PREDICTING BUSINESS FAILURE IN THE HOTEL INDUSTRY: THE CASE OF KENYA TOURIST DEVELOPMENT CORPORATION HOTELS

PRESENTED BY: Sabina N. Nyamu

A Research Project Submitted In Partial Fulfillment of the Requirements for the Degree of Master of Business Administration (MBA), School of Business, University of Nairobi

NOVEMBER 2010

DECLARATION

This management research project is my original work and has not been presented for a degree in any other university.

Signed: ______________________ Date: 17/11/2010

Sabina N. Nyamu

REG: D61/70620/2008

This management research project has been submitted for examination with my approval as the university supervisor.

Signed: ______________________ Date: 17-11-2010

Mr. Josephat Lishenga

Lecturer

Department of Finance and Accounting

DEDICATION

This thesis is dedicated to my little nephews Kelvin and Kent.

ACKNOWLEDGEMENT

I would like to take this opportunity to thank all those that assisted me in this research, with special mention to:

My project paper supervisor, Mr. Lishenga for his invaluable time, patience, and ideas in guiding me to complete this project. Mr. Lishenga, given your already heavy workload, I truly appreciate all the help you have given me.

All the MBA lecturers who helped in coming up with this research paper.

The KTDC fraternity for their cooperation in providing data to support this research to its conclusion. You all aided me in ways that I can hardly express, and for that I thank you.

My dear friend Kam's for his unending love, impulsion and charm throughout the one year of study and the research period .Without you around me , I truly believe I could not have made it this far and this paper would not have been possible.

Last but not least, I would like to extend my innermost thanks to all my family members for their utmost patience during my studies. I would like to thank them for their continuous

encouragement, love, moral and unreserved best wishes, persistence and prayers during my period of study. May God bless you.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF ABBREVIATIONS

ANN's	–	Artificial Neural Networks
CEO	–	Chief Executive Officer
DFI	–	Development Financial Institution
EBIT	–	Earnings Before Interest Tax
KTDC	–	Kenya Tourist Development Corporation
MDA	–	Multiple Discriminate Analysis
MIM	–	Moody's Industrial Manual
MVE	–	Market Value of Equity
RE	–	Retained Earnings
RMA	–	Robert Morris Associate's
TA	–	Total Assets
TL	–	Total Liabilities
USA	–	United States of America
WTTC	–	World Travel and Tourism Council

ABSTRACT

Using financial distress models to predict failure in advance is for most businesses absolutely essential in their decision making process. Hence, this study involved a critical investigation in the applicability of the Altman (1968) Z -score models in predicting financial distress in hotels owned by Kenya Tourist Development Company. Testing the model in Kenyan context was important to determine the practical applicability and relevance of the model. The main objective of the study was to test the Altman model in determining practical predictive ability of failure in selected hotel companies.

The sample companies were 10 failed and 20 nonfailed hotel companies owned by KTDC from 1999 to 2003. The study employed an analysis of financial statements and derived the Z-score of the sampled companies to test the predictive ability of the models in forecasting bankruptcy. The analysis utilized ratios, which are related to the model in the study. The results reported in the empirical study for total failed and nonfailed sample companies shows that the model is able to predict failure and non-failure amongst Kenyan companies in hotel industry. Therefore, the study concluded that the Altman bankruptcy prediction model is justifiable to be applied to predict bankruptcy in Kenyan hotel industry. Hence, it is advisable to use these models in predicting failure in the non-manufacturing firms, especially in Kenyan context.

CHAPTER ONE: INTRODUCTION

1.1 Background

One of the most significant threats for many businesses today, despite their size and the nature of their operations, is insolvency. According to Bruno & Leidecker (2001) no two experts agree on a definition of business failure. Some conclude that failure only occurs when a firm files for some form of bankruptcy. Others contend that there are numerous forms of organizational death, including bankruptcy, merger, or acquisition. Still others argue that failure occurs if the firm fails to meet its responsibilities to the stakeholders of the organization, including employees, suppliers, the community as a whole, and customers, as well as the owners.

Beaver (1966) defined "failure" as the inability of the firm to meet its maturing financial obligations. Operationally, a firm is said to have failed when any of the following events occur; bankruptcy, bond default, an overdrawn bank account, or the non-payment of a preferred stock dividend. This definition of failure is shared by Altman (1968), Charktou (2000), and a host of other researchers.

The factors that lead businesses to failure vary. Many economists attribute this 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. According to Brigham & Gapenski (1996) studies show that financial difficulties are usually the result of a series of errors, misjudgments, and interrelated weaknesses that can be attributed directly or indirectly to management, and signs of potential financial distress are generally evident before the firm actually fails.

The alternatives for failing business as discussed by Moyer et al. (2001) are: Voluntary or informal basis: attempt to resolve its difficulties with the creditors, it can petition the courts for assistance and formally declare bankruptcy (Formal) or the creditors may also petition the courts, and this may result in the company being involuntarily declared bankrupt.

Altman (1993) states that voluntary bankruptcy is business failure, which is characterized by cessation of operation following assignment or bankruptcy, execution, foreclosure, or attachment; and those voluntary withdraw leaving unpaid obligations, or have been involved in court actions, and those voluntarily compromise with creditors and result in losses to the creditors. It is also the bankruptcy itself, which is the formal declaration of bankruptcy through legal means to either liquidate its assets or attempt a recovery program. Economic failure means the realized rate of return on invested capital, with allowance for risk considerations, is significantly and continually lower than prevailing rates on similar investments;

Indeed, the need for reliable empirical models that predict corporate failure promptly and accurately is imperative, in order to enable the interested parties to take either preventive or corrective action. Over the years, statistical ratio models have been developed which determines probability of bankruptcy within a certain period. These models are used to analyze a company's financial statements. A score is produced, which predicts the probability of insolvency within a certain period. A variety of models have been developed in the academic literature using techniques such as multiple discriminant analysis, logit, probit, recursive partitioning, hazard models, and neural networks,(Bruno, A.V. & Leidecker, J.K. 2001).

According to Mossman et al (1998), there are four types of bankruptcy prediction models based on financial statement ratios, cash flows, stock returns, and return standard deviations. Using the financial statement ratios, different approaches were developed to predict business failure. There are three distinct types of models to predict bankruptcy: (1) statistical (multiple discriminate analysis [MDA], logit analysis, and probit analysis) models, (2) Gambler's ruin mathematical/statistical models, and (3) artificial neural network models.

Gambler's ruin model assumes that the firm has a given amount of capital, K, and that a change in K is Z, which is random. Positive changes in K result from positive cash flows from operations. Under these assumptions the firm will go bankrupt if $K+Z < 0$. The capital K can be measured by either market or accounting values leading to different specifications (Laitinen 1995). Deakin (1977) used such an approach in his study.

Most neural network studies in bankruptcy prediction centered on the comparison of performance (prediction accuracy) of neural networks and other methodologies such as discriminant analysis, logit analysis, genetic algorithms, decision tree, and others. A number of studies report that the performance of neural networks is slightly better that of other techniques, but generally the results are contradictory or inconclusive. The first attempt to use ANNs to was made by Odom & Sharda (1990). A number of studies further investigated the use of ANNs in bankruptcy or business failure prediction.

In spite of the variety of models available, both the business community and researchers often rely on the models developed by Altman (1968) and Ohlson (1980). Both researchers and the business community typically use the original parameter estimates in spite of the fact that both models were estimated with relatively small samples, using data that is now 30 to 60 years old, and for a restricted set of industries. Altman's model was estimated using 66 manufacturing firms (33 bankrupt and 33 non-bankrupt) over the years 1946 to 1965. Ohlson's model was estimated using 105 (2,058) bankrupt (non-bankrupt) industrial firms from the period 1970 to 1976. The suitability and performance of these models in the new millennium is an empirical question since there have been many changes in business conditions since these models were estimated. For example, there have been changes to business practices, such as increased tolerance of debt financing, changes to bankruptcy laws, and varying economic cycles.

Thus the primary objective of this study was to test the practical applicability of Altman's (1968) bankruptcy prediction model to Kenyan hotel industry and in particular to hotels owned by K.T.D.C considering the original parameter estimates of the Z score model.

Sessional paper No. 4 of 2005 on privatization of state corporations and investments earmarks the hotels owned by K.T.D.C for privatization in line with the Parastatal Reform and Privatization Policy on Allocation of proceeds of Privatization. The policy requires Development Finance Institutions such as K.T.D.C to sell mature investments to release the funds to finance new projects. The researcher wais therefore interested in finding out the potential of these hotels ahead of this process as this study will go a long way in helping all the concerned parties to this process. The main reason this study tested Altman's model is because the model is popularly used and publicly available. It is also easy to understand and apply. The researcher was interested in finding out whether this model is also applicable to service companies in Kenya, given that the model was originally developed for manufacturing and retail companies.

1.2 Statement of the Problem

In looking back at the reasons cited by Beaver and Altman as to what constitutes the motivation and purpose for their research, it is amusing that this was driven more by chance and convenience than by market demand. Given the volatility and uncertainties prevalent in the global economy, we would have expected these issues to drive any study on corporate distress and failure. Perhaps the economic climate between the 1960's and that of the new millennium are quite different. But, given the high costs of financial failure and restructuring, the understanding of financial distress and bankruptcy is as vital today as it would have been then.

According to Dine (1992), the tourism industry is an extremely sensitive industry to fluctuations in demand though it is the number one foreign exchange earner for Kenya ahead of coffee and tea. The industry is a vital sector for the Kenyan economy as it contributes up to 5% of the Gross National Product. Thus performance of this sector should be evaluated continuously so that healthy returns are realized from the sector. Hotels are only a small fraction of the industry but of most importance as they are concerned with providing direct service. The hotel sector offers a perishable product in that the number of rooms rented tends to vary from weekdays to weekends and from season to season. This implies that forces outside the control of management that affect travel usually have an impact on hotel performance. For example, the Gulf War had a devastating impact on the travel industry and the hotel business in many countries.

In 1998, due to the terrorist attack and bombing at the United States Embassy in Nairobi and the subsequent travel ban to Kenya by the US and Britain, hotels in Kenya lost hundreds of billions of dollars in revenue and value. According to Wachira (2004), it is estimated that the impact of such an alert can be devastating if it is borne in mind that income from tourism-related industries drops by at least 70 per cent whenever such alerts are issued against countries that are dependent on revenue from tourism. African economies are sensitive to terror scares. In particular, the tourism-related service sectors, including airlines, hotels, entertainment, retail and restaurants, are affected as travelers cancel trips. When a travel warning is issued against a country that relies heavily on tourism, hotel occupancy rates drop significantly due to cancellations. This in turn leads to layoffs, not just of hotel employees but also in other industries that rely on tourists, such as art and craft stalls.

While some may argue that this attack was predicted in some ways, it was clear that due to the lack of research and understanding of the factors that trigger distress, the event had caught almost everyone by surprise. While the effects of the travel ban were unprecedented, the reality is that it clearly adversely affected hotels in Kenya. Though some were more affected than others, clearly more had to be done to distinguish and regulate high risk activities. By 2003, the impact and effects of the travel ban and alert on Kenya could still be seen on the Tourism industry. This was evidenced by mounting debts, huge accumulated losses, poor cash flows and high levels of liquidation and failure.

