neurons are organized in layers inside the network. The first layer is the input layer, and the last is the output layer. Hidden layers exist between the input and output layers, and there can be several hidden layers for complex applications

Prior to the development of quantitative measures of company performance, agencies were established to supply a qualitative type of information assessing the credit-worthiness of particular merchants. One of the classic works in the area of ratio analysis and bankruptcy classification was performed by Beaver. According to Beaver (1967) a number of indicators could discriminate between matched samples of failed and non-failed firms for as long as five years prior to failure. The study implies a definite potential of ratios as predictors of bankruptcy. In general, ratios measuring profitability, liquidity, and solvency prevailed as the most significant indicators. However, the order of their importance is not clear since almost every study cited a different ratio as being the most effective indication of impending problems.

1.1.3 Insurance Industry in Kenya

The insurance industry is governed by the Insurance Act and regulated by the Insurance Regulatory Authority. According to Insurance regulatory Authority annual report (2010) there were 43 insurance companies and 2 locally incorporated reinsurance companies licensed to operate in Kenya. Of the licensed insurance companies, 20 were general insurers, 7 long term insurers and 15 were composite (both life and general) insurers. In addition, there were 201 licensed brokers, 21 medical insurance providers (MIPS), 2,665 insurance agents, 23 loss adjusters, 1 claims settling agent, 8 risk managers, 213 loss assessors/investigators and 8 risk managers in 2007.

Insurance industry in Kenya is faced by several challenges that make their operation in the Kenyan market difficult. These challenges are dependent on the people, the status of the market, laws governing insurance in Kenya and the lack of proper information about insurance.

The Kenyan people don't have enough trust in the insurance business mainly due to the number of unpaid claims that remain unpaid in the market. Many claims have not been paid due to prolonged investigations to the point that, rather than other insured's recommending insurance to their friends, they end up discouraging them. Most of those who seek insurance always do so in order to gain the benefit of tax reduction that comes with the package. The Kenyan market is also a young market that is still not well versed with the diversity of the insurance industry because many people are not used to paying premiums in order to alleviate the risks. Most Kenyans therefore consider these rates high and therefore they don't seek insurance. This has been bad for business in the industry as most insurance companies cannot meet their budget and pay claims (IRA Report, 2010)

Mismanagement of insurance companies is also a notorious factor that hampers insurance industries in Kenya. Some insurance companies lack proper management due to lack of transparency, which has led to customers losing their money in the process and thus making the public lose trust in the industry. Incompetent management could lead to unrealistically low premiums that make insurance affordable yet not payable. Incompetency is also found in the relay of wrong messages to the public by insurance agents who are often unqualified. Laws set by parliament to govern the insurance industry have also sometimes failed to meet the unique needs of the third world market. When insurance companies are forced to pay large amounts of money for a license is a burden that passed to the public thus premium, rates are also affected. Lack of proper research in decision making, especially as to insurability of risks and setting rates and premiums accordingly (IRA Report, 2010)

1.2 Statement of the Problem

The prediction of an organizations chance of failing is an important exercise for most organizational stakeholders. As a result the need for reliable empirical models that predict corporate failure promptly and accurately is imperative to enable the stakeholders concerned to take either preventive or corrective action (Fauzias and Chin, 2002).

The economic cost of business failures is significant; evidence shows that the market value of the distressed firms declines substantially prior to their ultimate collapse and therefore if an organizational failure could be detected early, it would be possible to minimize failure associated cost by undertaking such actions as shareholders withdrawing their investment, consumer looking for alternative markets, the managers making turn around strategies before it's too late.

The Kenyan insurance industry has been playing an important role in the national economy and being an active player in making good losses incurred by both individuals and corporate entities. The industry has registered a moderate growth rate of 18 % over the last five years and from 47companies that operated in the year 2000, the industry has currently 47 companies in operations. Despite what can be termed as a good industry performance over the period, the sector has also experienced the collapse of some of the players. Some of the companies that have collapsed over the last 15 years include United insurance company, now under statutory management, Kenya National Assurance Company, Access, Stallion, Lake star and Liberty Insurance Co Ltd. With their collapse, billions of shillings in cash belonging to policy holders, pension schemes and life funds are lost. This therefore begs the question of whether insurance companies are disclosing enough information to enable investors make informed decisions.

Several studies have been undertaken locally and internationally on the issue of predicting corporate failure. Keige (1991) undertook a study on business failure prediction using discriminant analysis model. However, he observed that the discriminant model adopted is not free from defects because it largely depends on some restrictive assumptions such as linearity, normality and independence amongst input variables. Kiragu (1993) on his part researched on the prediction of corporate failure using price adjusted accounting data while Kogi (2003) researched on the analysis of discriminant corporate failure prediction model based on stability of financial ratios. Odipo and Sitati (2000) did a study on the evaluation of applicability of Altman Revised model in prediction of financial distress "a case of companies quoted in the Nairobi Securities exchange." Among their conclusions was that corporate failure models derived in one country is not necessarily applicable in another country or sector.

Grice and Dugan (2001) conducted a study to evaluate the Zmijewski (1984) models and found that the models are sensitive to time periods; whereby, accuracy of the models decreased when applied to different periods of the original models. From the above studies, all studies have attempted to test the validity of already existing models in different set up without necessarily attempting to localize the model to particular environment. It is on the basis of this gap that the current study will wish to compare the results of failure prediction by Altman model (1968) as well as results from predicting the failure rate using particular financial ratio.

1.3 Objectives of the study

The purpose of this study was to assess the suitability of Altman's bankruptcy prediction model in analyzing the corporate health of Insurance companies in Kenya. The objectives of the study were to:

i. To investigate whether the model is useful in predicting corporate failure in the local Insurance companies.

ii. To test the applicability of Particular financial ratios as alternative to Altman's model in predicting corporate failure in the insurance companies in Kenya.

1.4 Significance of the study

The understanding of a model in predicting corporate failure will help policy makers governments and other stakeholders to design targeted policies and programs that will actively stimulate the growth and sustainability of the insurance companies in the country, as well as helping policy makers to support, encourage, and promote the establishment of insurance companies. Regulatory bodies such as Association of Kenya Insurance, Capital Markets Authority and Kenya Revenue Authority will use findings of the study to improve the framework for regulation.

The study findings will benefit management and staff of insurance firms who will gain insight into how their institutions can effectively predict the risk of default and bankruptcy and as a result of the same put in place effective policies to mitigate against the risk. This study will also offer an understanding on the importance of maintaining an optimal level of balance sheet variables to minimize the bankruptcy risk in a firm.

This study will also create a monograph which could be replicated in other sectors of the economy. Most importantly, this research will contribute to the literature on the prediction of corporate failure and it is hoped that the findings will be valuable to academicians, who may find useful research gaps that may stimulate interest in further research in future and recommendations will be made on possible areas for future studies.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

In this chapter both theoretical and empirical literature on the research subject area will be revised .Empirical studies on effects of predicting corporate failure and theory thereon discussed as they relate to the study objectives. Section 2.2 theoretical frameworks on corporate failure, Section 2.3 Bankruptcy prediction variables, section 2.4 techniques of predicting corporate failure and section 2.5 Empirical literature.

2.2 Theoretical Framework Corporate Failure

Corporate failure includes creditors' or voluntary liquidation, and appointment of receiver (Bankruptcy Yearbook and Almanac, 2001). In theory, corporate insolvency is indicated either by fall in the asset value or due to liquidity shortage and thus the organization falls in the ability to raise capital to finance project. There are many ways in which the likelihood of corporate failure may be reviewed. Whilst normative theories attempt to explain by deductive reasoning why a certain proportion of businesses might be expected to fail, positive theories attempt to explain by inductive reasoning why in practice they do fail.

These theories are usually supported by empirical results. Although the majority of bankruptcy studies were conducted in line with the positivistic paradigm, very few researchers clearly identified an underlying theory. Instead, they chose to select the potential predictor variables based on their intuition, popularity and predictive success in previous similar studies. However, the weakness that relates to the lack of theoretical analysis is mitigated to some extent by validating the model against a holdout sample from a future time period.

2.2.1 Credit Risk Theories

Credit risk theories, closely related to Basel I and Basel II accords; mostly refer to the financial firm. The proposed Basel II framework consists of three pillars: minimum capital requirements, currently set equal to 8%, according to a purposely-defined capital ratio, supervisory review of an institution's internal assessment process and capital adequacy, effective use of public disclosure to strengthen market discipline as a complement to supervisory efforts. As noted by Westgaard and Wijst (2001), credit risk is the risk that a borrower/counterparty will default. Credit risk includes all of the counterparties and reasons for which they may default on their obligations to repay. Following Basel II guidelines, in the last few years, a number of attempts have been made to develop internal assessment models to measure credit risk. A few of them have gained more respect than others including JP Morgan's CreditMetrics, Moody's KMV model, CSFP's CreditRisk+ and McKinsey's CreditPortfolio View. More importantly, with one or two exceptions, these models and risk predictions thereof have been based on either micro or macroeconomic corporate finance theories. Collectively these models may be referred as credit risk theories.

The most famous microeconomic theory is related to the theory of option pricing as suggested by Black and Scholes (1973) and later developed by Merton (1974). An option is a security that gives the holder a right to execute a transaction (to buy or sell an asset) in future at a price determined today. Options are of two types: a call option gives the right to buy, whereas the put option means the right to sell. Options are used in many instances including speculation, hedging a borrowing, capital preservation, covered call etc. A simple example is a call option on a common stock, in which the payout on the call is determined solely by the value of the stock. Excess of stock price over the strike price determines the payout to holder who will exercise the call. In the opposite case, payout will be zero and the holder will not exercise his right. Right pricing or valuation of options is important. Black and Scholes presented a complete general equilibrium theory of option pricing that constructed a valuation formula, which is based on observable variables. Both Black and Scholes and Merton recognize that their approach could be applied in developing a pricing theory for corporate liabilities in general. They determine the option value as the solution of a partial differential equation to which the price of any option must conform, subject to boundary conditions given by the form of the payout. Under this asset value option pricing approach, firms' default process is endogenously related to its capital structure. As a result, firms would default on its obligations to the bank, if the value of its assets falls below certain critical level determined by the respective credit risk model.

2.2.2 Cash Flow Theory

Cash flow theory suggests that even though cash flow from operating activities may be the most important predictor of financial distress, other net cash flows should also have incremental predictive usefulness. However, he questions why if it is so, why then have prior financial distress studies failed to show that net cash flow from investing and financing activities are useful in predicting financial distress Gilbert et al (1990). One possible explanation is that the usefulness of cash flow information is industry specific. Cash flows that are important in predicting financial distress in one industry may not be important in predicting financial distress in another industry. Since previous researchers normally match healthy and distress firms by industry and pool data across various industries, results might misleading. Strong results in one industry could offset by weak results in another industry thus showing weak statistical interference when pooled across industries (Ward, 1992).