In view of the proven potential and sensitivity of the tourism sector, there is a need to investigate whether the Altman model is applicable in order to assist development financial institutions such as K.T.D.C who are direct players in the tourism industry to predict failure accurately. This would help avert the consequences that would result from such business failure. The purpose of this research therefore, was to test the practical applicability of Altman's bankruptcy prediction model in forecasting business failure in the Kenyan hotel industry.

Kibandi I. N (2005) carried a research on failure prediction on insurance companies in Kenya. However, no study has been carried out in Kenya to forecast business failure in the hospitality industry. Thus this research helped in creating a new body of knowledge.

1.3 Objectives of the Study

The objectives of this study were:

- To test the practical applicability of Altman's bankruptcy prediction model in predicting failure in Kenyan hotel industry and in particular among the hotels owned by K.T.D.C
- To investigate whether the model is useful in predicting bankruptcy for non-manufacturing firms, such as those in the hotel industry, as it is for predicting bankruptcy of manufacturing firms.

1.4 Justification of the Study

From a lender's point of view, by having a better grasp of the factors affecting corporate distress and bankruptcy, firm specific risks can be determined. By more accurately identifying the factors that can drive a company to distress and bankruptcy, lenders can evaluate firm financial positions more confidently. Charìkou (2005) states that while lenders are concerned with the burden of bad loans and the premium value needed to undertake those risks, borrowers want to borrow at lowest possible rates. As a result, this benefits the lender as they are able to "price" their investment to reflect the risks borne. K.T.D.C being a lender to the hospitality industry will benefit from the results of this study.

The Government on the other hand, will benefit from this study in that K.T.D.C is a state owned enterprise. The funds K.T.D.C lends to investors in the hospitality industry are advanced to it by the Government (Sessional paper No.10 of 1983). The government in such case is an indirect investor in the hospitality industry. This study will therefore go a long way in assisting the government in evaluation and monitoring of their investments by applying the results of the study .Doing so ensures that the potential returns from investments reflect the risks borne by investor.

From the point of view of business managers, by understanding of the topic better, the insights provided exposes them to the challenges that lie ahead. Through proper planning and resource allocation, courses of action can be put into place.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

In this chapter, the literature review in relation to past studies in corporate failure prediction models is presented. The chapter gives the definition of financial distress and business failure, causes of financial distress, types of bankruptcies, the importance of bankruptcy prediction, and background of the company under study.

2.2 Business Failure

The definition of financial failure or bankruptcy is diverse, and it is not uniform in the literature. The application of a general concept of insolvency that includes financial distress presented by Beaver (as cited in Laitinen and Laitinen, 2000) is the inability of a firm to pay its financial obligations as they mature. Beaver classified a company as failed when any of the following events occurred: Bankruptcy, Bond defaults, an overdrawn bank account, or Nonpayment of preferred stock dividend.

According to Altman (1993), based upon the criteria of the International Shoe decision, Blum stated one of the these three events constitutes failure: Inability to pay debts as they come due, Entrance into a bankruptcy proceeding, or an explicit agreement with creditors to reduce debts. Gilbert et al (1990) puts it best when she states that "Bankruptcy filing can be viewed as a strategic and voluntary response by management to financial problems". So given the huge window of opportunity available to rectify the situation and the high costs of bankruptcy, the high cost of failure should provide reason enough for us to want to identify the situation early.

According to Elloumi and Gueyie (2001), when a firm's business deteriorates to the point where it cannot meet its financial obligations, the firm is said to have entered the state of financial distress. The first signals of distress are usually violations of debt covenants coupled with the omission or reduction of dividends. Entry into financial distress can be defined as the first year in which cash flows are less than current maturities' long-term debt. As long as cash flow exceeds current debt obligations, the firm has enough funds to pay its creditors. The key factor in identifying firms in financial distress is their inability to meet contractual debt obligations.

Timmons & Spinelli (2004) stated that external forces not under the control of management could increase the occurrence of financial distress. Among the most frequently mentioned are recession, interest rate changes, changes in government policy, inflation, the entry of new competition, and industry or product obsolescence. Most causes of failure could be found within company management. Although there are many causes of trouble, the most frequently cited fall into three broad areas that is; inattention to strategic issues such as misunderstood market niche, mismanaged relationships with suppliers and customers, diversification into an unrelated business area, mousetrap myopia, the big project, and lack of contingency planning. Secondly, general management problems are lack of management skills, experience, and know-how, weak finance function, turnover in key management personnel, big-company influence in accounting, and thirdly poor financial/accounting systems and practices are like poor pricing, overextension of credit, and excessive leverage, lack of cash budgets/projections, poor management reporting, lack of standard costing, and poorly understood cost behavior.

Another reason of failure for commercial banks and financial institutions are decision-making problems in credit evaluation and their risk measurements due to the high level of risk associated with wrong decisions. Among these, the important risks to deal with have been a worldwide structural increase in the number of bankruptcies, more competitive margins on loans, and an increasing cost associated with monitoring solvency in order to control the risks (Altman and Saunders, 1997; Wolf, 1995).

The definition of financial distress, including bankruptcy, of this study resembles the definition of Altman. Financial distress is the cessation of operation, not payment of current obligations due to cash flow problems, the firm's total liabilities are in excess of total assets, and the formal declaration of bankruptcy.

2.3 The Causes of Business Failure

According to Bruno and Leidecker (1988), research findings indicate that business failure results from definable causes and that an understanding of these causes can help prevent failure. Although bankruptcy may be caused by environmental or macroeconomic factors, most of the time bankruptcy to the established and historically profitable firms is due to faulty managerial decision-making.

Charan and Useen (2002) contend that causes of failure are in addition to acts of God, managerial error, relaxation due to success, acts of competitors, bad news is not welcome by CEO's, and overdosing on risk. The main factors that can be associated with bankruptcy are economic recession, change in technology, and bad management. Businesses can be under stress and the chance of failure may be increased due to a general recession or more localized declines in the economic environment.

According to Norton (1989), the main factors that can be associated with bankruptcy are economic recession, change in technology, and bad management. Businesses can be under stress and the chance of failure may be increased due to a general recession or more localized declines in the economic environment. New technology is another environmental factor, which destroys the demand for old products or services; also the demographic and cultural trends may reduce demand. Governmental regulation may affect competition. However, in the same circumstances, some businesses survive while others fail.

Bruno and Leidecker (1988) states that financial factors such as inadequate cash flow, excessive debt, or loss of creditor confidence are attributed to bankruptcy in the finance literature. These are not the exact causes of bankruptcy, but they are the symptoms of decline and failure. Initial under capitalization and assuming debt too early are the two important exceptions from the factors cited as reasons for failure of firms in the 1960's to the 1980's such as product timing, product design, inappropriate distribution or selling strategy, unclear business definition, over reliance on one customer, problems with the venture capital relationship, ineffective team, personal problems, one-track thinking, and cultural/social factors.

According to Brigham and Gapenski (1996) studies show that financial difficulties are usually the result of a series of errors, misjudgments, and interrelated weaknesses that can be attributed directly or indirectly to management, and signs of potential financial distress are generally evident before the firm actually fails.Ohlson (1980) identifies four basic factors that affect the probability of failure (within one year): size, financial structure, profitability, and liquidity. Rees (1990) suggests that there are many possible causes of insolvency, including: low and declining real profitability, inappropriate diversification, deteriorating financial structures and inadequate control over working capital and failure to eliminate actual or potential loss-making activities.

2.4 Types of Bankruptcies

The alternatives for failing business as discussed by Moyer et al. (2001) are: Voluntary or informal basis: attempt to resolve its difficulties with the creditors, it can petition the courts for assistance and formally declare bankruptcy (Formal) or the creditors may also petition the courts, and this may result in the company being involuntarily declared bankrupt.

In the case of forced bankruptcy, which is initiated by creditors, the process requires the involvement of the civil authorities in the settlement of the credits. Schwartz (1996) summarizes that bankruptcy law enables the right of the creditors to collect, guarantee ratable distribution of asset value among creditors according to contractual priorities, and provide debt restructuring possibilities. In many cases bankruptcy is the action forced by creditors. However, some governments protect firms from forced bankruptcy.

According to White (1996), the US discourage involuntary bankruptcy filings by requiring that three or more creditors together initiate an involuntary bankruptcy petition, where as European bankruptcy laws encourage any involved party or creditors, managers, members of the boards of directors, workers' representatives, and the bankruptcy court itself to initiate involuntary bankruptcy filings. Therefore, the creditors only control the timing of the bankruptcy.

Barniv, Agarwal and Leach (2002) stated that following bankruptcy filing event, the court confirm one of three possible final resolutions, namely, acquisition, emergence or liquidation. If the firm is reorganized according to legal proceedings, there is often a partial liquidation of assets with the surviving firm being diminished in size. Bankruptcy also affects the final outcome by transferring primary control from the owners to the creditors and the bankruptcy court. This is due to the firm failure to be profitable, to turn around, and finally failure in finding an asset-preserving ability, which is seen as management failure.

Altman (1993) states that voluntary bankruptcy is business failure, which is characterized by cessation of operation following assignment or bankruptcy, execution, foreclosure, or attachment; and those voluntary withdraw leaving unpaid obligations, or have been involved in court actions, and those voluntarily compromise with creditors and result in losses to the creditors. It is also the bankruptcy itself, which is the formal declaration of bankruptcy through legal means to either liquidate its assets or attempt a recovery program. Economic failure means the realized rate of return on invested capital, with allowance for risk considerations, is significantly and continually lower than prevailing rates on similar investments;

Hopwood et al. (1994) discussed three types of corporate failures, the first type includes companies whose failure occurs before they become established, the second type includes companies whose failure is precipitated by a slide into insolvency and portended by signs of financial stress in the financial ratios, and the third includes companies whose failure is sudden and with no apparent signs of financial distress.

2.5 The Importance of Bankruptcy Prediction

Zavgren (1985) stated that Beaver (1966) pioneered empirical research in business failure prediction using a univariate model. The approach used achieved a moderate level of predictive accuracy, although it had certain shortcomings especially a lack of integration of the various ratios. Later multivariate studies usually employed discriminant analysis. There are both theoretical and practical reasons for studying corporate failure and bankruptcy prediction. O'Leary (1998) discussed the importance of bankruptcy prediction as, "…bankruptcy probably is one of the most important business decision-making problems facing prediction of auditors, consultants, management and government policy makers".

The crisis of business failure may make patterns visible that would be difficult to detect under more normal circumstances. Also the stressful decision making environment may have different responses than those observed under more normal circumstances. Therefore, if certain patterns can be detected which appear to have predictably negative effects on corporate survival, that would be useful information for managers and investors, whether or not they were likely to face with corporate failure. Nowadays big, successful and promising companies are seen going bankrupt due to lack of prediction of future financial status. Charan and Useem (2002) stated "…each month seems to bring the sound of another giant crashing to earth, Enron, WorldCom, Global Crossing, K-mart, Polaroid, Arthur Anderson, Xerox, Qwest, they fall singly, they fall in groups, they fall with the heavy thud of employees laid off, families hurt, shareholders furious… and not just any companies, but big, important, fortune 500 companies that aren't supposed to collapse."