The belief that usefulness of cash flow is industry specific is consistent with cash flow theory. Cash flow theory can be traced to the concept of financial flexibility advocated by Heath (1978). According to Heath (p-20) financial flexibility is the capacity of the firm "to control cash receipt and payment to survive a period of financial adversity". The ultimate aim of financial flexibility is to achieve a state of equilibrium in total cash flow so that available purchasing power will be equal to needs set by established limits management decisions.

The concept of financial flexibility indicates that the occurrence of certain events trigger unexpected drop in total cash flow, thus forcing a company to take corrective action to regain cash flow equilibrium.

2.2.3 Gambler's Ruin Theory

The basic idea of this theory relates with the game of a gambler, who plays with an arbitrary sum of money. Gambler would play with some probabilities of gain and loss. Game would continue until the gambler loses all his money. Theory would also talk about gambler's ultimate ruin and expected duration of the game (Morris, 1998). In context of the firm's financial distress, firm would take the place of a gambler. A firm would continue to operate until its net worth goes to zero point where it would go bankrupt. The theory assumes that firm has got some given amount of capital in cash, which would keep entering or exiting the firm on random basis depending on firm's operations. In any given period, the firm would experience either positive or negative cash flow. Over a run of periods, there is one possible composite probability that cash flow will be always negative. Such a situation would lead the firm to declare bankruptcy, as it has gone out of cash. Hence, under this approach, the firm remains solvent as long as its net worth is greater than zero. This net worth is calculated from the liquidation value of stockholders' equity (Morris, 1998) .

2.2.4 Balance Sheet Decomposition Measure Entropy theory

One way of identifying firms' financial distress could be a careful look at the changes occurring in their balance sheets. Following this procedure, the argument would tag along this guideline: "like any enterprise, firms would tend to maintain a state of equilibrium that ensures sustaining existing firms' structure". If a firm's financial statements reflect significant changes in their balance sheet composition of assets and liabilities over a reasonable period of time, it is more likely that the firms are incapable of maintaining the equilibrium state. Since these changes are likely to become uncontrollable in future, one can foresee financial distress in these firms. This economic rationale of firms' likely failure is the argument entropy theory (Dimitras et al. 1999).

2.3 Factors affecting Bankruptcy of a Firm

A number of variables have been identified that affects failure rate of an organization. These factors have been researched on and found that if an organization exhibits the said problem, the likely hood of the same organization to go under. A company is financially distressed whenever its EBITDA is less than its interest expenses. Financial leverage involves the substitution of fixed-cost debt for owner's equity in the hope of increasing equity returns. Financial leverage improves financial performance when business financial prospects are good but adversely impact on financial performance when things are going poorly. As a result, increasing the ratio of debt to equity in a company's capital structure implicitly makes the company relatively less solvent and more financially risky than a company without debt.

2.3.1 Liquidity

Using data on Japanese keiretsu and bank relationships, Hoshi et al. (1991) show that, liquidity constraints of group member firms' are weaker than those of stand-alone companies. If access to cash is less restricted within an organization, this could lead to a situation where companies belonging to a business group pay less attention to liquidity as compared to stand-alone companies, as the latter have no choice but to resort to expensive short-term financing in case of liquidity shortages. Deloof (2001) empirically confirms this for private Belgian companies. For a firm belonging to a business group, low liquidity need therefore not necessarily reflect a higher probability of failure.

For many small and newly formed businesses, liquidity is often the single most important reason for business failure. The problem arises when the money coming into the company from sales is not enough to cover the costs of production. It is important to remember that it is a case of having the money to be able to pay debts when the debts are due not simply generating enough revenue during a year to cover costs (Patrick, 2004).

2.3.2 Performance

A business group may decide to keep a subsidiary afloat, even if it incurs severe losses and has been doing so for several years. This may be an economically sound decision, based on strategic, taxation, control or other group-specific reasons. Alternatively, internal capital markets may cause "socialism" within a group or conglomerate a situation where stronger divisions subsidize weaker ones (Scharfstein and Stein, 2000). Empirical evidence of this phenomenon is reported in Claessens, Fan and Lang (2002). To reinforce this point Lamont (1997) shows that US oil companies subsidized underperforming non-oil activities during the early 1980s when profits from oil operations were extremely high. He points out that after the oil shock of 1986, subsidized nonoil investments were significantly reduced or stopped altogether. Preceding findings and arguments imply that adding information on group level performance could be useful for bankruptcy prediction purposes. Specifically, strong group performance should positively affect survival chances of subsidiaries.

Falling sales might be a sign that there might be something wrong with the product or the price or some other aspect of the marketing mix. Sometimes the fall in sales might be as a result of the competition providing a better product or service - in part the business can do something about this they have to recognize it in the first place (Moyer, 2006). Changing tastes, technology and fashion can cause demand for products to fall - the business needs to be aware of these trends. Demand might fall for other reasons not in the firm's control. It might be due to a change in the economic climate of the country. If the economy is experiencing a downturn then maybe people may not have as much money to spend on the businesses products or services. The Bank of England may have increased interest rates and this has led to people cutting back their spending (Sipika and Smith, 2002).

2.3.3 Leverage

High firm leverage may be less important for the survival chances of group member companies as compared to those of stand-alone firms. Hoshi et al. (1990) argue that the costs arising from information asymmetries at debt renegotiations are smaller within business groups. These decreased potential costs of financial distress allow group members to ex ante take on more debt, thus realizing more tax gains and avoiding relatively expensive equity issues (cf. Myers and Majluf, 1984). A coinsurance effect across activities in diversified groups could further decrease costs of debt, but according to Berger and Ofek ***(***1995), this should be of rather limited importance.

Furthermore, an intra-group optimization process may take place via the internal capital market to reduce costs at all levels (cf. Faccio et al., 2001; Bianco and Nicodano, 2002), again increasing ex ante optimal leverage. Finally, the subsidiary may also receive intra-group debt guarantees which could increase debt bearing capacity even more.

Many new businesses will have to put together a business plan to present to the bank before it receives loans or financial help. The time and effort put into these plans is crucial for success. Bad planning or poor information on which the plan is based is likely to lead to difficulties for the firm. For example, if the firm plans to sell 2,000 units per month in the first year because it used only limited market research and ends up only selling 500 per month, it will soon be in serious danger of collapse (Chiritou, 2002).

2.3.4 Size

Ceteris paribus, larger companies have a higher capacity to bear debt throughout difficult business periods and should have a lower risk of failure (Rajan and Zingales, 1995). Because of the close ties between the different group members, group size may better measure the size effect then the size of the subsidiary proper. This is empirically confirmed by, for instance, Manos and Green (2001). These authors find that the size of Indian group affiliates has no impact on their capital structure, but that group size does. Belonging to a – preferably large - business group may also have other non-quantifiable beneficial effects: the group's reputation may change perception and behavior of banks and other creditors, thus increasing access to external finance in times of need (Schiantarelli and Sembenelli, 2000).

2.3.5 Efficiency

Following Altman (1968), managerial efficiency in the bankruptcy prediction literature is often defined as sales-generating ability (proxied by a capital turnover ratio). Ceteris paribus, the more efficient a business group, the better its performance. As argued above, this may have positive effects on the survival chances of the subsidiary. Costs of production can rise for a number of reasons. There may have been wage rises, raw material prices might have increased (for example the price of oil or gas) the business might have had to spend money on meeting some new legislation or standard and so on.

In many cases, a firm can plan for such changes and is able take them into account but if the costs rise unexpectedly, this can catch a firm off guard and tip them into insolvency (Kip, 2002).

2.4 Indigenization Theories of Culture Transplantation

Scholarly conceptualization from Europe and the United States of America concerning management in Africa have tended to disparage its development, creating a binary management systems of "developed" western management theories and concepts and "underdeveloped" African management thoughts. Gbadamosi (2003) aptly notes that: "Western management concepts and writings have dominated the thinking of academics and managers in Africa for a long-time. Such writings have not shown how culture might be taken into account in managerial practice (p. 274).

Any management education programme that facilitates the entrenchment of western management theories and practices in Africa is not desirable. According to Fashoyin (2005, p.45), the desire for training "must enable the African manager to transform imported theories and concepts into acceptable cultural norms which can then be applied to management practices in Africa." This can further create the opportunity for the development of indigenous African management principles and practices, which will recognize and accommodate our cultural social, political and environmental factors.

2.4.1 Extant knowledge of management in Africa

Management as a human responsibility and a process that drives economic development and activities is as old as human civilization or history. Africa as part of the global community has existed in her own unique ways and unique cultures and managed the environment subsistent throughout history. The quiet of this environment was extensively disrupted in the 19th century when the Europeans scrambled for and partitioned Africa. This marked the beginning of colonialism in Africa where the people thought processes and cultures were altered through western “civilization” influences. African management thought was a major culprit of these western influences.

Unfortunately, despite the acknowledgement of the existence of such high-level management skills in Africa, management as practiced in Egypt was tagged “pre-scientific”, a connotation of uncivilized management practice. Even though the Egyptian management accomplishments were significant and remembered today, “they provided limited information about how to actually manage” according to Bartol and Martin (1991, p. 41). The authors went further to distinguish between management practice and management knowledge by stating: “Thus there is a major difference between practicing management well and adding to knowledge about the field of management so that others also can learn to manage” (Bartol and Martin, 1991, p. 41).

Formal treatment of the history of management theories and practices among western scholars are wont to trace their provenance to classical theories and scientific management theory or Taylorism (Youngcourt and Watrous, 2006 and Yoo, Lemak and Choi, 2006). These textbooks and publications make no reference to other great ancient civilizations in Africa like Timbuktu, Songhai, Empire of Mali, and Mapungunbwe (Diop,1987). The composite effect of colonialism and the disparagement of scholarship in management is the denial of African management system, and the continuing subjugation of African management to western management theories and practices.

2.4.2 Management Principles

Building a case for African management theories and practices requires one to understand the principles. The principles of management enhance the individual's understanding of what management entails, and also prepares him for the task of analyzing management issues and appreciating their values in society. Principles in management are considered as fundamental truths existing at a given time, and which explain the relationships that exist between two or more sets of variables. Principles are intended to guide thoughts and actions. They are developed from experience acquired through our interaction with the environment in the normal course of working, and carrying out responsibilities in organizational setting.

There are several of these principles of management in western management literature (Fayol's (1949) fourteen principles of management). The African situation is rather unfortunate since colonialism did not permit the nurturing of indigenous management principles. If these principles were developed, they would have furnished the framework for theorizing in management, within the African context. The benefits of developing African management principles would be the promotion of research in management. The principles would also help in the attainment of social objectives (Jaja and Zep-Obipi, 1992). Through the application of principles, the manager co-ordinates the efforts of individuals thereby, reaching the social attainment by summation of the various individual objectives. Principles facilitate management analysis and set the benchmark for training of managers. Osuala(2000) notes the value of management principles in helping mangers make more accurate decisions, since principles are developed from experience and can be applied. Principles enable people pass information from one generation to the next and thus avoiding waste of re-inventing the wheel.

2.4.3 Management Theories

Management theory increases managerial efficiency by providing the guidelines to help the managers solve problems in the organization. The theory also helps in crystallizing the nature of management – in terms of analyzing management job and the training of managers. Management theory formulation brings about improvement in research and management practice, leading logically to the attainment of social goals and human development.

Porth and Mccall (2001), note that, management theories emphasize the importance of an organization's ability to acquire and leverage knowledge that produces meaningful change and innovation.

A related concept to management theory that needs clarification for our purpose is organization theory. Organization theory as a discipline studies the structure and design of organization. It explains, "how organizations are actually designed and suggests the appropriate structural design to improve organizational effectiveness" (Robbins, 1983, p. 7). Organization theory is therefore the study of the structure and functioning of organizations and behaviour of social groups and individuals within them (Pugh, 1966). The central concern here is with people who are aggregated into departments and organizations - both recognizing differences in structure and behavioural differences.

Organization theory as a way thinking about organization is different from management theory. Organization theory is considered as a set of variables describing the parameters of organization. It attempts to predict the effect of certain structural arrangement on performance and behaviour (Rao & Narayana, 1998). On the other hand, management theory is interested in facts and sound principles, which prescribe what to do to achieve desired outcome in the organization (Daft, 1986). Management theory is therefore related to management practice.

2.5 Techniques of Predicting Corporate Failure

2.5.1 Traditional Ratio Analysis

The detection of company operating and financial difficulties is a subject which has been particularly amenable to analysis with financial ratios. Prior to the development of quantitative measures of company performance, agencies were established to supply a qualitative type of information assessing the credit-worthiness of particular merchants. One of the classic works in the area of ratio analysis and bankruptcy classification was performed by Beaver (1967). According to Beaver (1967) a number of indicators could discriminate between matched samples of failed and non-failed firms for as long as five years prior to failure. The study implies a definite potential of ratios as predictors of bankruptcy. In general, ratios measuring profitability, liquidity, and solvency prevailed as the most significant indicators. However, the order of their importance is not clear since almost every study cited a different ratio as being the most effective indication of impending problems.

Grunert et al.,(1997) pointed out that although these works established certain important generalizations regarding the performance and trends of particular measurements, the adaptation of the results for assessing bankruptcy potential of firms, both theoretically and practically, is questionable. In almost every case, the methodology was essentially univariate in nature and emphasis was placed on individual signals of impending problems. According to Altman (1981) ratio analysis presented in this fashion is susceptible to faulty interpretation and is potentially confusing. For instance, a firm with a poor profitability or solvency record may be regarded as a potential bankrupt. However, because of its above average liquidity, he points out that the situation may not be considered serious. The potential ambiguity as to the relative performance of several firms is clearly evident. Altman further argues that the question that will eventually have to be asked on the use of ratios in predicting corporate failure is on which ratios are most important in detecting bankruptcy potential as well as determining what weights should be attached to those selected ratios.

Altman Z-Score Model

Altman set out to combine a number of ratios and developed an insolvency prediction model - the Z–Score model. This formula was developed for public manufacturing firms and eliminated all firms with assets less than $1 million. This original model was not intended for small, non-manufacturing, or non-public companies, yet many credit granters today still use the original Z score for all types of customers. Two further prediction models were formulated by Altman (sometimes referred to as model 'A' and model 'B') to the original Z score (Altman, 1968).

Altman's 1968 model took the following form:

$$Z = 1.2A + 1.4B + 3.3C + 0.6D + 0.999E \text{……………………………..Eq.(1)}$$

When, $Z < 2.675$; then the firm is classified as "failed"

Where A = Working Capital/Total Assets

B = Retained Earnings/Total Assets

C = Earnings before Interest and Taxes/Total Assets

D = Market Value of Equity/Book Value of Total Debt

E = Sales/Total Assets

Altman's Revised Z-Score Model

Rather than simply inserting a proxy variable into an existing model to calculate the Z-Scores Altman advocated for a complete re-estimation of the model, substituting the book values of equity for the Market value in D. This resulted in a change in the coefficients and in the classification criterion and related cut-off scores. The revised Z score model took the following form:

$$Z' = 0.717T_1 + 0.847T_2 + 3.107T_3 + 0.420T_4 + 0.998T_5 \text{…………………Eq. (2)}$$

Where:

T_1 = (Current Assets-Current Liabilities) / Total Assets

T_2 = Retained Earnings / Total Assets

T_3 = Earnings before Interest and Taxes / Total Assets

T_4 = Book Value of Equity / Total Liabilities

T_5 = Sales/ Total Assets

Zones of Discrimination:

Z' > 2.9 -“Safe” Zone

1.23 < Z' < 2. 9 -“Grey” Zone

Z' < 1.23 -“Distress” Zone

X1, Working Capital/Total Assets (WC/TA).

The working capital/total assets ratio, frequently found in studies of corporate problems, is a measure of the net liquid assets of the firm relative to the total capitalization. Working capital is defined as the difference between current assets and current liabilities. Liquidity and size characteristics are explicitly considered. Ordinarily, a firm experiencing consistent operating losses will have shrinking current assets in relation to total assets and therefore the working capital ratio is valuable in predicting a firm propensity to go under. Two other liquidity ratios tested were the current ratio and the quick ratio. There were found to be less helpful and subject
to perverse trends for some failing firms.

X2, Retained Earnings/Total Assets (RE/TA).

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

The age of a firm is implicitly considered in this ratio. For example, a relatively young firm will probably show a low RE/TA ratio because it has not had time to build up its cumulative profits. Therefore, it may be argued that the young firm is somewhat discriminated against in this analysis, and its chance of being classified as bankrupt is relatively higher than that of another older firm, *ceteris paribus*.

X3, Earnings Before Interest and Taxes/Total Assets (EBIT/TA).

This ratio is a measure of the true productivity of the firm's assets, independent of any tax or leverage factors. Since a firm's ultimate existence is based on the earning power of its assets, this ratio appears to be particularly appropriate for studies dealing with corporate failure. Furthermore, insolvency in a bankrupt sense occurs when the total liabilities exceed a fair valuation of the firm's assets with value determined by the earning power of the assets. As we will show, this ratio continually outperforms other profitability measures, including cash flow.

X4, Market Value of Equity/Book Value of Total Liabilities (MVE/TL).

Equity is measured by the combined market value of all shares of stock, preferred and common, while liabilities include both current and long term. The measure shows how much the firm's assets can decline in value (measured by market value of equity plus debt) before the liabilities exceed the assets and the firm becomes insolvent. It also appears to be a more effective predictor of bankruptcy than a similar, more commonly used ratio; net worth/total debt (book values). At a later point, we will substitute the book value of net worth for the market value in order to derive a discriminant function for privately held firms (Z') and for non-manufacturers (Z"). More recent models, such as the KMV approach, are essentially based on the market value of equity and its volatility. The equity market value serves as a proxy for the firm's asset values.

X5, Sales/Total Assets (S/TA).

The capital-turnover ratio is a standard financial ratio illustrating the sales generating ability of the firm's assets. It is one measure of management's capacity in dealing with competitive conditions. This final ratio is quite important because it is the least significant ratio on an individual basis. In fact, based on the univariate statistical significance test, it would not have appeared at all. However, because of its unique relationship to other variables in the model, the sales/total assets ratio ranks second in its contribution to the overall discriminating ability of the model. Still, there is a wide variation among industries in asset turnover, and we will specify an alternative model (Z"), without X5 at a later point.

2.5.2 Discriminant Analysis

Although not as popular as regression analysis, multiple discriminant analysis (MDA) has been utilized in a variety of disciplines since its first application in the 1930's. During those earlier years, MDA was used mainly in the biological and behavioral sciences. Altman et.al. (1981) discusses discriminant analysis in-depth and reviews several financial application areas. According to Altman (1981), MDA is a statistical technique used to classify an observation into one of several a *priori* groupings dependent upon the observation's individual characteristics. It is used primarily to classify and/or make predictions in problems where the dependent variable appears in qualitative form, for example, male or female, bankrupt or non-bankrupt. Therefore, the first step is to establish explicit group classifications.

Some analysts refer to discriminant analysis as "multiple" only when the number of groups exceeds two. After the groups are established, data are collected for the objects in the groups; MDA in its most simple form attempts to derive a linear combination of these characteristics which "best" discriminates between the groups. If a particular object, for instance, a corporation, has characteristics (financial ratios) which can be quantified for all of the companies in the analysis, the MDA determines a set of discriminant coefficients. When these coefficients are applied to the actual ratios, a basis for classification into one of the mutually exclusive groupings exists. The MDA technique has the advantage of considering an entire profile of characteristics common to the relevant firms, as well as the interaction of these properties. A univariate study, on the other hand, can only consider the measurements used for group assignments one at a time.

2.5.3 Logistic Regression Analysis

There are five financial ratios that can give an indication on the likelihood of a company to going bankrupt of facing financial distress. These ratios include current asset turnover; asset turnover; day's sales in receivables; cash flow to total debt from cash flow ratio group; and total liabilities to total assets from debt ratio.

The asset turnover ratio measures the firm's efficiency at using its assets to generate sales or revenue and it has a negative correlation with the dependent variable in this study. This means that the higher the asset turnover ratio, the lower the probability of a firm going into financial distress. This is because when a company is productive in generating sales or revenue; there will be a higher level of cash inflows into the particular company, reducing the risk of falling into financial distress. The asset turnover variable is found to be a significant ratio in Altman and Lavallee's (1981).

Days sales in receivables is another significant variable, as it is reflected through the average number of days that a firm takes to collect revenue after a sale has been made. The faster revenue is collected, the faster it can be used to settle debts. As such, liquidity of the firm is higher lowering the probability of a firm to fall into financial distress. This demonstrates a positive relationship with the dependent variable; the lower the day's sales in receivables ratio, the lower the chances of corporate failure.