The lack of sound credit and evaluation policy may cause financial problems and even bankruptcy. Shin and Lee (2002) mentioned that many financial institutions are paying a heavy price for their indiscriminate practices, and corporate bankruptcies have put several institutions on the brink of insolvency. According to Timmons and Spinelli (2004) the obvious benefit of being able to predict crisis is that owners, employees, and significant outsiders, such as investors, lenders, trade creditors – and even customers- could see trouble brewing in time to take corrective actions.

2.6 Corporate Failure Prediction Models

Bankruptcy prediction was a dominant theme in the study of business failure. In the formulation of bankruptcy predicting models, many variations of models have been proposed. Most of the cases discriminate between bankrupt and non-bankrupt firms over some period before the firm status become known, and the accounting and financial variables are then examined to determine whether they can classify the firms appropriately. According to Mossman et al., 1998, there are four types of bankruptcy prediction models based on financial statement ratios, cash flows, stock returns, and return standard deviations. Using the financial statement ratios, different approaches were developed to predict business failure. There are three distinct types of models to predict bankruptcy: (1) statistical (multiple discriminate analysis [MDA], logit analysis, and probit analysis) models, (2) Gambler's ruin mathematical/statistical models, and (3) artificial neural network models.

2.7 The Statistical (Multiple Discriminant, Logit and Probit Analysis) Models

Financial variables (ratios) are used to test multiple discriminant analysis (MDA) and logit models. However, as Mar-Molinero and Serrano-Cinca (2001) stated, both logit and discriminant analysis require, before implementation, a selection of the variables that enter the model, and the selection of the final set of variables is complex, delicate and important. As summarized in bankruptcy prediction (available on-line at http://www.solvency.com/bankpred), the multivariate statistical models are developed and refined by Lev (1974), Deakin (1972), Ohlson (1980), Taffler (1982), Platt & Platt (1990) and Hall and Young (1990), and almost all the traditional models have been either matched-pair multi-discriminate models such as Altman's or logit models such as Ohlson's.

2.7.1 Beaver (1966)

As summarized by Altman (1993), Beaver defined failure as the inability of a firm to pay its financial obligations as they mature. The sample was composed of 79 failed firms representing 38 different industries during the years 1954 to 1964. The classification of failed firms was according to industry and asset size.

Beaver (1966) used 30 ratios, which are computed for each of five years prior to failure. The criteria in selecting these ratios were: (1) popularity in the literature, (2) performance in previous studies, and (3) definition of the ratio in terms of a cash flow concept. Beaver selected the following six variables as best, based on the lowest percentage error for each group in the five year period, (1) cash flow to total debt, (2) net income to total assets, (3) current plus long-term liabilities to total assets, (4) working capital to total assets, (5) current ratio, and (6) no-credit interval.

Beaver's empirical experiment was conducted in three major steps. First the comparison of mean value, which is referred as a profile analysis to indicate that it described the general relationships between failed and non failed firms. Here he found the anticipated differences in the mean values for each of the six ratios in all five years before failure. As the year of failure approached, the average failed firm showed substantial deterioration. On the other hand the performance of the average non failed firm was relatively constant. In the second step he performed the classification test using dichotomous prediction. After arranging the 30 ratios in ascending order for both failed and non failed firms, Beaver found out the cutoff point that minimized the percentage of incorrect prediction.

Beaver concluded the cash flow to total debt ratio is the overall best predictor. Beaver's Type I error (error in predicting bankrupt firm) was increased substantially as the number of years before failure increased from 22% to 47%, but the Type II error (error in predicting non bankrupt firm) was fairly low and stable between 3 to 8%. Type I errors are more costly than Type II errors; therefore a truly minimized misclassification rate should incorporate these differing costs. Beaver treated the costs of misclassification as being symmetrical and employed a priori probability of failure of .5.

Beaver's most important contribution is that to suggest a framework for the evaluation of accounting data not merely for failure prediction. The major findings were financial data or accounting data subject to some important qualifications have the ability to predict failure for at least five years before failure. The important qualifications are needed because first not all ratios predict with the same degree of accuracy. The other reason is higher level of success achieved predicting non-failure than failure, and finally financial ratios should be complemented by frequency distributions and likelihood ratios for decision making purposes.

2.7.2 Deakin (1972)

Deakin (1972) proposed an alternative business failure model to the ones developed by either Beaver (1966) or Altman (1968). Deakin considered Beaver's empirical results for the predictive accuracy and Altman's multivariate approach because of its intuitive appeal, and to capture the best of both of these studies by employing the 14 ratios Beaver used and to search for the linear combination of these ratios with greatest predictive accuracy. His analysis was based on 32 firms that failed between 1964 and 1970, and then each failed firm was matched with a nonfailed firm on the basis of industry classification, asset size, and year of financial data.

Deakin's 14 ratios that are used on the classification result, using the cash flow-to-total-debt ratio is similar to that of Beaver (1966). The failed firms analyzed by Deakin show highly volatile movements in total debt compared to the monotonic upward trend observed by Beaver. The cash flow, net income, and total debt have relatively stable movements for the nonfailed firms in both samples. The classification error increased substantially when Deakin tried to reduce the number or variables. He concluded that discriminant analysis could be used to predict business failures as far as three years in advance with a fairly high accuracy. Deakin suggested that further testing is required before a conclusive judgment about his model can be rendered due to the relatively small sample size.

2.7.3 Edmister (1972)

Edmister's (1972) purpose was to develop, test, and analyze financial ratios to predict the failure of small business; those with a loan from the Small Business Administration. Included in the sample were borrowers and guarantee recipients from the Small Business Administration for the period 1954 to 1969. He analyzed 19 financial ratios, which were important in previous failure prediction studies. Edmister focused upon testing four hypotheses: A ratio's level as a predictor of small business failure, the three-year trend of a ratio as a predictor of small business failure, the three-year average of a ratio as predictor of small business failure, and the combination of the industry relative trend and the industry level for each ratio as a predictor of small business failure.

Edmister developed a seven-variable, zero-one linear regression equation:

$$Z = 0.951 - 0.523\, X_1 - 0.293\, X_2 - 0.482\, X_3 + 0.277\, X_4 - 0.452\, X_5 - 0.352\, X_6 - 0.924\, X_7$$

Where;

Z = Zero-one dependent variable

X_1 = Annual funds to Current liabilities

X_2 = Equity to Sales

X_3 = Net working capital to Sales, divided by RMA* average ratio

X_4 = Current liabilities to Equity, divided by RMA average ratio

X_5 = Inventory to Sales, divided by RMA average ratio

X_6 = Quick ratio divided by the trend in RMA quick ratio

X_7 = Quick ratio divided by RMA quick ratio and

RMA ratios are average ratios for firms in a similar industry and of similar size, as developed by Robert Morris Associates. The model's classification result achieved accuracy of at least 90%. Using $Z > 0.530$ to determine non-failure and $Z < 0.530$ for failure, all of the failed firms and 86% of the nonfailed firms were classified correctly for an overall accuracy rate of 93%. Edmister found two useful points, dividing a ratio by its respective industry average, and classifying ratios by quartiles.

2.7.4 Zavgren (1985)

Zavgren (1985) used logistic regression (logit) techniques to generate a probability of failure as a financial risk measure, and to test the pattern of significance of the financial attributes in the models over a five year period prior to failure. He analyzed a sample of 45 failed and 45 non-failed manufacturing firms, which filed during the 1972 to 1978. The failed and healthy firms are matched according to the industry code and total asset size. The concluding points by Zavgren is that the models estimated were found to be highly significant at greater than the 99 percent confidence level in distinguishing between failing and healthy firms over the five year period. The significance of the coefficients for each of the variables in the models was traced for each of the five years. The efficiency ratios were found to have the most significance over the long run, which indicated that efficiency in the utilization of assets is difficult to modify over the short run. Profitability was not found to be a significant distinguishing characteristic. The negative coefficient and high significance of the acid test ratio in later years would indicate that ability to meet current obligations is a very important factor in avoiding bankruptcy. The coefficients of the liquidity measure in earlier years and its negative sign indicate that the failing firms were more interested in liquidity than productive opportunities. Debt proved to be a significant characteristic and was consistently higher for ailing than for healthy firms.

2.7.5 Nam Jinn (2000)

Nam and Jinn (2000) applied the logit maximum likelihood estimator as a statistical technique for a sample of 46 non-financial listed firms from a variety of industries. They studied the predictive model of business failure using the sample of listed companies that went bankrupt during the period from 1997 to 1998, when a deep recession driven by International Monetary Fund sanctions started in Korea. The measure of firm's ability of serving short-term debts, interest expenses to sales and account receivables turnover ratio are variables that comprise the prediction model.

The Type I accuracy was 80.4% and the Type II accuracy was 73%, and most of the firms that went bankrupt during the economic crisis from 1997 to 1998 had shown signs of financial distress long before the crisis, they concluded the crisis was not just a temporary foreign exchange crisis, but also a result from poor performance of Korean firms over a long period.

2.8 Gambler's Ruin Mathematical/Statistical Model

Gambler's ruin model assumes that the firm has a given amount of capital, K, and that a change in K is Z, which are random. Positive changes in K result from positive cash flows from operations. Under these assumptions the firm will go bankrupt if $K+Z < 0$. The capital K can be measured by either market or accounting values leading to different specifications

2.8.1 Deakin (1977)

Altman (1983) stated that Deakin extended his 1972 analysis to a 1977 study building upon Libby's factor analysis contribution to assess the impact, frequency, and nature of bankruptcy misclassification. His purpose was to provide an indication of the frequency and nature of misclassification of nonfailing companies, and to compare auditors' opinions with the model's predictive ability. Deakin's sample consisted of 80 firms randomly selected from Moody's Industrial Manual and matched only by year of data, and 63 failed firms, 32 companies from his 1972 study and 31 firms from a 1974 study by Altman and McGough that failed in 1970 and 1971. The five-ratio set derived by Libby is computed for the 143 firms, using data two years prior to failure.

Deakin analyzed 47 companies that went bankrupt form 1972 to 1974, as an alternative test of his model. This is done to assess the model's accuracy with respect to a holdout sample of "hard-core" failures. The five variable-models correctly identified 39 of the failure, two years prior to failure. There was a misclassification of one firm, and seven companies were identified as in need of further investigation.

Deakin (1977) model is as follows:

$$\mathbf{I = -1.369 + 13.855X_1 + 0.060X_2 - 0.601X_3 + 0.396X_4 + 0.194X_5}$$

Where, I = Overall index

X_1 = Net income/ total assets

X_2 = Current assets/ total assets

X_3 = Cash/ total assets

X_4 = Current assets/ current liabilities

X_5 = Sales/ current assets

2.9 Artificial Neural Networks Models (Ann's)

Beginning in the late 1980s, neural networks became the dominant research methodology in artificial intelligence; researchers actively applied neural networks to classification problems including bankruptcy prediction. Most neural network studies in bankruptcy prediction centered on the comparison of performance (prediction accuracy) of neural networks and other methodologies such as discriminant analysis, logit analysis, genetic algorithms, decision tree, and others. A number of studies report that the performance of neural networks is slightly better that of other techniques, but generally the results are contradictory or inconclusive.