Cash flow to total debt ratio is negatively correlated to the probability of a firm going into financial distress. Cash flow to total debt ratio is found to be significant in Westgaard and Van der Wijst (2001). This means that the higher the ratio, the lower the probability of a firm to fall into financial distress. If a firm has more earnings than its liabilities, it will be less likely to face bankruptcy.

Total liabilities to total assets ratio is another significant financial ratio and it has a positive relationship with the probability of a firm going financially distress. The higher the ratio, the higher the probability of a firm falling into financial distress as a company with more debt than assets is more likely to fail. This is consistent with the results reported by Nur Adiana et al. (2008)

2.6 Empirical Studies

Pantalone and Platt (1987) and Graham, Lemmon and Schallheim (1998) reported on the applicability of Altman's Z score model in evaluating loan processes in the business loan industry, which is an important function of commercial banks and other financial institutions. In the loan process, the evaluation of the loan applicant's financial statements is an important link and Altman's 1968 model allowed for the integrated analysis of the many variables common to business loan evaluations. Furthermore, in his 1970 journal article, "Corporate Bankruptcy Prediction and its implications for Commercial Loan Evaluation," Altman stressed the usefulness of the MDA in evaluating loan portfolios. Laitined (1992) reported that Altman (1983) found that failure statistics show the main number of failed firms consists of small and newly founded firms. Several studies have shown that the main part of small business failures can be associated with management shortcomings consisting of either management inexperience or incompetence (Grover, 2001).

Koh and killough (1987) used stepwise discriminant analysis and come up with a historical costs model for predicting corporate failure. The model had an overall accuracy of 92.65%, the following emerged as the most important ratio, quick ratios, Retained earnings to total assets, Earning per share and Dividend per share. Odipo and Sitati (2009) used a sample of 20 firms selected from the NSE. 10 firms that continued to be listed and 10 firms that were delisted in the NSE between 1989-2008; the study revealed that Edward Altman financial distress prediction model was found to be applicable in 8 out of 10 failed firms that were analyzed which indicated a 80% successful prediction of the model. The study concluded that Edward Altman model of predicting financial failure of company is a useful tool for investors in the Kenyan market.

Keige (1991) applied the MDA in line with Alman's (1968) model on quoted companies in Kenya and observed that ratios that will be best discriminate between failing companies and successful companies appeared to differ from place to place. Further observation was that financial ratios like current ratio, fixed charge coverage, retained earnings and total assets return on total assets, return on net worth, average collection period and sales to total assets can be used success in predicting failure up to two years before it occurs. Kibandi N.I (2006) noted that multi discriminate analysis (MDA) technique can be applied in a varied number of financial ratios and yield useful results since the study revealed that it was possible to classify failing and non failing companies.

The consistency of the results on status of the companies for a period of over 5 years and in at least100% of failed and 80% of non failed companies implies that it is possible to apply MDA in developing a failure prediction model for the insurance industry in Kenya

Nyamu (2010) used a sample of 10 companies that failed or experienced financial distress in years 1999 – 2004 and 20 health companies from the same industry sector but different size and turnover levels. She used Altman motivation discriminate variable; working capital, retained earnings, earnings before interest and tax, equity as well as total assets and total book debts. She concluded that Altman's model shows and average classification results of 91% percent accuracy rate in the failed sampled companies it validates the application of the Altman's model in the hotel industry and 68% in the non failed companies which were strong compared to Altman's of 96%. The findings of the study was that that Altman model was an accurate predictor and advisable to be used in predicting failure in non-manufacturing firms in Kenya hospitality industry.

The importance of efficient and effective portfolio adjustments protocol is an area of grave concern to corporate management and common stock ownership of firms. Management has to be savvy in their selection of investments and the costs of capital. Altman's model has been proven as a useful and valuable technique for screening out undesirable investments and for recommending appropriate investment policy. Individual investors have also benefited from Altman's Z score model in determining investment selection criteria. If investors held stocks in a firm with dismal future, according to the model they should sell to avoid further prices declines (Grover, 2001).As presented Altman's original 1968 study has been expanded and proven to have utility in most firms today, specifically as mentioned in general business areas, the loan industry, small business and the investment industry. Considering these applications of Altman's 1968 study, it is prudent therefore to make application of the same to assess liquidation of Kenya's commercial and services companies, as the model has been used with success there before as aforementioned.

2.6.1 Recent Studies in Predicting of Corporate Failure

Litschutz S. and Jacobi A. (2010) Conducted a study to investigate whether it is possible to rely on two versions of the Altman Model (1968) to predict financial failure of publicly traded companies in Israel between 2000 and 2007. The findings of the study indicated that given the sample and the study term, the preferable model for predicting financial failure of Israeli companies is the Ingbar version of the Altman Model with a critical value of 1 and with the addition of the gray area. In particular, a survival index above 1 predicts a high likelihood of survival, while a lower index predicts low likelihood of survival. According to the study, the model was able to predict bankruptcy of companies with a 95% accuracy rate one year prior to bankruptcy and with an 85% accuracy rate two years prior to bankruptcy.

The study noted that the Altman Model is only a single tool in evaluating the risk of bankruptcy for Companies and therefore other information, both qualitative and quantitative, must be used to evaluate the Solvency of companies. This is done in the banking industry as part of managing and controlling credit risks. They concluded that the most important advantage of the model compared to more advanced ones is its simplicity and the low cost of its application. Using an objective, quantitative indicator represented by a single number, the credit risk can be estimated. They believed the issue to be of great importance now, in light of the significant growth in recent years in the amount of information companies include in financial statements. The model allows users to focus attention on a single number in an era when we are "flooded" with financial information, when we “cannot see the forest for the trees."

Gerantonus et al (2008). carried out a study of all firms listed in Athens exchange using Altman (1993) Z-score model and evidence from findings indicated that the model was useful in identifying financially troubled companies that may fail up to 2 years before bankruptcy, the model is useful, probably because it matches both accounting data and market value. The model predicted 54% of failure of companies one year before failure.

The results were interesting for both portfolio managers and company management. If companies have the improvement abilities to their financial position during good years in capital markets, while being unable to improve them in the long run, then Altman Z-score are useful indication to the company management to proceed to a merger with other companies, so as to preserve the company value.

Ghodrati et al (20012), carried out research study on the efficiency of Altman, Shirata , Ohlson, Zmijewsky , CA Score, Fulmer and Farajzadeh Gentitie and Mc Gkee Genetic models in terms of providing accurate prediction results, compares the efficiency and predictive results of these models with each other and determine the power of these models. In predicting the bankruptcy of these companies admitted to the stock exchange of Tehran. The results of tests the first hypothesis showed that the Zmijewsky, Springate, CA. Score, Farajzadh Genetic and Mc Gkee Genetic models used to predict financial distress are sufficiently able to predict continuation of activities of those companies admitted to the stock exchange of Tehran.

The second hypothesis was also confirmed and it was proven that those models developed by artificial intelligence technique were more capable than those developed by statistical techniques (Classical models) in terms of bankruptcy prediction.

2.6.2 Recent Prediction Models

Generally the bankruptcy prediction models can be categorized into three categories namely; statistical models, artificial intelligent expert system models (AIES) and theoretical models. Statistical models focus on symptoms of failure that is drawn mainly from the company accounts and could be univariate or multivariate in nature. Thus, they follow the classical standard modeling. The artificial intelligent expert system model is as a result of technological advancement and international advancement and heavily depends on the computer technology. A recent trend in the bankruptcy prediction models is the theoretical based model in which it focuses mostly on the qualitative causes of failure. It is drawn mainly from information that could satisfy the theoretical argument of firm failure. The method usually adopts a statistical technique to provide a quantitative support to theoretical arguments.

Under the statistical models of corporate failure, the probit model advanced by Morris (2008) is considered a recent model in which the dichotomous dependent of logit model is the logarithm of odds (probability) that an event of (fail/not fail) will occur. Such transformation of the linear probability model (LPM) is accomplished by is accomplished by replacing the LPM distribution. With a logistic distribution cumulative function of a vector of explatory variables. In application to bankruptcy, a probability of 0.5 implies an equal chance of company failure or non-failure. Therefore, where 0 indicates bankruptcy, the closer the estimate is to 1 the less the chance of the firm becoming bankrupt

Cumulative sum control chart (CUSUM) procedures are among the most powerful tools for detecting a shift in a distribution from one state to another. In the case of bankruptcy prediction, the time series behaviour of the attribute variables for each of the failed and non-failed firms is estimated by a finite order VAR model (Kahya and Theodossiou, 2009). The overall performance of the firm at any given point in time is assessed by a cumulative (dynamic) time-series performance score (a CUSUM score). As long as a firm’s time-series performance scores are positive and greater than a specific sensitivity parameter, the CUSUM score is set to zero, indicating no change in the firm's financial condition. A negative score signals a change in the firm's condition.

Neural networks (NN) (Yang et al., 1999) perform classification tasks in a way intended to emulate brain processes. The ‘‘neurons’’ are nodes with weighted interconnections that are organized in layers. Each node in the input layer is a processing element that receives a variety of input signals from source objects (information about firms, in the case of bankruptcy prediction) and converts them into a single output signal. The latter is either: accepted as a classifying decision; or re-transmitted as an input signal to other nodes (possibly including itself). Signal processing continues until a classifying decision is reached (with some probability, the firm will fail) that satisfies pre-specified criteria

Genetic algorithms (GA) (Shin and Lee, 2002) are based on the idea of genetic inheritance and Darwinian Theory of natural evolution (survival of the fittest). The genetic algorithms work as a stochastic search technique to find an optimal solution to a given problem from a large number of solutions. It executes this search process in three phases: genetic representation and initialization, selection, and genetic operation (crossover and mutation). The process continues until the actual population converges towards increasingly homogeneous strings In order to solve a classification problem like bankruptcy, researchers extract a set of rules or conditions using GAs. These conditions are associated with certain cut-off points. Based on these conditions, the model would predict whether or not a firm is likely to go bankrupt.

However studies show that the statistical techniques (MDA and Logit models in particular) have been most frequently used while the AIES approach is relatively new and that theoretical models are relatively uncommon. While predictive accuracy is observed to be generally good across all models, it also suggests that AIES and theoretical models have slightly better average predictive accuracy than statistical models; although this measured superior performance is based on a smaller number of studies. On the other hand, the consistently high predictive accuracy of MDA and Logit models and their low Type I and II error rates has been achieved in a relatively large number of studies (with smaller adjusted standard deviations), suggesting that these models may provide overall the most reliable methods of bankruptcy prediction.

2.7 Summary

The concept corporate failure has been expounded on its causes and effect on companies operations in both literature and empirical studies done on the subject area. In all, there are several models that have been developed to predict corporate failure of different firms in different organizations. The importance of coming up with an effective model to accurately predicts the rate of failure of a firm was emphasized in the studies due to the serious consequences that a failed firm will have. Examples were at the same time cited.

However, it is evident from the literature that none of the studies has been able enough to develop a corporate failure model that will assist managers to establish a failure under different operating environments or even industries. Instead the literature and studies suggest a number of corporate failure models without necessarily suggesting an applicable model for a given circumstance.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter sets to explain the research design, the population of interest, the basis of sample selection, the type of secondary data to be used, the sources of data, the techniques of analysis used and the data analysis. A multivariate model is estimated using the SPSS.

3.2 Research Design

The research design adopted was a cross-sectional study in which data was gathered over the period 2000 to 2011. As such, the causal study was undertaken in a non-contrived setting with no researcher interference. The unit of analysis was the individual insurance firms operating in country.

This study was carried out through the use of secondary data as detailed in the organization's annual reports from which the researcher obtained data for various variables included in the study. This data was then analyzed through the use of regression and correlation analysis to determine the effect and direction of the various factors identified on the level of the firms' default rate.

3.3 Population of the Study

The population of interest in this study was all the Insurance firms in Kenya that have operated between 2000 and 2011. Currently, there are 47 Insurance companies operating in Kenya (Appendix I). The reason as to why this industry is chosen is due to the availability and the reliability of the financial statements in that they are subject to the mandatory audit by internationally recognized audit firms.

3.4 Sample and Sampling Procedure

In order to obtain a representative sample from the population, a number of filters were applied. Observations of firms with anomalies such as negative values in their total assets, current assets, fixed assets, capital, depreciation or the interest paid was eliminated. In addition, only firms that had continuously operated over the period 2007 to 2011 were considered in the study. Further, observations of items from the balance sheet, and profit and loss accounts showing signs contrary to reasonable expectations were removed. Subject to the foregoing, it is intended that the study be a census survey in which all Insurance firms were studied, due to the manageable numbers involved.

3.5 Data Collection

Data will be collected from annual reports submitted to the Insurance Regulatory Authority covering the period 2007 and 2011. All companies that had continually operated over the period were included to ensure that the sampling frame was current and complete.

3.6 Variables and Variable Measurement

Regression analysis was used to analyze the data that was collected. On the basis of the sample data, the researcher estimated the value of the variable Z corresponding to a given value of variable X. The Z-score is a linear combination of four or five common business ratios, weighted by coefficients. The coefficients were estimated by identifying a set of firms which had been declared bankrupt. These are matched by sample of firms which had survived, matching being done by industry and asset size. Five measures were objectively weighted and summed up to arrive at an overall score that then becomes the basis for classification of firms into one of the a priori groupings (distressed and non-distressed).

The Z score formula:

$Z'=1.02X_1+0.14X_2+0.033X_3+0.006X_4+0.999X_5$……………….(3)

X_1 = (Current Assets - Current Liabilities) / Total Assets

X_2 = Retained Earnings / Total Assets

X_3 = Operating profit / Total Assets

X_4 = Book Value of Equity / Total Liabilities

X_5 = Net Insurance Premium / Total Assets

Z' Score Bankruptcy Model:

$Z' = X_1 + X_2 + X_3 + X_4 + X_5$

Zones of Discrimination:

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

$Z' < 1.23$ -“Distress” Zone

To complement the regression analysis, correlation analysis was carried out to find the direction of the relationship between Z and the independent variables. The Statistical Package for Social Sciences (SPSS) Version 17.0 was used to analyze the data.

CHAPTER FOUR

DATA ANALYSIS AND RESULTS INTERPRETATION

4.1 Introduction

The chapter was devoted to the testing of Altman's (1968) model to its practical prediction ability. The research objective was to determine the applicability of Altman's failure prediction models in the Insurance Companies in Kenya. The test of applicability of the model was done using a sample of 40. The estimation sample consisted of 40 firms, grouped into two, 5 failed and 35 non-failed firms. The failed firms are classified group 1 and the non-failed firms are classified as group 2. The paired sample approach was adopted, because it is simple, easily understood, and relatively manageable to the researchers.

The financial ratios developed by Altman were calculated and individual firms' Z-scores were derived and the results presented. The Altman's Z score equation was applied as follows;

$Z=1.02X_1+0.14X_2+0.033X_3+0.006X_4+0.999X_5$

Where

X1 = Working Capital/Total Assets,

X2 = Retained Earnings/Total Assets,

X3 = Earnings before Interest and Taxes/Total assets,

X4 = Market Value Equity/book value of Total Liabilities,

X5 = Sales/Total Assets, and

Z = Overall Index.

The decision rule was that: $Z < 1.23$: Bankruptcy region, for $1.23 < Z > 2.9$: Grey Zone and $Z > 2.9$: Safe zone. No sign of bankruptcy at all.

4.2 Data Analysis

The prediction results of the model to the sample of failed and non-failed companies are discussed below. The empirical results are evaluated and presented using; the sample containing only failed and non-failed companies. In the following discussions, N is used to indicate the number of sample companies. As in real world the failed proportion is smaller than the non failed companies, the failed to non failed test proportion used was 0.28 to 0.72. Z_1 refers to the Z-score one year prior to bankruptcy (to fail) while Z_5 refers to the Z-score five years prior to failure.

4.2.1 Analysis of Failed Companies

The results in Table 4.1 indicate that the model predicted accurately on the failed companies. The result for one year prior to failure was 80% while two years prior to failure was also 80%. The average accuracy result for the two years was 80%. The results show that even though the accuracy rate was lower than the original results achieved by Altman, the 80% prediction rate shows that it is convincing to say that the model was highly accurate to predict failure.

Table 4.1: Failed Companies Prediction

		Category	N	Observed proportion
Z_1	Group 1	<=2.9	4	.8
	Group 2	>2.9	1	.2
	Total		5	1.0
Z_2	Group 1	<=2.9	4	.8
	Group 2	>2.9	1	.2
	Total		5	1.0

Table 4.2: Classified result of the failed companies over the years

Sample Companies	Year 1	Year 2	Classified
BlueShield	0.550	1.344	Correctly
Standard	1.558	0.791	Correctly
Invesco	3.145	2.962	Incorrectly
United	1.184	0.674	Correctly
Lake star	0.436	0.257	Correctly

Blue shield Insurance Company Limited was one of the oldest domestically owned insurance companies in Kenya as it was established in 1982 and operated branches across Kenya. The company was in 2011 placed under statutory management by the commissioner of insurance as it was unable to meet its obligations to policy holders and creditors. The Z score predicted the company's failure as it was below the acceptable level of 2.9 in the two years before its insolvency. The causes of failure in the company was attributed to false claims perpetuated by individuals and cartels mostly from passenger service vehicles which accounted for 50% of the general business of the company.

Standard Insurance company was established in 1991, and licensed to transact all classes of insurance business both life and general business. The company was placed under statutory management over its failure to settle over Shs. 100 million in outstanding claims owed to policy holders and creditors. The Z-score predicted the company's failure in the two years before it failed as it was below the acceptable level of 2.9. The failure of the company was attributed to low insurance penetration and serious corporate governance challenges.

4.2.2 Analysis of Non-Failed Companies

Altman's Z-score classification result for non failed companies was shown in Table 4.3 while the classification of the companies over the years was shown in Table 4.4. The correct classification result for one year financial statement was 69%; and for two year financial statement was 66%; three years financial statement classification resulted at 66% while the classification for the fourth and fifth years was 67% and 68% respectively. The average accuracy rate for the five years was 67%. The increasing percentage shows the abnormality of the model in predicting non failed sample companies.

Table 4.3: Non-Failed Companies Prediction

		Category	N	Observed proportion
Z_1	Group 1	<=2.9	11	.31
	Group 2	>2.9	24	.69
	Total		35	1.00
Z_2	Group 1	<=2.9	12	.34
	Group 2	>2.9	23	.66
	Total		35	1.00
Z_3	Group 1	<=2.9	12	.34
	Group 2	>2.9	23	.66
	Total		35	1.00
Z_4	Group 1	<=2.9	12	.33
	Group 2	>2.9	24	.67
	Total		36	1.00
Z_5	Group 1	<=2.9	11	.32
	Group 2	>2.9	23	.68
	Total		34	1.00

Table 4.3 above shows the correct classification result for one year financial statement was 69%; and for two year financial statement was 66%; three years financial statement classification resulted at 66% while the classification for the fourth and fifth years was 67% and 68% respectively. The average accuracy rate for the five years was 67%. The increasing percentage shows the abnormality of the model in predicting non failed sample companies.

Table 4.4: Classification result of Non-failed companies

Sample Companies	Year 1	Year 2	Year 3	Year 4	Year 5	Classification
AIG(CHARTIS)	4.66	3.944	3.797	3.155	3.1815	Correctly
AMACO	6.285	3.623	3.767	3.211	3.166	Correctly
APA	4.096	3.532	3.246	3.221	3.106	Correctly
BRITISH AMERICAN	5.692	3.548	3.176	3.649	3.4	Correctly
CANNON	3.807	3.449	3.216	3.182	3.027	Correctly
CFC LIFE	3.687	3.984	3.44	3.349	3.133	Correctly
CONCORD	2.121	2.107	2.891	2.393	2.335	Incorrectly
COOPERATIVE	8.487	8.152	7.56	7.187	6.463	Correctly
CORPORATE	3.984	3.573	3.348	3.292	3.747	Correctly
DIRECT LINE	7.159	6.512	5.594	4.076	3.641	Correctly
EAST AFRICA-RE	3.356	3.874	3.907	3.209	3.816	Correctly
FIDELITY SHIELD	5.034	4.923	4.369	3.166	3.607	Correctly
FIRST ASSURANCE	4.413	4.118	3.668	3.122	3.676	Correctly
GATEWAY	7.811	7.459	6.808	6.163	7.661	Correctly
GEMINIA	4.567	3.086	3.258	3.085	3.242	Correctly
GENERAL ACCIDENT	2.016	2.601	2.362	2.136	2.547	Incorrectly
HERITAGE AII	6.731	4.012	3.629	3.133	3.536	Correctly
I.C.E.A	5.667	5.179	3.891	3.969	4.631	Correctly
INTRA AFRICA	2.201	2.816	2.779	2.754	2.822	Incorrectly
JUBILEE	4.32	4.356	3.528	3.131	3.616	Correctly
KENINDIA	6.612	3.119	3.364	3.108	3.514	Correctly
KENYA ORIENT	3.946	3.723	3.91	3.495	3.907	Correctly
KENYA RE	-	-	-	3.108	3.452	Correctly
KENYA ALLIANCE	2.317	1.814	1.793	1.984	1.316	Incorrectly
LION OF KENYA	1.481	1.602	1.431	1.394	1.468	Incorrectly
MADISON	1.925	2.019	2.178	2.178	2.141	Correctly
MERCANTILE	4.128	4.109	3.777	3.114	-	Correctly
MAYFAIR	3.902	4.101	3.658	3.151	2.952	Correctly
OCCIDENTAL	3.757	3.076	3.035	3.108	3.305	Correctly
PACIS	2.896	2.743	2.598	2.813	2.518	Incorrectly
PHOENIX OF E.A	2.36	1.041	1.287	1.547	2.263	Incorrectly
REAL	2.691	1.895	1.778	1.624	-	Incorrectly
TAUSI	1.712	2.823	2.678	2.852	2.857	Incorrectly
THE MONARCH	1.563	1.781	2.714	2.626	2.478	Correctly
TRIDENT	1.908	2.118	1.908	1.977	1.402	Incorrectly
UAP PROVISIONAL	3.043	3.993	3.526	3.475	3.148	Correctly