The first attempt to use ANNs to predict bankruptcy is made by Odom and Sharda (1990). A number of studies further investigated the use of ANNs in bankruptcy or business failure prediction. Rahimian et al. (1993) tested the same data set used by Odom and Sharda (1990), using three neural network paradigms: back propagation network, Athena and Perception. Recent studies in artificial neural networks (ANNs) show that ANNs are powerful tools for pattern recognition and pattern classification due to their nonlinear nonparametric adaptive-learning properties.

Shah and Murtaza (2001) stated that as the system require less storage, more robust to noise or missing data, and have generalization ability, the neural systems are much faster than conventional statistical approaches. They also argued that the statistical approach like discriminant analysis required assumptions, which are fairly restrictive because the Gaussian distribution has to be assumed, and such assumptions might not be traceable to real world problems. On the other hand, using a neural network approach such assumption can be avoided since the application does not-require Gaussian distribution assumptions. They used a sample of 60 firms with six bankrupt and 54 non-bankrupt firms, which is successful in the prediction of 73% of all firms correctly. Eighty three percent of the sample of bankrupt firms and 72% of non-bankrupt firms were predicted accurately into respective categories in the fourth year of operations, and they concluded that the model was successfully applied and improved current methodologies. They suggested that the model will have an immediate and practical application in the fields of accounting information systems, the state and national regulatory agencies, the banking industry and the securities market.

2.10 Criticism of Ratio Based Failure Prediction Models

Robertson and Mills (1991) criticized the ratio-based failure prediction models. They commented on the problems encountered in meeting the strict mathematical standards of these failure prediction models and other such as the application of industry based models to evaluate companies in other industries, the validity of models in observing trends, the validity of arbitrarily changing cut-off points, the validity of changing the specification of any of the ratios contained in the model, and the validity of using parts of a corporate failure model for decision making during a company turnaround. The models also do not cope with financial theories, as they are concerned with inadequate data in the form of financial ratios, and the models are offered without detailed operating instructions. They suggested an alternative neural prediction model, which is based on a new approach to fundamental ratio analysis, allowing the researcher to examine ratios across calculating different means, the calculation of a misclassification and the calculation of a year-to-year change factor.

2.11 Edward Altman's Z-Score

Chuvakhin and Gertmenian (2002) discussed the critical breakthrough in bankruptcy prediction came in 1968 when Edward Altman decided to abandon the search for a single ratio and built a comprehensive, statistical model using a technique called multiple discriminant analysis. He stated that Altman conducted three subsequent tests, 86 companies that had gone bankrupt in 1969-1975, 110 in 1976-1995, and 120 in 1997-1999. Then he recommended a lower cutoff of 1.81 and treating Z-scores between 1.81 and 2.675 as a "gray area" or "ignorance zone." A company in the ignorance zone means the company in question has a chance to go bankrupt. Interestingly, Altman found that in 1999, 20 percent of U.S. industrial firms referenced in Compustat data tapes had Z-score below 1.81. In other words, the unusually high incidence of bankruptcy in 2001-2002 was to be expected.

According to Altman (1993) the initial sample was composed of 66 corporations with 33 firms failed and 33 firms non-failed groups. The bankrupt group was manufacturers that filed a bankruptcy petition under chapter X of the national bankruptcy act of the U.S. from 1946 through 1965. The aim was to examine a list of ratios in period t in order to make predictions about other firms in the following period (t + 1), but this was not possible due to data limitations.

The sample's mean asset size was $6.4 million, with a range of between $0.7 million and $ 25.9 million. Due to the industry and size differences, there was a careful selection of non-bankrupt firms. Group 2 consists of a paired sample of manufacturing firms' chosen on a stratified random basis. The firms were stratified by industry and by size, with the asset size range restricted to between $1 and $25 million. The mean asset size of the firms in Group 2 ($9.6 million) was slightly greater than that of Group 1, but matching exact asset size of the two groups seemed unnecessary. Firms in Group 2 were still in existence in 1966. The data collected were from the same years as those compiled for the bankrupt firms. For the initial sample test, the data were derived from financial statements dated one annual reporting period prior to bankruptcy.

The data were derived from Moody's Industrial Manual and selected annual reports. The average lead-time of the financial statements was approximately seven and one-half months. Balance sheet and income statement data were collected for the firms selected. As large number of variables found to be significant indicators of corporate problems in past studies, a list of 22 potentially helpful variables (ratios) are compiled for evaluation. Grice and Ingram (2001) stated that Altman compiled a list of 22 financial ratios and classified each into one of five categories – liquidity, profitability, leverage, solvency, and activity.

The ratios were not selected on a theoretical basis, but rather, on the basis of their popularity in the literature and Altman's belief about their potential relevancy to bankruptcy. There were also few new ratios included in the analysis. The cash flow to debt ratio, which was the best single predictor in the study of Beaver study (1967), was not considered because of the lack of consistent and precise depreciation data. As discussed by Altman (1993), the five variables were selected from the original list of 22 variables, which were doing the best overall job together in the prediction of corporate bankruptcy.

The profile did not contain all of the most significant variables measured independently as this would not necessarily improve upon the univariate, traditional analysis described earlier. The final discriminant function is as follows:

$$Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5$$

Where: X_1 = working capital/total assets,

X_2 = retained earnings/total assets,

X_3 = earnings before interest and taxes/total assets,

X_4 = market value equity/book value of total liabilities,

X_5 = sales/total assets, and

Z = overall index.

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

The working capital/total assets ratio is a measure of the net liquid assets of the firm relative to the total capitalization. Working capital is the difference between current assets and current liabilities. Here, the liquidity and size characteristics are explicitly considered. Altman (1993) explained the logic behind this ratio as a firm experiencing consistent operating losses will have shrinking current assets in relation to total assets.

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

Retained earnings is the account which reports the sum of past year's profit or losses of a firm over its entire life. Altman (1993) noted that the retained earnings account is subject to change via corporate quasi reorganizations and stock dividend declarations. While these occurrences are not evident in the study, it is conceivable that a bias would be created by a substantial reorganization or stock dividend and appropriate readjustments that could be made to the accounts.

X_3, Earnings before Interest and Taxes/Total Assets (EBIT/TA)

This ratio is the firm's earnings power from the investment on assets without the influence of taxes and interest. This is useful to compare firms in different tax situations and different degrees of financial leverage. 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. Insolvency in a bankrupt sense occurs when the total liabilities exceed a fair valuation of the firm's assets, in which the value is determined by the earning power of the assets.

X_4, Market Value of Equity/Book value of Total Liabilities (MVE/TL)

The market value of equity is the market price of common stock share multiplied by the number of common shares outstanding. The liabilities include current and long-term liabilities. 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. Altman (1993) stated that this ratio adds a market value dimension, which other failure studies did not consider.

X_5, Sales/Total Assets (S/TA)

This ratio is a measure of a firm's use of its total resources to generate sales and it is a summary measure influenced by the asset management ratios. Altman stated that this final ratio is important because it is the least significant ratio on an individual basis. In fact, based on the statistical significance measure, 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.

Many individuals found that a more convenient specification of the Altman's model is of the form:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$$

Using this formula needs inserting the more commonly written percentage, for example, 0.10 for 10%, for the first four variables ($X_1 - X_4$) and round the last coefficient off to equal 1.0 from 0.99. The last variable continues to be written in terms of number of times. The score for individual firms and related group classification and cutoff scores remain identical.

Altman (1993) performed an F-test to test the individual discriminating ability of the variables. This test relates the difference between the average values of the ratios in each group to the variability (or spread) of values of the ratios within each group. He stated that one useful technique in arriving at the final variable profile is to determine the relative contribution of each variable to the total discriminating power of the function. The relevant statistic observed is a scaled vector. Since the actual variable measurement units are not all comparable to each other, simple observation of the discriminant coefficients is misleading.

The logic behind the high negative correlation in the bankrupt group discussed by Altman is that as firms suffer losses and deteriorates toward failure; their assets are not replaced as much as they were in healthier times. Also, the cumulative losses have further reduced the asset size through debits to retained earnings. Brigham & Gapenski (1996) discussing the practical applicability of Altman's model stated; the model has been used by Salmon Brothers, Morgan Stanley, and other investment banking houses to appraise the quality of junk bonds used to finance takeovers and leveraged buyouts.

2.12 Hospitality Industry

According to Go and Pine (1995), the hotel industry is a major sector of the tourism industry, which, in turn, is one of the most rapidly expanding fields in the service industry. It is very capital intensive industry which requires a huge capital base for an investor to start operations in this industry hence implying that such investor's source for external funding. According to the world travel and tourism council (WTTC), travel and tourism has become the leading economic contributor to the world and national economies in terms of gross output, value added, capital investment, employment, and tax contributions. But travel and tourism are far from being recognized as such in most countries around the world. Because it caters to the accommodation needs of the 'away from home market', the hotel industry is of central importance to the development of travel and tourism.

Dune (2004) states that the evolution and performance of the contemporary hotel industry has been shaped by a set of economic characteristics. These characteristics are that it is a labor intensive industry with an emphasis on personal service, to provide quality service employees in the industry have to be properly trained, motivated and supervised. Though it is costly, training is a necessity because the 'moments of truths' or the impressions, both positive and negative, an employee makes on the guest have a direct influence on whether the guest will return. The hotel industry is an extremely competitive industry. The consequences of overbuilding and excess capacity have produced intense competition. In addition, the globalization process has increased the number of 'players' in the hotel industry and significantly increased competition in many markets. It is an industry which is extremely sensitive to fluctuations in demand.

The hotel industry offers a perishable product in that the number of rooms rented tends to vary from weekdays to weekends and from season to season. Hotels serve both business and pleasure travelers. This implies that forces outside the control of management that affect travel usually have an impact on hotel performance. For example, the Gulf War had a devastating impact on the travel industry and the hotel business in many countries. The curtailing of business travel and entertainment during a recessionary period typically has adverse effects on the expenditures on hotel room, food and beverage expenditures and therefore hotel profitability, (Dune 2006).

In general, a stable and expanding economy tends to influence hotel performance positively. Conversely, rising inflation causes expenses for labour, energy, and construction to increase and profit margins to erode, especially when the hotel is unable to raise room rates proportionately due to prevailing market conditions.

2.13 Kenya Tourist Development Corporation

Kenyan Tourist Development Corporation (KTDC) is one of the six state corporations under the Ministry of Tourism. It was created in November 1965 through an Act of Parliament, Cap. 382 of the laws of Kenya, (The Kenya Tourist Development Act).

Section 3 of the Act states the core mandate of the Corporation as that of securing the investigation, formulation and carrying out of projects for developing the tourist industry in Kenya, carrying on undertakings which appear to the corporation to be needed for or in connection with the promotion or expansion of new or existing enterprises and to assist other authorities or persons either financially or in any other way to perform any function that is empowered on them.

In 1983 under the sessional paper No. 10, the Government of Kenya identified the main constraints to human development as poverty, disease, and ignorance and consequently issued a directive to the Corporation to set up hotels in all regions in the country with an aim to open up these regions and provision of employment to the locals in those regions. This necessitated the Corporation to invest in hotels all across the country by building such hotels and running its operations until such a time when these hotels could be able to run independently. The Corporation also undertook selective financial participation in aviation, tour and travel operations and other tourism enterprises through provision of venture capital. This was aimed at creating employment opportunities, distributing tourism benefits and increasing foreign exchange earnings hence alleviating poverty while maintaining commercial viability and sustainability.