CFC Life Insurance Company was incorporated as Kenya American Company in 1964 and in 2004 it was bought by CFC bank and the CFC life assurance company ltd was formed. In 2004 the bank merged with Stanbic Bank into CFC life Stanbic Bank holdings. The Z-score for the company was well above the acceptable level of 2.9. The model predicted correctly the solvency of the company.

Chartis Kenya formerly AIG Kenya insurance has been in operation for the last 37 years and a leading general insurance company in Kenya. Chartis has subsidiaries in major countries in the world. The Z-score for the company was well above the acceptable level of 2.9. The score predicted the solvency level of the company correctly.

APA Insurance Company was incorporated in 2003 from the merger of pan African general insurance company limited and Apollo insurance company. The Z-score for the company was well above the acceptable level of 2.9. The score predicted the solvency level of the company correctly.

British American Company was incorporated in1965 and in 2004 the company did a share swap whereby the ownership of British American Company moved to British American Investment Company. The company had a gross premium of 4.3 billion in 2010 and total assets of 25.4 billion and investment of over 4.7 billion in 2010. The Z-score for the company for the last five years has been above the acceptable level of 2.9. The model predicted correctly the solvency of the company.

Cannon insurance Co was incorporated in 1964 and the company has grown and in 2010 the company had total gross asset in excess of 3.4 billion and cross premium income of 937 million in 2010. The Z-score for the company was well above the acceptable level of 2.9. The score predicted the solvency level of the company correctly.

The cooperative insurance company of Kenya was established in 1978 and the company underwrites both life and general insurance business and was listed in the NSE in mid-2012 by introduction. The company made a profit of 605 million in 2010 and gross premium of 4.6 billion and total asset base of 3.5 billion. The Z-score for the company was well above the acceptable level of 2.9. The score predicted the solvency level of the company correctly.

Jubilee Insurance Company was incorporated in 1937 and is wholly owned subsidiary of Jubilee holdings limited. The company is the largest composite insurance company in Kenya and East Africa and it has eight branches across the region and listed in the Nairobi security exchange. The company has issued share capital of Kenya shillings 225 million. The company in 2010 reported a gross premium of 11.5 billion and a pretax profit of 2.053 billion. The Z-score for the company was well above the acceptable level of 2.9. The score predicted the solvency level of the company correctly.

East African Re-Insurance Company was incorporated in 1993 and has paid up share capital of 750 million. The Z-score for the company was well above the acceptable level of 2.9. The score predicted the solvency level of the company correctly.

Kenindia Assurance Company of Kenya is the largest non-life insurance company and has 13 branches in Kenya and subsidiary company abroad. The company was formed in 1979 by the merger of new India assurance, oriental insurance, united India insurance and the life insurance corporation of India. The company has a market share of above 8% in the nonlife business in Kenya. The Z-score for the company was well above the acceptable level of 2.9. The score predicted the solvency level of the company correctly.

4.3 Comparing Failed and Non failed Companies

Altman’s model binomial test classification results of failed and non failed companies indicate that the accuracy rates were lower than the Altman’s 95% classification accuracy rate, using the original sample reported by Altman (1968). The predictive ability of the failed companies and non-failed was acceptable. The ability to predict failed and non failed companies validates the general applicability of the model in the insurance industry in Kenya.

4.3.1 Predictive result one year prior to Failure

The findings in Table 4.5 shows the results using data compiled for one year prior to bankruptcy for the failed companies and one year financial statements for non failed companies. The model classification accuracy was 70% of the total sample. The measure of success of the model in classifying the firms is calculated by adding the correctly classified sample companies (4+24) divided by total number of sample companies (40). The type I error which was the prediction of failed companies as non failed was 3%, while the type II error when companies which are actually non failed are predicted as failed was 28%. This implies that companies can be wrongly predicted with financial problems while actually it is the opposite. Mismanagement of the insurance companies is a factor that hampers insurance industry in Kenya as some insurance companies lack proper management due to lack of transparency, which has led to unrealistically low premiums that make insurance affordable yet not payable. The accurate percentage of type I error was 97% and that of type II error was 80%.

Table 4.5: Predictive result one year prior to failure

Actual	Predicted		Total
	Failed	Non Failed	
Failed	4	1	5
Non-Failed	11	24	35

4.3.2 Predictive result for two years prior to failure

The results in Table 4.6 for classification results of the model for companies using data compiled two years prior to bankruptcy indicate that the classification accuracy was 68%. The type II error was at 30% an indication that there is a risk that the model could classify a company incorrectly.

Table 4.6: Predictive result for two years prior to failure

Actual	Predicted		Total
	Failed	**Non-Failed**	
Failed	4	1	5
Non Failed	12	23	35

4.3.3 Z-Score long range predictive results

The long range predictive accuracy of the model showed in Table 4.7 depicts the Altman model Z-score predictive results. The table includes the results for years one and two which was already calculated to support the comparison of the results for the year's three to five. The results achieved for three to five years was 66%, 67% and 66% respectively are better than the Altman's original result for three, four and five years which was 48%, 29% and 36% respectively (Altman, 1993:195). The conclusion that can be drawn from the results was that though the Altman model was quite good in prediction of failure using three to five years financial results, it is equally good in the first two years prior to failure thus validating the predictive ability of the model.

Table 4.7: Z-Score long range predictive results

		Hits			Misses			Percent
Year	N	Failed	Nonfailed	Total	Failed	Nonfailed	Total	Correct
1	40	4	24	28	1	11	12	70%
2	40	4	23	27	1	12	13	68%
3	35	0	23	23	0	12	35	66%
4	36	0	24	24	0	12	36	67%
5	35	0	23	23	0	11	35	66%

4.4 Discussion

Financial failure of an organization can take the form of bankruptcy or insolvency. The performance of the firm however can be determined through calculation of ratios to assess the current and future prospects of the firm. The ratios used include current ratio, quick ratio, and working capital to total debt, total debt to total assets, profit margin to sales and return on total assets (Ahn, 2000). The insurance industry in Kenya is faced by several challenges that make operations in Kenya market difficult. The challenges are dependent on the people, the status of the market and laws governing insurance industry in Kenya. The Kenya market is young and still not well versed with the diversity of the insurance industry because many people are not used to paying premiums in order to alleviate the risks. Most Kenyans therefore consider these rates high and therefore do not seek insurance. This has been bad for business in the industry as most insurance companies are constrained in meeting their budgets and paying claims.

The results of the study which was achieved through the use of financial ratios (working capital over total assets, retained earnings over total assets, earnings before interest and taxes over total assets, market value of equity over book value of total liabilities and sales over total assets) indicate that there was 80% accuracy of failure of the companies in year one before failure while year two before failure yielded 80% correctly. The results were consistent with Altman (2003) who used financial ratios to predict occurrence of bankruptcy and he was able to predict 94% occurrence correctly, one year before bankruptcy occurred and 72% two years before its actual occurrence.

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter presents a summary of the key findings of the study as well as the conclusions, limitations of the study, and recommendations for further research.

5.2 Summary

The study aimed at establishing the applicability of Altman's failure prediction models in the Insurance Companies in Kenya and towards the realization of the research objective regression analysis was undertaken.

The study found out that the Z-score for the failed companies indicate that of the five companies which had failed, four of the companies two years prior to failing confirmed that they were insolvent. The Altman model's bankruptcy classification accuracy ranges from over 70 percent one period prior to bankruptcy to 66% five annual reporting periods. The type I error was constant for the two years prior to the companies failing due to equal number of companies that failed during the period while there was a slight increase in type II error from 28% to 30%. It is important that error I accuracy is high as this is where the most damage can be caused by companies becoming insolvent. The misclassification is critical in the analysis as this could classify a company as being on the right path and not potentially insolvent.

The results indicate that the Of the 11 and in another instant 12 companies misclassified firms in this secondary sample, 10 have Z-Scores between 1.81 and 2.67, which indicates that although they are classified as bankrupt, the prediction of their bankruptcy is not as definite as it is for the vast majority in the initial sample of bankrupt firms.

5.3 Conclusion

The Altman financial distress prediction model was found to be accurate prediction on 4 out of the 5 failed firms resulting in 80% validity for the model. On 10 non-failed firms, 9 of them proved that Edward Altman's financial distress prediction model was correct a 90% validity of the model. This result is convincing that the Altman model was reasonably accurate to classify the failed companies correctly over five years. In the one year prior to failure, the Altman model was 70% accurate to classify sampled companies correctly, with type I and type II errors of 3% and 28% respectively and these indicate that the Altman model was significantly strong to classify the sampled companies correctly as failed and non failed.

The classification accuracy two years prior to failure was 68% while for the third, fourth and fifth year was 66%, 67% and 66% respectively. Although the predictive accuracy of the Altman model was decreasing on two and three years prior to failure, the strong result of one year prior to failure validates the predictive ability of the model. The findings indicate that the overall accuracy rate of Altman model was reduced when used on the insurance industry. Although the results are good, the fine-tuning of Altman's Z-score model was of benefit as it was an accurate predictor and thus can be applied in the insurance industry.