As indicated in the Government's Economic Recovery Strategy for Wealth and Employment creation 2003-2007 and the letter of Development Policy, the Corporation was formed as a specialized development financial institution, to provide financing to investors in the tourism industry. This was necessitated by the fact that Kenya obtained independence in 1962 and as a newly independent country; there was need to rapidly develop the industrial, agricultural, and tourism sectors. K.T.D.C would thus be an instrument of choice to accelerate long term investments, achieve economic growth and create employment in the tourism industry as envisioned in the national development plans. At the time of formation of the Corporation, the financial sector traded in traditional commercial banking activities that did not support long term investment in national development.

K.T.D.C was therefore created as a major development conduit for the Government in long term project financing in Kenya. The Government being the major shareholder of the Corporation has enabled the Corporation to provide project finance on soft terms. Initially, this was being done through annual budgetary allocations to the Corporation however this ceased in 1980/81 financial year thus allowing the Corporation to run independently on its internally generated funds as cited in Sessional paper No. 10 of 1983.

In pursuit of the above outlined mandate and as stated in its service delivery charter, the corporations operations are organized into loan and equity financing. These are operationalised through: revolving loans Programme whose objective is to provide concessional credit to entrepreneurs within the tourism sector by offering loans on a maximum amount of Kshs. 10 million over a maximum loan term of 10 years at reduced rates of interest, Commercial Loans Programme where loans are advanced to new or existing tourist enterprises at commercial rates of interest , for a maximum period of 10 years for any amounts over Kshs. 10 million to a maximum of Kshs. 50 million and Equity financing in form of joint partnerships where the Corporation can invest up to a maximum of 25% of the total project cost. Partnership can be formed by teaming up in joint ventures or strategic alliances with prospective investors. The Corporation also provides advisory services to tourism sector enterprises at competitive prices. The services range from preparation of feasibility studies, business evaluation and provision of market trends, (Dine 2008).

According to Dine (2008), the Corporation has provided loan financing to nearly 200 tourism related facilities in various regions across the country. In doing this and considering the volatility of the tourism sector in the economy, the Corporation has faced challenges of default on repayments of these loans leading to huge amounts of bad debts incurred on both Commercial and Revolving Fund Programmes. As per treasury investment guidelines of February 1991, the Corporation is responsible for these bad debts. Hence the need for the Corporation to determine an effective model that can be used to predict the possibility of failure of these business that are financed by them. The Altman prediction model if tested to be effective in predicting business failure could be a useful tool to be used by the credit manager in evaluating the performance of the hotels that have been financed by the Corporation.

2.14 Conclusion

Since the pioneering works of Beaver (1966) and Altman (1968), a lot of research has been conducted to try and understand corporate bankruptcy. Despite the large volume of research on the topic however, findings from the studies have proven to be inconsistent and inconclusive. Furthermore, as most research had focused their studies on understanding and predicting corporate bankruptcy, little effort has been paid to understanding corporate financial distress. For researchers, a common reason often cited to explain this is due to the unavailability of any consistent measure of what defines corporate distress. From the review, most of the studies are based on the original findings of Altman as such showing that the Altman model is very popular among researchers.

The works of Beaver and Altman are continually cited by contemporary researchers as the basis of their own studies. And with the spurt of interest created and generated, academicians and contemporary researchers use it as a foundation to develop, create, and identify newer and more accurate approaches to understanding and predicting corporate bankruptcy. Review the literature shows that the factors that differentiate healthy and distressed firms mainly centers on their levels of liquidity and profitability. Another important characteristic found to differentiate between healthy and potentially distressed firms is given by their levels of profitability. Firms with better profitability are often seen as being better managed. There is need for more research on the applicability of financial ratios as predictors of corporate failure in order to find out whether these characteristics found to differentiate healthy and distressed firms are as identified.

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Introduction

As discussed by Mouton (2001), research methodology focuses on the research process and the kind of tools and procedures to be used. This chapter outlines the research design that is suitable to the investigation, the target population, the research sample, data collection, and statistical test applied in the study.

3.2 Research Design

Research design is defined by Welman and Kruger (2000) as a plan according to which research participants (subjects) are selected in order to collect information. The critical significance of the $research design is to hold all the parts and phases of the enquiry together. The research design tries to answer questions like what kind of study to be done, and what study type will best answer the research question.

The research design choice of this study was quantitative, which focused on determining the relationship between one thing (an independent variable) and another (a dependent or outcome variable) in a population. The independent variable under study within this research comprised of 5 financial ratios as stated in the Altman's model. The dependent variable was the financial classification of the hotels owned by K.T.D.C. Firms were either classified as normal healthy companies or distressed companies.

The sample period under study was from 1999 to 2003.This sample period was chosen for the reason that the terrorist attack at the United States Embassy in Nairobi in 1998 severely impacted most hotels in Kenya. Given the unusual occurrence, the researcher begun with data from 1999 to ensure that the broad ranging effects of the terrorist attack were minimized.

3.3 Target Population

The target population for this research was companies listed at K.T.D.C's data base. The sample consisted of both liquidated companies (where the host-company suffered losses as a result of the liquidations), and companies that are still active and financially healthy.

3.4 Sampling Procedure

Emory and Cooper (1995) defines two methods of survey sampling namely: the conventional sample, whereby a limited number of elements smaller than the chosen population are chosen (typically randomly) in such a manner as to accurately represent (without bias) the total population and the census approach, where an attempt is made to survey every element within the population. For the purposes of this research, a sample was chosen from an existing database of the host company, of companies that have been liquidated over the last six years as well as companies that are still operating and are considered as non-failed organizations. The data sample consisted ten (10) companies that failed or experienced financial distress between 1999 and 2004 and twenty (20) healthy companies. Both samples were companies in the same industry sector but different size and turnover levels. The research employed a paired sampling design where samples were paired according to their size and turnover levels. Beaver realized that while a paired design sample selection methodology mitigates the disruptive influence of asset size and industry, its use would also virtually eliminate any predictive power these factors might have had.

3.5 Data Collection

A list of liquidated and healthy companies was identified from K.T.D.C data base and is as listed in Appendix A attached. The data on each of these companies was obtained from the K.T.D.C's database and used in the analysis. This was the preferred method since it was thought to be a faster and cheaper method of obtaining information. In addition it was considered more cost effective to obtain information by visiting the Corporation instead of the hotels which are located in various parts of the country.

To achieve the objectives of this study, the data required were those of the discriminating variables that included: Working capital, Retained earnings, Earning before interest and tax, Equity as well as Total assets and Total book debts as derived from the annual financial statements of the companies.

3.6 Data Analysis

The method of data analysis used was the same as that used by Edward I. Altman in developing the Z score model. The financial statement figures were subjected to the Z score test using the Altman's Z score discriminant model. This meant calculating the Z score for each and every firm. For each of the variables the mean was calculated for all the firms in the sample, that is, all firms' X_1 mean was calculated and this was done for all the other variables. The F- test value was then computed to determine whether the Z score test would indicate a difference between the bankrupt and non- bankrupt hotels. The accuracies of the models z-score was calculated by dividing the number of firms correctly predicted by the total number of firms in the sample.

The discriminant function used in data analysis was as follows:

$$\mathbf{Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5}$$

Where, X_1 = Working Capital/Total Assets (WC/TA).

X_2 = Retained Earnings/Total Assets (RE/TA).

X_3=Earnings Before Interest and Taxes/Total Assets (EBIT/TA).

X_4, Book Value of Equity/Book Value of Total Liabilities (MVE/TL).

X_5, Sales/Total Assets (S/TA).

CHAPTER FOUR: DATA ANALYSIS AND RESULTS INTERPRETATION

4.1 Introduction

This chapter is devoted to the testing of Altman's (1968) model to its practical prediction ability. The research question is whether the model is also applicable to companies in hotel industry in Kenya, given that the model was originally developed for manufacturing and retail companies. The test of the applicability of the model using a sample of 30 companies in Kenyan hotel industry as listed in Kenya Tourist Development Corporation's database is described. In this part of the study, the most important ratios developed by Altman are calculated, the individual firms' z-scores are derived and the results are presented.

The Altman's Z score equation was applied as follows:

$$\mathbf{Z=1.02X_1 + 0.14X_2 + 0.033X_3 + 0.006X_4 + 0.999\,X_5,}$$

Where:

X_1	=	Working Capital to Total Assets
X_2	=	Retained Earnings to Total Assets
X_3	=	Earnings Before Interest and Taxes to Total Asset
X_4	=	Value of Equity to Total Book Debt
X_5	=	Gross Earnings to Total Assets

The decision rule was that: For $Z<1.81$: Bankruptcy region, for $1.81<Z>2.675$: High bankruptcy potential, for $2.675<Z<2.99$: Low bankruptcy potential and for $Z>2.99$ Strong; No sign of bankruptcy at all.

Using the final year coefficients to predict bankruptcy based on data before the final year has the advantage of requiring data gathered for only one year for the matching firms. This is based on the assumption that the relationship between the variables is stable over time, which may not be logical. Following the pattern of changes in the variables over time may be useful in understanding the decline process. Therefore, in this study, the binomial statistical technique is applied to test the predictive ability of the models on data available up to five years before bankruptcy for both failed and nonfailed companies, and the analysis is repeated for each year. The raw data used to calculate the coefficients and the calculation of the Altman model is shown in Appendix B.

4.2 Data Analysis

The prediction results of the model to the sample of failed and nonfailed companies are discussed below. The empirical results are evaluated and presented using: the sample containing only failed companies, the sample containing only nonfailed companies and the sample containing both failed and nonfailed 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 nonfailed companies, the failed to nonfailed test proportion used is 0.28 to 0.72. Z_1 refers to the Z-score one year prior to bankruptcy (to failed) or the results for the financial year 2003 (to nonfailed), while Z_5 refers to the Z-score five years prior to failure or the Z-score for the financial year 1999. The summary of Z score calculations is shown in Appendix C.

4.2.1 Analysis of Failed Companies

Table 4.1 discusses the classification result of failed companies using the Altman's model Z-score while table 4.2 depicts the classification results for each company over the years. The model seems to be working in predicting the failed companies accurately. The accurate classification results for: one year financial statement prior to failure is 90 percent, Two years is 90 percent, Three years is 88 percent, Four years is 86 percent, Five year is 75 percent, and the average accuracy result for the five years is 86%. These results show that even though the accuracy rate is slightly lower than the original results achieved by Altman, the 90 percent prediction rate is convincing to say the model is fairly accurate to predict bankruptcy. The declining rate shows the model's predictive ability reduces as failure becomes more remote. The overall average (86 percent) is good enough to conclude the Altman model is classifying reasonably the sample failed companies.

Table 4.1 Failed Companies Prediction

		Category	N	Observed Prop.
Z_1	Group 1	<=2.675	9	.90
	Group 2	>2.675	1	.10
	Total		10	1.00
Z_2	Group 1	<=2.675	9	.90
	Group 2	>2.675	1	.10
	Total		10	1.00
Z_3	Group 1	<=2.675	7	.88
	Group 2	>2.675	1	.12
	Total		8	1.00
Z_4	Group 1	<=2.675	6	.86
	Group 2	>2.675	1	.14
	Total		7	1.00
Z_5	Group 1	<=2.675	3	.75
	Group 2	>2.675	1	.25
	Total		4	1.00

Table 4.2: Classification Result of the Failed Companies Over the Years

Sample Companies	Year 1	Year 2	Year 3	Year 4	Year 5	Classified
1.Milimani Hotel	0.116	1.559	1.337	1.559	-	**Correctly**
2.Kabarnet Hotel	1.044	1.137	1.471	1.471	3.013	**Correctly**
3.Meru Mulika Lodge	2.067	2.114	-	-	-	**Correctly**
4. African tours & hotels Ltd	0.673	2.134	-	-	-	**Correctly**
5. Mt. Elgon Lodge	0.653	0.799	1.591	1.233	1.646	**Correctly**
6. Solar Hotel	(2.117)	(0.841)	(0.841)	-	-	**Correctly**
7. Buffalo springs	(12.321)	(11.147)	(11.147)	(6.936)	(6.936)	**Correctly**
8. Marsabit Hotel	2.838	3.003	3.003	3.192	-	**Incorrectly**
9.Church Road Development	0.110	0.044	0.044	0.131	0.131	**Correctly**
10. Kitui Tourist Hotel	(9.088)	(11.080)	(9.088)	(9.802)	-	**Correctly**

Kabarnet Hotel Ltd. is a subsidiary of KTDC with a shareholding of 98%; it was started in 1969 with a purpose of running a hotel in Kabarnet town. The score is well below the acceptable level of 2.60 in all the years. The Z score predicted the company's insolvency accurately.

Meru Mulika Lodge was started in 1969 and located in Meru National park. It is an investment by KTDC in collaboration with Kenya Wildlife Services. The financial statements for the lodge for years 5 to 3 prior to bankruptcy were not available. The Z sore correctly classified the lodge as failed.

African Tours and Hotels Ltd. is a subsidiary of KTDC, with KTDC holding 53% of its total shareholding. The mandate of the company was that of managing several hotels within Kenya. The Company failed in 2004 and thus the model predicted correctly its status.

Mt. Elgon lodge is a subsidiary company of KTDC with a shareholding of 73 percent. The lodge was started in 1969 with its location at Mt. Elgon National park in Western Kenya. The Z score of the company deteriorated year to year and predicted correctly the status of the lodge.

The Solar Hotel is a company that was registered in Kenya in the year 1998 and is involved in operating a hotel in Kisumu Town. The company did not maintain annual financial statements in the years 1999 and 2003.The Z score for the three years is far below the acceptable level of 2.60. The Z score predicted the company's insolvency accurately.

Buffalo Springs is an associate company of KTDC with a shareholding of 41 percent; it was started in 1980 with an aim of running a lodge in Buffalo Springs National Reserve in Samburu District. The Z score for this company has deteriorated over the years and is well below the acceptable level of 2.60. The Z score predicted the company's insolvency accurately.

Marsabit Hotel is situated within Marsabit Town, it was advanced credit by KTDC in 1980 and the Corporation confirmed that the hotel could not be able to repay the loan. This called for the need for a write off of the same from the KTDC's books. The score shows a relatively high figure which is rare and the misclassification needs investigation.

Church Road Development Company was established in 1994 with a purpose of operating a hotel in Lavington area of Nairobi City. KTDC advanced the company a loan in 1998 to finance its operations thus a loanee to the Corporation. The Z score deteriorates over the years and is well below the acceptable level of 2.60.

Kitui Tourist Hotel is located at Kitui Town, the financial statements for 1999 could not be obtained from KTDC hence no score for that year. The Z score for the years is well below the acceptable level of 2.60.The Z score correctly predicted its insolvency.

4.2.2 Analysis of Non- Failed Companies

Altman's Z-score classification results to nonfailed companies are depicted in table 4.3 and the classification of the companies over the years is as shown in table 4.4.

The correct classification result for one year financial statement is relatively high at 70 percent; two year financial statement at 60 percent, three years financial statement classification result at 65 percent. The correct classification in years four and five is 70 percent. The average accuracy rate for the five years is 67 percent. The increasing percentage shows the abnormality of the model in predicting nonfailed sample companies.

Table 4.3: Non- Failed Companies Prediction

		Category	N	Observed Prop.
Z_1	Group 1	<=2.675	16	.30
	Group 2	>2.675	4	.70
	Total		20	1.00
Z_2	Group 1	<=2.675	8	.40
	Group 2	>2.675	12	.60
	Total		20	1.00
Z_3	Group 1	<=2.675	7	.35
	Group 2	>2.675	13	.65
	Total		20	1.00
Z_4	Group 1	<=2.675	6	.30
	Group 2	>2.675	14	.70
	Total		20	1.00
Z_5	Group 1	<=2.675	6	.30
	Group 2	>2.675	14	.70
	Total		20	1.00

Table 4.4: Classification Result of Nonfailed Companies Over The Years

Sample Companies	Year 1	Year 2	Year 3	Year 4	Year 5	Classified
1.Mombasa Beach Hotel	2.878	3.500	3.233	2.945	2.728	**Correctly**
2.Voi Safari Lodge	3.450	2.919	2.857	2.806	2.607	**Correctly**
3.Hilton Hotel Ltd	8.178	7.565	7.228	8.179	8.558	**Correctly**
4. Ngulia Safari Lodge	3.046	2.949	2.797	3.084	3.372	**Correctly**
5. Proland Ltd	1.442	1.368	1.429	1.513	1.442	**Incorrectly**
6. Bomas Of Kenya	1.436	1.216	1.317	1.384	1.505	**Incorrectly**
7. Garden Hotel Ltd	3.097	3.159	3.146	3.142	3.414	**Correctly**
8. Sunset Hotel ltd	2.684	2.544	2.536	2.846	3.177	**Incorrectly**
9.Hotel Big Five	0.110	0.183	0.149	0.117	0.340	**Incorrectly**
10. Golf Hotel Ltd	(8.082)	(6.251)	(6.258)	(10.407)	(10.075)	**Incorrectly**
11. Jacaranda Hotel Ltd	9.142	10.033	9.973	8.473	8.552	**Correctly**
12. Fairview Hotel Ltd	1.234	1.156	1.114	1.413	1.452	**Incorrectly**
13. Sosa Cottages	13.145	12.387	10.417	12.298	12.677	**Correctly**
14. Cross Culture Craft Ltd	3.046	2.949	2.797	3.084	3.372	**Correctly**
15. Metro Enterprises Ltd	2.969	2.666	2.723	2.638	2.648	**Correctly**
16. Illusions Hotel Ltd	8.909	6.001	7.018	6.298	5.969	**Correctly**
17. Mountain Lodges Ltd	3.869	3.337	3.206	3.170	3.597	**Correctly**
18.Intercontinental Hotel Ltd	4.702	4.402	4.020	4.984	4.634	**Correctly**
19. Mararal Safari Lodge	2.772	2.769	2.941	3.059	3.093	**Correctly**
20. Ark Hotel Ltd	0.347	0.434	0.428	0.448	1.102	**Incorrectly**

Mombasa Beach Hotel is a subsidiary of KTDC at a shareholding of 63%.The Z score for the company shows a reducing trend from year five to year one. However, the score is well above the acceptable level of 2.60.The model therefore correctly predicted the solvency of the hotel.

Voi Safari Lodge is a subsidiary of KTDC at a shareholding of 63 percent. The Z score has improved from year 5 to year 1.The model predicted the solvency of the lodge correctly.

Hilton hotel is located in Nairobi City and is an associate of KTDC at 34 percent shareholding. The Z score of this hotel is well above the acceptable level of 2.60 in all the years. The model predicted correctly the solvency of the hotel.

Ngulia Safari Lodge is a subsidiary of KTDC at a shareholding of 63 percent. The Z score for the lodge is well above the acceptable level of 2.60.The model predicted the solvency of the lodge correctly.

Proland Ltd is a company that was registered in 1990 with an aim of operating a hotel in Kisumu town. KTDC advanced the company a loan in 1993 under its Revolving loan Programme for it to finance the operations of the hotel. KTDC confirms that the hotel is financially sound and manages its loan obligations well. The Z score result of this company is below the acceptable level of 2.60. The model predicted the company's solvency inaccurately.

Bomas of Kenya was started in 1971 as a wholly owned subsidiary company of KTDC. The company was established to preserve, maintain and promote the rich and diverse cultural values of various ethnic groups of Kenya and to act as a tourist attraction centre. The Z score of this company is below the acceptable level of 2.60.Z score predicted solvency inaccurately. Although this score predicted insolvency, KTDC confirmed that the company restructured its operations probably saving if from going into liquidation.

Garden hotel is located in Machakos Town in Eastern Province. KTDC advanced the hotel a loan in 1997 under its Commercial Fund Programme for the hotel to finance its operations. KTDC confirmed that the hotel maintains its account with them well. The Z score of this company is well above the acceptable level of 2.60. The Z score predicted solvency accurately.

Sunset Hotel Ltd is a subsidiary of KTDC at 95 percent shareholding. The Z score for this hotel has deteriorated over the five years. In years 3 and 2, the Z score was below the acceptable level of 2.60. KTDC confirmed that in 2003, the hotel refurbished its facilities and restructured its operations probably saving it from liquidation. Z score correctly predicted the solvency of the hotel.

Hotel Big Five was established in 1995 to operate a hotel in Nyanza Province. KTDC advanced the hotel a loan in 1998 under the Revolving Fund Programme. From KTDC database, the hotel has maintained its account well and is on schedule on its loan repayments. The Z score for this hotel is well below the acceptable level of 2.60. Z score predicted the solvency of the hotel incorrectly.

Golf Hotel Ltd is a subsidiary company of KTDC, with KTDC shareholding being at 80%. The Z score for this hotel is well below the acceptable level of 2.60. Z score predicted the solvency of the hotel incorrectly.

Jacaranda Hotel is a company that was advanced a loan by KTDC under its Commercial Fund Programme in 1994. From KTDC's records, the company has maintained its account with KTDC well and is repaying its loan as per the loan agreement. The Z score for this company is above the acceptable level of 2.60. Z score predicted the solvency of the hotel correctly.

Fair View Hotel was advanced a loan by KTDC under its Commercial Fund Programme in 1990. From KTDC's records, the company has maintained its account with KTDC well and is repaying its loan as per the loan agreement. The Z score for this company is well below the acceptable level of 2.60. Z score predicted the solvency of the hotel incorrectly.

Sosa Cottages Ltd was advanced a loan by KTDC under its Commercial Fund Programme in 1992. From KTDC's records, the company has maintained its account with KTDC well and is repaying the loan as per the loan agreement. The Z score for this company is above the acceptable level of 2.60. Z score predicted the solvency of the hotel correctly.

Cross Culture Craft advanced a loan by KTDC under its Commercial Fund Programme in 1993. From KTDC's records, the company has maintained its account with KTDC well and is repaying the loan as per the loan agreement. The Z score for this company is above the acceptable level of 2.60. Z score predicted the solvency of the hotel correctly.

Metro Enterprises is a company that was advanced a loan by KTDC under its Commercial Fund Programme in 1991. KTDC confirmed that the company has maintained its account with KTDC well and is repaying the loan as per the loan agreement. The Z score for this company is above the acceptable level of 2.60. Z score predicted the solvency of the hotel correctly.