5.4 Limitation of the Study

The study was undertaken using the financial results for the companies before the introduction of new laws that that include increase in the minimum capital requirements for insurers, increase in the solvency margin for long term insurers, introduction of ‘cash and carry’ rules which will require that insurers shall assume risk upon receipt of the premium, relaxation of investment limits for general insurers, introduction of penalties on late settled claims, change in the rules on taxation of long term insurance business and taxation of dividend income earned by a financial institution. This would in turn have changed the operating environment of the firms as the firms have to adhere to the new laws.

The study further did not differentiate between the sizes of the insurance companies. This is because the insurance firms which are quoted at the securities market will be accessible to a variety of capital sourcing in order to finance its operations. At the same time the duration the company has been in operation would influence how it operates in the market as they are expected to have put in place mechanisms that would ensure that they compete effectively unlike a new company that has not been in existence for a longer period.

The competition in the industry and the new legislations has given rise to mergers and acquisitions and these would help companies to develop complementary earnings streams, realize opportunities for cost-saving synergies and strengthen their presence in the regional markets. However, these would impact on the true position of the company as there is pooling of resources by the companies.

5.5 Recommendation

This study makes a few recommendations that have policy implications for decision makers.

The study found out that the model predicted an 80% failure of the companies which had failed and it is recommended that the creditors and investors should apply the model to ascertain the financial viability of the insurance firms before undertaking an insurance cover with the insurance firms in order to safeguard itself from losses occasioned by inability of the companies to meet the claims due from them.

The ratios calculated in order to predict the failure of the companies may not give the true picture of the company and it is recommended that other indicators that affect the industry are included in the model so that it can give true results of the company and avoid scenarios where there is conflicting outcomes.

The study confined itself to insurance companies and when already the government has put in place measures to streamline the industry as a result of insolvency of a number of insurance firms. It is recommended that a study be undertaken after the full implementation of the sector reforms so as to establish the effect of the reforms on the solvency of the firms. Another study be undertaken also before the introduction of the reforms in the sector so that a comparison can be made.

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APPENDIX 1: LIST OF REGISTERED INSURANCE COMPANIES

1. African Merchant Assurance Company Ltd.
2. Chartis Kenya Insurance Co. Ltd
3. APA Insurance Co. Ltd
4. Apollo Life Insurance Company Ltd
5. Blue Shield Insurance Company Ltd
6. British American Insurance Co (k) Ltd
7. Cannon Assurance (K) Ltd
8. Consol Insurance Co. Ltd
9. CFC Life Assurance Co Ltd
10. Co-operative Insurance Co Ltd
11. Corporate Insurance Co Ltd
12. Direct line Assurance Co Ltd
13. East African Re Insurance Co Ltd
14. Fidelity Shield Insurance Company Ltd
15. First Assurance Co Ltd
16. Gateway Insurance Co
17. Gemini Insurance Co. Ltd
18. General Accident Insurance
19. Heritage A.I.I Insurance Co Ltd
20. Insurance Company of East Africa
21. Intro Africa Assurance Co Ltd
22. INVESCO Assurance Co Ltd
23. Jubilee Insurance Co Ltd
24. Kenindia Assurance Co Ltd
25. Kenya National Assurance (2001) Ltd
26. Kenya Orient Insurance Co Ltd
27. Kenya Reinsurance Corporation Ltd
28. Kenya Alliance Insurance Co Ltd
29. Lion of Kenya Insurance Co.
30. Madison Insurance co (k)Ltd

31. Mayfair Insurance Ltd
32. Mercantile Insurance Co Ltd
33. Metropolitan Life Insurance (k) Co Ltd
34. Accidental Insurance Co Ltd
35. Old mutual insurance Co Ltd
36. Pacis Insurance Co Ltd
37. Pan African Life Insurance Ltd
38. Phoenix of East African Insurance Ltd
39. Pioneer Assurance Co Ltd
40. Real Insurance company of East Africa
41. Shield Assurance Company Ltd
42. Standards Assurance Ltd
43. Tausi Insurance Co Ltd
44. The Monarch Insurance Co Ltd
45. Trident Insurance Co Ltd
46. Trinity Life Assurance Co Ltd
47. UAP Life Insurance Co Ltd
48. UAP Insurance Co Ltd
49. United Insurance Co Ltd
50. Xplico Insurance Company Ltd
51. Zep- Re (PTA) Reinsurance company Ltd
52. African Reinsurance corporation

APPENDIX 2: OTHER STUDIES IN CORPORATE FAILURE

	AUTHOR YEAR	TITLE OF STUDY	OBJECTIVES	METHODOLOGY
1	NYAMU S.N(2010)	Predicting business failure in the hotel industry; The case of Kenya Tourist Development Corporations Hotels	To test the practical application of Altman's bankruptcy prediction model in predicting failure in Kenyan hotel industry To investigate whether the model is useful in predicting bankruptcy for non-manufacturing firms, such as Hotels	The researcher used the entire population of 30 Hotel companies whereby 10 failed and 30 were classified as non-failed between 1999-2003 The researcher applied Multi-Discriminant Analysis of five key ratios. The accuracy rate was 75% one year prior to failure and 73% 5 years to failure. **Knowledge Gap** The model was used in the hotel industry using the original Altman's (1968) model, then can be applied in another industry and give the same results.
2	NGANGA I.K(2006)	Failure prediction of insurance companies of Kenya	To ascertain indicators of companies exhibiting characteristics of company failure To develop a business failure prediction model for companies in Kenya	The period of study was 1989-2004 The researcher applied Multi-Discriminant Analysis. Input variables 6 ratios in the general insurance companies Population of study were 43 Registered insurance companies The Results of study, The model indicated 100% correct classification for failed companies and 80% of non-

				failed companies. **Knowledge Gap** There is need for indigenous variable that reflect the economic factors relevant to the Kenyan economy
3	Awino, F.O (2005)	Estimating firms book to market ratio using Altman's Z-score ratios: A study of firms at NSE	To find and establish the extent to which Altman's Z-score ratios are useful in grouping firms at the NSE into high and low book to market ratios	The study sample 32 firms out 49 listed firms in the NSE between 1996-2003. The researcher applied Multi-Discriminant Analysis. The findings showed that Altman's model can predicted 78.1% in grouping firms into low and high book values. **Knowledge Gap** To confirm if the Altman's model is applicable in the insurance industry and the indigenization of the variables in the model
4	Odipo M.K and Sitati A. (2000)	Evaluation of applicability of Altman's revised model in prediction of financial distress: a case study of companies quoted in the Nairobi stock exchange	To assess whether Altman's financial distress prediction model can be useful predicting business failure in Kenya	The population of study was composed of all the firms listed in NSE between 1989-2000. The study selected 10 firms for the study (10 delisted and 10 continuing firms). The study results indicated 80% successful prediction model for non-failed firms and 90% for non-failed firms **Knowledge Gap** The study analyze the difference in the results using the original Altman's study and own variables derived from local firms operating in the Kenya

				economy between 2005-2011
5	Keige P.N(1991)	Business failure prediction using discriminate analysis	To develop a discriminant function for use in predicting failure in Kenya	The study selected 20 companies between 1980-1990 Seven input variables were selected in the study. The researcher applied Multi-Discriminant Analysis. The study yielded an overall classification 95% in the first year prior failure **Knowledge Gap** The study tested the applicability of other ratios that were not by Keige's(1991) and to find out whether the Altman model is applicable to the insurance industry.

Appendix 3

x5	1.145832	0.882744	0.950873	0.49483	0
Z	1.343507	0.790953	3.117	0.673653	0.257418

Non failed

	AIG	AMACO	APA	BRITISH AMERICAN	CANNON	CFC LIFE	CONCORD	COOPERATIVE	CORPORATE	DIRECT LINE	EAST AFRICA-RE	FIDELITY SHIELD	FIRST ASSU
2006													
X1	0.2760	0.2399179	0.222284	0.3610817	0.1815858	0.1154564	0.6246081	0.5478366	0.1144381	0.369294	0.4848062	0.299317	0.22
X2	0.100117	0.081224	0.376043	0.221705	0.199907	0.034887	0.012454	0.036551	0.063691	0	0.096959	0	
X3	0.5945587	0.374197	0.257629	0.417364	0.311904	0.136995	0.665306	0.677414	0.444168	0.694055	0.707459	0.383437	0.4
X4	7.5031391	27.122781	6.0834651	10.173316	9.483707	12.022121	4.8406616	1.4812045	1.0759685	4.7480009	1.3785403	1.5962644	2.16
X5	0.1185863	0.208223	0.132686	0.123098	0.125632	0.073894	0.433251	0.258448	0.360018	0.28807	0.311368	0.176054	0.1
Z	4.66	6.285	4.096	5.692	3.807	3.687	2.121	8.487	3.984	7.159	3.356	5.034	
2007													
X1	0.083136	0.330612	0.322682	0.303676	0.215858	0.152649	0.599746	0.614792	0.287894	0.420425	0.548689	0.277611	0
X2	0.044732	0.105026	0.263976	0.2989	0.172022	0.068293	0.042434	0	0.067962	0	0.118218	0	
X3	0.493162	0.513784	0.369104	0.33409	0.348104	0.237726	0.642603	0.751105	0.453527	0.732605	0.787186	0.370183	0.4
X4	15.456	14.44593	5.162765	19.135	9.063465	29.13165	6.246148	2.722763	3.265093	7.532486	0.545632	3.327602	1.5
X5	0.100026	0.220244	0.156786	0.108621	0.160307	0.059233	0.406203	0.147171	0.244429	0.014263	0.284295	0.177831	0.1
Z	3.944	3.623	3.532	3.548	3.449	3.984	2.107	8.152	3.573	6.512	3.874	4.923	
2008													
X1	0.218975	0.438729	0.373721	0.473682	0.302859	0.130182	0.555094	0.581629	0.273055	0.782527	0.554981	0.238229	0.5
X2	0.064762	0.143337	0.289177	0.221903	0.047238	-0.21319	0.066969	0	0.0426	0	0.156704	0	