Illusions Hotel was advanced a loan by KTDC under its Commercial Fund Programme in 1991. KTDC confirmed that the company has maintained its account with KTDC well and is repaying the loan as per the loan agreement. The Z score for this company is above the acceptable level of 2.60. Z score predicted the solvency of the hotel correctly.

Mountain Lodges Ltd is an associate company of KTDC with KTDC have a shareholding of 40 percent. The Z score for this company is above the acceptable level of 2.60. Z score predicted the solvency of the hotel correctly.

Intercontinental Hotel is an associate company of KTDC with KTDC have a shareholding of 40 percent. The Z score for this company drastically reduced in year three. This could be attributed to rehabilitation of the building housing this hotel done during the year. The Z score result is well above the acceptable level of 2.60. Z score predicted the solvency of the hotel correctly.

KTDC holds 16 percent shareholding in Maralal Safari Lodge Ltd. The Z score result for this company has remained consistent over the years. The Z score result is well above the acceptable level of 2.60. Z score predicted the solvency of the hotel correctly

KTDC holds 6 percent shareholding in the Ark Hotel Ltd. The Z score result for this company has remained consistent over the years. The Z score result is far below the acceptable level of 2.60. Z score predicted the solvency of the hotel incorrectly

4.3 Comparing Failed Versus Nonfailed Companies

Altman's model binomial test classification results of failed and nonfailed companies indicates the accuracy rates were significantly lower than the Altman's 95 percent 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 nonfailed companies validates the general applicability of the model in the hotel industry in Kenya.

4.3.1 Predictive Result One Year Prior To Failure

Table 4.5 shows the results using data compiled one financial statement prior to bankruptcy for the failed companies and one year financial statements of nonfailed companies. The model's classification accuracy is 77 percent of the total sample. The measure of success of the model in classifying the firms is calculated by adding the correctly classified sample companies (9+14) divided by total number of sample companies (30). The type I error, which is the prediction of failed companies as nonfailed is 3 percent, while the type II error, when companies which are actually nonfailed are predicted as failed, is much higher (20 percent). This implies that companies can be wrongly predicted with financial problems while it is actually the opposite. Businesses, such as credit organizations, may not be willing to supply credit to these wrongly predicted companies in fear of potential bankruptcy. However, the accuracy percentage of type 1 and type 11 errors is extremely high at 97 percent and 80 percent respectively.

Table 4.5: Altman's Z-Score Classification Result, One Year Prior To Failure

Actual	Predicted		Total
	Failed	Non Failed	
Failed	9	1	10
Non failed	6	14	20

4.3.2 Predictive Result Two Years Prior To Failure

The figures displayed in table 4.6 shows the classification result of the model for companies using data complied two statements prior to bankruptcy. The classification accuracy is 70 percent. This result is expected to be weaker than the one year prior result, as impending failure is more remote and the indications are less clear. The type II error is higher than the one year prior at 27 percent, which means that there is a risk that the model could classify a company incorrectly.

Table 4.6: Altman's Z-Score Classification Result, Two Years Prior To Failure

Actual	Predicted		Total
	Failed	Non Failed	
Failed	9	1	10
Non failed	8	12	20

4.3.3 Z-Score Long-Range Predictive Results

The long-range predictive accuracy of the model shown in table 4.7 below depicts the Altman model Z-score predictive results. The table includes the results for years one and two, which was already discussed, to support the comparison of the results for the years three to five.

This analysis is important to examine the overall predictive effectiveness of the model for a longer period of time prior to failure, as many studies showed firms exhibiting failure tendencies as much as five years prior to actual failure. In determining these results, financial statements are gathered up to five years prior to failure. As some of the firms are in existence for less than three years, the number of sampled companies is reduced. It is expected to see the deteriorating results of predictive accuracy as the number of years to failure becomes more remote. However, the results achieved in this study for three to five years (71, 74, and 75 percent, respectively) are better than the Altman's original result for three, four and five years (48, 29, and 36 percent, respectively), (Altman, 1993:195).

It is also interesting to note that the results improve over the five year period. There seems to be no logical reason for this phenomenon. This could be considered as a warning sign to the person assessing the company and would intimate further investigations may be necessary before the score is accepted. It is therefore concluded that, though the Altman model is quite good in prediction of failure three to five years prior to failure, it is equally good in first two years prior to failure thus validating the predictive ability of the model.

Table 4.7: Altman's Z-Score Classification Result, Five Years Prior To Failure,

Year	N	Hits			Misses			Percent
		Failed	Nonfailed	Total	Failed	Nonfailed	Total	Correct *
1	30	9	14	23	1	6	7	77%
2	30	9	12	21	1	8	9	70%
3	28	7	13	20	1	7	8	71%
4	27	6	14	20	1	6	7	74%
5	24	4	14	18	0	6	6	75%

***Total hits divided by total sample**

CHAPTER FIVE: SUMMARY, CONCLUSIONS AND RECOMMEDATIONS

5.1 Summary of Results

The central theme of the study was to investigate the prediction ability of Altman (1968) bankruptcy prediction model in sampled companies in Kenyan hotel industry. As financial analysts and researchers use bankruptcy prediction models routinely to evaluate the financial health of companies, testing the practical applicability of models is essential. Improper application of models may lead into mistaken managerial judgments and misunderstanding of actual facts that may lead to wrong conclusions and decisions. It is important for the business society such as creditors, customers, suppliers, employees, and government in general to know the financial well being of companies. Early awareness of financial distress may help finding immediate solutions to the problems, or the partners may know the consequences of the problems and be aware in advance. Failing to predict bankruptcy causes damage not only for the company failing but also affects all the creditors of the failing business as well as the economic environment of a society. The major reason why business failure has such a major impact on the economy of a country is the costs associated with going bankrupt.

Table 4.8 summarizes the results of Z score classification for the five years. The accuracy of the model is extremely high at 75% for one year prior to failure and an average of 73% for the five years. The type 1 and 11 errors resulted in an average accuracy percentage of 91% and 67% respectively. It is important that error 1's accuracy is high as this is where the most damage can be caused by companies becoming insolvent. The 9% and 33% misclassification is critical as this means that the model could classify a company as being on the right path and not potential insolvency. Another interesting fact is the high scores in some instances, especially companies that eventually liquidated. This could also be considered as a warning signal for the person assessing the company and would therefore intimate that further investigations may be necessary before the score is accepted.

Table 4.8: Classification of Results of Failed and Non Failed Companies

	Number Correct	Percent Correct	Percent Error	N	Actual	Predicted failed	Predicted Nonfailed
Year 1							
Type 1	9	90%	10%	10	Failed	9	1
Type 2	14	70%	30%	20	Nonfailed	6	14
Total	23	77%	23%	30			
Year 2							
Type 1	9	90%	10%	10	Failed	9	1
Type 2	12	60%	40%	20	Nonfailed	8	12
Total	21	70%	30%	30			
Year 3							
Type 1	7	88%	12%	8	Failed	7	1
Type 2	13	65%	35%	20	Nonfailed	7	13
Total	20	71%		28			
Year 4							
Type 1	6	86%	14%	7	Failed	6	1
Type 2	14	70%	30%	20	Nonfailed	6	14
Total	20	74%	26%	27			
Year 5							
Type 1	4	100%	0%	4	Failed	4	0
Type 2	14	70%	30%	20	Nonfailed	6	14
Total	18	75%	25%	24			

The Altman bankruptcy prediction model was developed using samples of predominantly manufacturing firms during 1968. Even though the model was developed about three decades ago, it still seems to be popular and applied regularly by financial institutions and other companies today to predict failure. The models' coefficient was also developed using sample companies during the 1960's, but these coefficients are continued to evaluate the financial health of companies at present. The models reliability when applied to current companies from hotel industries depends on the prediction ability of the model regardless the type of industry, time horizon and/or country. The models used to derive best discriminating variables using the original sample manufacturing companies. The problem is these variables may not be reliable predictors in other industries or time periods. As the relative importance of the variables changes over time, the coefficients may not be stable even if the variables included in the model were accurate predictors.

The main concern of the study was therefore to what extent the model was applicable to predict failure in the Kenyan hotel companies. Hence the primary objective of the study was to test the practical applicability of Altman's bankruptcy prediction models to Kenyan Hotel industry and in particular to hotels owned by Kenya Tourist Development Corporation while the secondary objective was to investigate whether the models are useful for predicting bankruptcy for non-manufacturing firms, such as those in the hotel industry, as they are for predicting bankruptcy of manufacturing firms.

The study attempted to address the objectives by employing a sample of 30 (10 failed and 20 nonfailed) companies in the hotel industry that are owned by Kenya Tourist Development Corporation. Two nonfailed companies are matched to each failed company by the similarity of turnover.

The main reasons for focusing on the companies in the hotel industry were threefold:

- The hotel industry is currently much more dominant than manufacturing, relative to 30 years ago.
- The industry is characterized by different sets of financial norms.
- The rapid change makes bankruptcy prediction more difficult in services companies.

5.2 Conclusion

The results on the failure prediction ability of Altman model to the companies in the hotel industry is as discussed in chapter 4. The analysis was conducted in two steps. Firstly, the prediction ability of the model was tested on the total sample of failed and nonfailed sampled companies up to five years prior to failure and the average prediction accuracy is analyzed. Finally, the model was tested on an annual basis prior to bankruptcy.

The main conclusions of the study according to the analysis are:

a. Concluding results of total failed and nonfailed companies

- The Altman model shows average classification results of 91 percent accuracy rate in the failed sampled companies. This result is convincing that the Altman model is reasonably accurate to classify the failed companies correctly over five years, but it is still a bit weaker than the Altman's original result (95 percent). It is the opinion of the researcher that the success rate is reasonably high at an average accuracy rate of 91 percent over 5 years to bankruptcy; therefore, it validates the application of the Altman model in the companies in the hotel industry to predict failure.

- The average classification accuracy of the Altman model to the nonfailed sampled companies is 67 percent, which is significantly strong to classify nonfailed companies as compared to the Altman's 96 percent accuracy using the original sample. Although the model seems to predict failed companies reasonably well, the major problem with the model is that it's relatively weak in predicting the nonfailing sampled companies correctly. It is of the opinion of the researcher that the model's accuracy rate is relatively strong at an average rate of 67 percent. This validates the general applicability of the Altman model in the hotel industry in Kenya.

b. Concluding results on comparing failed and nonfailed companies on annual basis

- In the one year prior to failure, the Altman model was 77 percent accurate to classify sampled companies correctly, with type I and type II errors of 3 and 20 percent, respectively. These results indicate that the Altman model is significantly strong to classify the sampled companies correctly as failed and nonfailed.
- The classification accuracy two years prior to failure is 70 percent. The results achieved for years three to five prior to failure are: 71 percent third year, 74 percent fourth year and 75 percent fifth year. Although the predictive accuracy of the Altman model is 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.

It is generally assumed bankruptcy prediction models are useful regardless of the industry and time horizon. The findings reported in the study indicate that the overall accuracy rate of the Altman model was reduced when used on the Kenyan sample. Although the results are good at 91% and 67%, the fine-tuning of Altman's z-score model will be of benefit to the credit granting fraternity. These results suggest that the Altman model is an accurate predictor, and consequently, it is advisable to be use the model in predicting failure in the non-manufacturing firms, especially, in current Kenyan companies in the hospitality industry.