X3	0.544435	0.562932	0.437616	0.481507	0.410951	0.216747	0.598343	0.656194	0.409006	0.80029	0.742157	0.326175	0
X4	6.939677	19.8578	3.625453	93.3841	7.871966	28.64271	2.252669	2.333904	3.084842	16.61382	1.401846	2.28654	0.9
X5	0.087794	0.161661	0.142644	0.086025	0.113802	0.062124	0.383164	0.12722	0.232178	0.012551	0.28662	0.169628	0.1
Z	3.797	3.767	3.246	3.176	3.216	3.44	2.891	7.56	3.348	5.594	3.907	4.369	
2009													
X1	6.89E-07	2.79E-06	1.04E-06	2.48E-05	3.06E-06	8.79E-06	2.27E-05	6.27E-06	5.59E-06	1.53E-05	0.001746	2.06E-06	1.
X2	0.072845	0.130858	0.264115	0.177078	0.102128	-0.87364	0.036532	0.121964	0.117438	0	188.5542	0	
X3	0.456587	0.553035	0.383337	0.354606	0.431362	0.499203	0.571094	0.624169	0.397695	0.6851	717.1789	0.297104	0.4
X4	5.846994	11.10904	5.603873	90.96634	9.217832	25.71781	3.425272	3.870932	1.40481	6.677227	1.21696	1.851412	0.6
X5	0.095033	0.108367	0.138651	0.06666	0.098754	0.057069	0.348973	0.126623	0.254662	0.013707	271.1101	0.145407	0.1
Z	3.155	3.211	3.221	3.649	3.182	3.105	2.393	7.187	3.292	4.076	3.209	3.166	
2010													
X1	0.039567	0.447917	0.230349	0.234374	0.309186	0.135389	0.53594	0.461509	0.454328	0.55371	0.607528	0.182191	0.5
X2	0.100566	0.142638	0.23134	0.202301	0.156653	-1.09894	-0.01292	0.098496	0.187066	0	0.217942	0.198107	
X3	0.406059	0.63648	0.283714	0.263967	0.369922	0.615618	0.602298	0.591144	0.473468	0.567301	0.746676	0.304554	0.6
X4	5.378493	6.837178	3.975985	15.03533	9.538204	7.336683	8.826725	0.69172	18.6544	9.579156	1.329402	1.58346	0.9
X5	0.081522	0.125558	0.765066	0.033719	0.119885	0.024757	0.318341	0.13824	0.130354	0.000413	0.133585	0.127749	0.0
Z	3.1815	3.166	3.106	3.4	3.349	3.133	2.335	6.463	3.747	3.641	3.816	3.607	

GATEWAY	GEMINIA	GENERAL ACCIDENT	HERITAGE AII	I.C.E.A	INTRA AFRICA	JUBILEE	KENINDIA	KENYA ORIENT	KENYA RE	KENYA ALLIANCE	LION OF KENYA	MADISON
0.5767137	0.3061049	0.2756815	0.5160288	0.4466229	0.4734715	0.3238271	0.4462595	0.4823806	0.3102091	0.2418557	0.4163869	0.2326722
0.055423	0.036472	0.041239	0.204647	0.25191	0.050432	0.099201	0.168009	0.035689	0.229763	0	0.162735	0.196149

0.62604	0.463205	0.277468	0.565512	0.489593	0.555298	0.439327	0.473407	0.61087	#VALUE!	0.289136	0.464045	0.538838
2.1479816	1.5474438	3.8755935	2.7223395	0.7256852	1.587604	0.8018273	1.1905096	3.0602096	0.6649063	0.9863781	0.6829482	0.4459806
0.175721	0.119508	0.087474	0.108998	0.087432	0.30882	0.081125	0.181128	0.415225	#VALUE!	0.05566	0.070819	0.268553
7.811	4.567	2.016	6.731	5.667	2.201	4.32	6.612	3.946		2.317	1.481	1.925

0.545053	0.246685	0.454453	0.275716	0.453205	0.421727	-0.06689	0.068273	0.266601	#VALUE!	-0.03672	0.030534	0.161879
0.07124	0.057618	0.133249	0.247518	0.280006	0.05805	0.128863	0.054534	0.036477	#VALUE!	0	0.154361	0.235016
0.604336	0.413627	0.484317	0.315945	0.4717	0.506321	0.077594	0.124327	0.334141	#VALUE!	0.018025	0.06172	0.266623
2.703848	2.223441	3.794137	2.03461	0.790601	20.72596	0.465505	0.872834	9.718488	0.107866	2.036677	0.461104	1.68031
0.152992	0.029241	0.097572	0.094028	0.031417	0.244198	0.096814	0.039393	0.378966	#VALUE!	0.011365	0.068891	0.227948
7.459	3.086	2.601	4.012	5.179	2.816	4.356	3.119	3.723		1.814	1.602	2.019

0.482942	0.261398	0.23376	0.460088	0.287004	0.418662	0.382467	0.289547	0.549359	#VALUE!	0.510178	0.508964	0.48031
0.137165	0.076504	0.12192	0.222371	0.325967	0.025813	0.148858	0.091329	0.011256	#VALUE!	0	0.188074	0.261559
0.530101	0.420662	0.251074	0.488597	0.352712	0.507218	0.566903	0.346643	0.652065	#VALUE!	0.547777	0.569851	0.587291
2.253828	1.113867	1.267781	3.200114	0.630647	2.647043	0.426651	1.055284	3.907776	4.955287	1.241881	0.466398	1.520473
0.138171	0.02795	0.090795	0.093217	0.035369	0.244866	0.095838	0.038123	0.303971	#VALUE!	0.011423	0.056072	0.256861
6.808	3.258	2.362	3.629	3.891	2.779	3.528	3.364	3.91		1.793	1.431	2.178

9.43E-06	2.78E-06	2.88E-06	3.44E-06	1.79E-06	6.01E-06	1.42E-06	2.65E-06	1.35E-05	1.07E-07	3.9E-06	2.03E-06	4.99E-06
0.046332	0.233524	0.108269	0.228914	0.230775	0.007361	0.167696	0.166796	0.004242	0.431289	0.142499	0.172552	0
0.604698	0.347994	0.47505	0.493831	0.39718	0.51167	0.461448	0.424317	0.659341	0.280737	0.498202	0.587232	0.721933
3.498665	1.19622	1.815948	1.744281	0.80633	2.348548	0.685577	1.137187	5.263463	0.573104	1.991344	0.650648	2.073656
0.11613	0.034045	0.094485	0.074237	0.046656	0.243702	0.088556	0.063917	0.295895	0.035312	0.024011	0.049519	0.277026
6.163	3.085	2.136	3.133	3.969	2.754	3.131	3.108	3.495	3.108	1.984	1.394	2.742

0.529422	0.192151	0.436478	0.413311	0.386424	0.491384	0.472259	0.35	0.545207	0.320361	0.32275	0.44778	0.553115
0.066408	0.058186	0.076911	0.132738	0.244638	0.048543	0.26361	0.242169	0	0.450902	0.20359	0.200708	0.140553
0.576538	0.347434	0.490822	0.458428	0.455654	0.542286	0.527355	0.409283	0.604746	0.367279	0.39539	0.512637	0.742715

4.782782	1.263599	1.371529	0.729814	0.712029	6.502232	0.516204	0.606417	6.424419	2.271819	1.536216	0.539196	1.312485
0.169313	0.019144	0.066649	0.076667	0.015341	0.257708	0.076999	0.106091	0.292362	0.036101	0.024051	0.040098	0.24169
7.661	3.242	2.547	3.536	4.631	2.822	3.616	3.514	3.907	3.452	1.316	1.468	2.141

MERCANTILE	MAYFAIR	OCCIDENTAL	PACIS	PHOENIX OF E.A	REAL	TAUSI	THE MONARCH	TRIDENT	UAP PROVINCIAL
0.7215915	0.7275043	0.4944312	0.2602509	0.1421487	0.4644468	0.7221686	0.3835056	0.726649	0.1249469
0	0	0.066401	-0.06832	0.217527	0.020761	0.002555	-0.0695	0.087793	0.186253
0.749396	0.804579	0.54133	0.397399	0.229235	0.569302	0.735953	0.514358	0.752781	0.152546
4.2127731	8.3689967	1.1355402	4.4603033	1.0713674	1.2637678	1.6752289	1.6420741	0.5953302	3.0947871
0.099688	0.082946	0.227322	0.174989	0.074003	0.189865	0.131792	0.146149	0.137704	0.043012
4.128	3.902	3.757	2.896	2.36	2.691	1.712	1.563	1.908	3.043
0.029286	-0.01101	-0.09042	-0.0626	-0.10569	-0.1325	-0.0189	-0.16787	-0.01608	-0.06294
0.153093	0	0.046253	0	0.15631	0.047199	0	-0.09155	0.092541	0.23415
0.060688	0.100714	0	0	0	0	0	0	0	0
5.464425	4.590834	3.727773	14.90151	0.986262	0.891326	3.884718	2.490537	1.510177	3.848305
0.042719	0.080588	0.145526	0.241977	0.046852	0.158563	0.01812	0	0.124076	0.020786
4.109	4.101	3.076	2.743	1.041	1.895	2.823	1.781	2.118	3.993
0.645868	0.532322	0.327749	0.384444	0.252213	0.336684	0.621092	0.664713	0.729777	
0.211558	0	0.061084	0	0.132972	0.071628	0	0	0.104393	0.220457
0.684739	0.658589	0.371554	0.444029	0.412791	0.558436	0.662677	0.737833	0.737797	0.292933
3.685051	3.802807	1.755545	6.043508	0.870244	0.410861	1.187333	2.095936	1.151291	7.2504
0.044087	0.070659	0.135101	0.155838	0.050247	0.144081	0.015915	0	0.117539	0.019658
3.777	3.658	3.035	2.598	1.287	1.778	2.678	2.714	1.908	3.526
2.31E-05	7.03E-06	8.93E-06	1.56E-05	1.54E-06	1.5E-06	8.05E-06	1.97E-05	3.51E-06	3.46E-07
0.27076	0	0.031507	0	0.166827	0.054753	0.022344	-0.12852	0.141617	0.225617

0.665551	0.688404	0.27993	0.427913	0.445838	0.569396	0.657691	0.566319	0.542678	0.389463
2.60865	3.151014	3.009976	4.867837	1.038005	0.786621	1.372461	4.271679	0.784245	4.98735
0.038091	0.077451	0.07705	0.150317	0.056655	0.131389	0.014676	0	0.05534	0.04163
3.114	3.151	3.108	2.913	1.547	1.624	2.852	2.626	1.977	3.475
#DIV/0!	0.553742	0.24158	0.323149	0.289799	#DIV/0!	0.627384	0.419503	0.28813	0.105393
#DIV/0!	0	0.006891	0	0.230856	#DIV/0!	0	-0.11519	0.141235	0.096962
#DIV/0!	0.677452	0.270179	0.390604	0.360013	#DIV/0!	0.663463	0.464846	0.374143	0.32143
#DIV/0!	2.512089	2.545887	6.033789	2.056894	#VALUE!	2.857301	8.587523	1.092176	6.5897
#DIV/0!	0.047254	0.034206	0.14028	0.022113	#DIV/0!	0.015277	0	0.06972	0.051261
	2.952	3.305	2.518	2.263		2.857	2.478	1.402	3.148