5.3 Recommendations

It is important for researchers and analysts to understand prediction models during their application. That is, practitioners should not assume that a model's predictive accuracy could transcend to industries other than those used in the development of the model. Models developed using firms from one set of industries may not be highly accurate in predicting bankruptcies for firms in other industries. The findings discussed above indicated that the use of Altman's model to predict failure for companies in the hotel industry is questionable. Hence, application of the model to Kenyan companies in the hotel industry is not advisable.

According to the empirical results the research study recommendations are as follows:

- The fine-tuning of Altman's z-score model will be of benefit to the credit granting fraternity. It is critical to have a model that could operate at a 90 percent or more accuracy level.
- The model is highly recommended to potential investors in companies as an assessment tool. The results could raise certain questions about the state of a

company and could ultimately result in an investor not investing or purchasing a company for a more realistic price.

- In the implementation of bankruptcy prediction models, the incorporation of other important indicators of financial soundness of business organizations, such as stock ratings, current legal affairs, government policies, and economic environment, are recommended.
- It is recommended that the practical applicability of Altman's Z score bankruptcy prediction model should be checked after some period of time as the economy changes. Therefore, the identification of reliable models will help analysts to predict financial distress precisely.

5.4 Limitations Of The Research Study

The purpose of this section is to suggest some problems that were not adequately covered in this study. The study deliberately excluded some important data because the availability of financial statements was insufficient to address the issues on hand for the failed companies. The data collection was more of a problem in this study.

5.5 Areas For Further Research

The study tried to strengthen the position of existing work in bankruptcy prediction, particularly based on the Altman model. A number of research areas could be provided from the practical application of bankruptcy prediction models. Presented below are few suggestions researchers might extend this research in several directions.

a) Testing the application of other models to the firms in the database developed in this study would be a useful extension.

b) Developing new bankruptcy prediction models using companies in the hotel industry.

c) Testing the application of Altman model in the manufacturing and retailing companies in Kenya.

d) Researchers should also investigate development of bankruptcy prediction models using different statistical methodology other than multivariate discriminant analysis, such as artificial neural networks (ANNs), logit or probit analysis, to compare and select the most efficient model.

REFERENCES

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

Altman, E.I. 1970. "A Reply" *Journal of Finance, 25(3): 1166-1172*

Altman, E.I. 1982. Accounting implications of failure prediction models. *Journal of Accounting Auditing and Finance, fall.*

Altman, E.I. 1983. Corporate Financial Distress: *A complete guide to Predicting and Avoiding Distress and Profiting from Bankruptcy.* USA, John Riley and Sons Inc.

Altman, E.I. 1984. An empirical investigation of the bankruptcy cost question. *Journal of Finance, 39(4): 1067-1089*

Altman, E. Haldeman, R. & Narayanan, P (1977). Zeta analysis: a new model to identify bankruptcy risk of corporations. *Journal of Banking and Finance, 1 (1): 29 - 54.*

Altman, E.I. (1993). Corporate financial distress and bankruptcy: *A complete guide to predicting and avoiding distress and profiting from bankruptcy.* New York: John Wiley and Sons.

Bruno, A.V. & Leidecker, J.K. (2001). *Causes of new venture failure: 1960 vs.1980.* Business Horizon. November-December 1988.

Court, P.W. (1991). An investigation into the significance of certain firm specific non-financial variables in a failure prediction model. De Ratione, 5(2):3-15.

Court, P.W. & Radoff, S.E. (1993). A two-stage model for the prediction of corporate failure in South Africa. *Investment Analyst's Journal, 38 (summer 1993/1994): 9-19.*

Coghlan, D. & Brannick, T. (2002). *Doing Action Research in your own organization.* London.

Charktou, A., Choriambus C. &Trigeorgis L. (2001). *Bankruptcy prediction based on option pricing theory using artificial neural networks methodology.* University of Chicago

Chuvakhin, N. & Gertmenian, L.W. *Predicting bankruptcy in the WorldCom age: How to determine when it is safe to grant credit.*

Deakin, E.B. (1972). A discriminant analysis of predictors of failure. *Journal of Accounting and Research.*

Deakin, E.B. (1977). *Business failure prediction: an empirical analysis, in E.I.*

Dine, R. (1992), *"African tourism: trouble in paradise"*, African Business.

Escott, P, Glormann, F, Kocagil F.E (2008), - *Moody's KMV, Modeling Methodology*, Retrieved from http://www. Moodyskmv.

Edmister, R.O. (1972). An empirical test of financial ratio analysis for small business failure prediction. *Journal of Finance and Quantitative Analysis, 7(2): 1477-1493.*

Emory, C.W. & Cooper, D. R. (1995). *Business Research Methods. Fifth Edition*. Irwin. Homewood, IL 60430. Boston, MA 02116.

Grice, J.S. & Ingram, R. W. (2001). Tests of the generalizability of Altman's bankruptcy Prediction model. *Journal of Business Research, 54.*

Hall, G. & Young, B. (1990). Factors associated with insolvency amongst small firms. *International Small Business Journal,* 9(2).

Hopwood, W., McKeown, J.C. & Mutchler, J.F. (1994). *A reexamination of auditors versus model accuracy within the context of the going-concern opinion decision.* Contemporary Accounting Research, 10.

Iain T. Christie and Crampton Doreen C., (2001). *Tourism in Africa.*

Katz, S., Lilien, S & Nelson, B. (2005). Stock market behavior around bankruptcy model distress and recovery predictions. *Financial Analysis Journal, 41(1): 70-74.*

Kritzinger A.A.C. 1980. *Credit Management.* Juta & Company.

Künnapas, T., Hallsten, L., & S¨oderberg, G. (1973). Inter individual differences in homomodal and heteromodal scaling.

Laitinen, E.K. (1995). The duality of bankruptcy process in Finland. *European Accounting Review, 4(3): 433-454*

Laitinen, E.K. & Laitinen T. (2000). Bankruptcy prediction: application of the Taylor's expansion in logistic regression. *International Review of Financial Analysis.*

Libby, R (1975). Accounting ratios and the prediction of failure: Some behavioural evidence. *Journal of Accounting Research.*

Mar-Molinero, C & Seranno-Cinca, C (2002). Bank failure: A multidimensional scaling approach. *The European Journal of France, 7(2):165-183*

Merton, Robert C. "On the pricing of corporate debt: The risk structure of interest rates." *Journal of Finance: http://www.igidr.ac.in/*

Mills, R. 1996. Developments in Corporate Finance. *Henley Management College, Manager Update, Volume 7, Issue 4.*

Mouton, J (2001). *How to succeed in your Master's and Doctoral studies: a South African guide and resource book*. Pretoria: Van Schaik Publishers.

Mossman, C.E., Bell, G.G., Swartz, L.M. & Turtle, H. (1998). An empirical comparison of bankruptcy models. *Financial Review, 33(2): 35-54.*

Nam, J. & Jinn, T. (2000). Bankruptcy prediction: evidence from Korean listed companies during the IMF crisis. *Journal of International Financial Management and Accounting.*

Norton, M.W. (1989). *Strategic and financial factors in business failure, bankruptcy and reorganization*. Unpublished doctorial thesis. University of Illinois.

Odom, M. & Sharda, R. (1990). *A neural network model for bankruptcy prediction, in: proceeding of the IEEE International Conference on Neural Networks,* II, 1990.

Ohlson, J. (1980). Financial ratios and the probalistic prediction of bankruptcy. *Journal of Accounting Research.*

O'Leary, D.E. (1998). Using neural networks to predict corporate failure. *International Journal of Intelligent Systems in Accounting Finance and Management, 7 (3), 187-198.*

Pacey, J.W. & Pham, T.M. (1990). The predictiveness of bankruptcy models: Methodological Problems and evidence. *Australian Journal of Management, 15(2): 315-337.*

Platt, H.D. & Platt, M.B. (1990). Development of a class of stable predictive variables: The case of bankruptcy prediction. *Journal of Business Finance &Accounting.*

Porter ME, 1980, *"Competitive Strategy: Techniques for Analyzing Industries and Competitors"*. The Free Press.

Press, J., & Wilson, S. (1978). Choosing between logistic regression and discriminant analysis. *Journal of the American Statistical Association*. Retrieved from: http://jht.sagepub.com

Rahimian, E., Singh, S., Thammachote, T. & Virmani, T. (1993). *Bankruptcy prediction by neural network. Neural networks in finance and investing: using artificial intelligence to improve real-world performance (pp. 159-176)*. Probus, Chicago, IL.

Robert S. Hamada. *The Journal of Finance, Vol. 27, No. 2. 435-452.*

Robertson, J. & Mills, R.W. (1991). The uses and abuses of corporate prediction models. *Management Accounting, 69(9): 20-22.*

Shah, J.R. & Murtaza, M.B. (2001). A neural network based clustering procedure for bankruptcy prediction. *American Business Review, 18(2):80 -86*

Samuels J.M, Brayshaw R. E. and Craner J.M. (1995). *Financial Statement Analysis in Europe.Chapman and Hall.*

Sekaran, U. (1992). *Research Methods for business: a skill building approach. 2nd ed.* New York: John Wiley & Sons.

Shin, K. & Lee, Y. (2002). *A genetic algorithm application in bankruptcy prediction modeling. Expert Systems with Applications, 23(3): 321-328.*

Taffler, R.J & Houston, W. (2007). How to Identify Failing Companies before it is Too Late. *Professional Administration. April 2007*

Taffler, R.J, (2008). The Z-Score Approach to Measuring Company Solvency. *The Accountant's Magazine, March 2008.*

Timmons, J.A. & Spinelli, S. (2004). *New venture creation: Entrepreneurship for the 21st century. 6th Ed.* New York; NY: McGraw-Hill.

Kibandi I. N (2005). *Failure prediction on insurance companies in Kenya.* Unpublished research project. University of Nairobi.

Walker, T. B., 2005. *Estimating default with discrete duration and structural models.* University of Iowa.

Yoon Y., Swales Jr. & Margavio T. (1993). A Comparison of Discriminant Analysis versus Artificial Neural Networks. *Journal of Operational Research Society. 44. 1. 51-60.*

Zavgren, C.V. (1985). Assessing the vulnerability to failure of American industrial firms: a logistic analysis. *Journal of Business Finance & Accounting, 12(1): 19-45.*

Zhang, G., Hu, M.Y., Patuwo, B.E. & Indro, D.C. (1999). *Artificial neural networks in bankruptcy prediction: general framework and cross-validation analysis.* European Journal of Operational Research, 116(1): 16-32.

Zmijewski, M.E. (1984). Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research. 22(1): 59-82.*

Zopounidis, C. & Dimitras, A. (1998). *Multicriteria decision aid methods for the prediction of business failure.* Kluwer Academic Publishers, Dordrecht.

UNIVERSITY OF NAIROBI
SCHOOL OF BUSINESS
MBA PROGRAM – LOWER KABETE CAMPUS

Telephone: 020-2059162
Telegrams: "Varsity", Nairobi
Telex: 22095 Varsity

P.O. Box 30197
Nairobi, Kenya

DATE 17/9/2010

TO WHOM IT MAY CONCERN

The bearer of this letter SABINA N. NYAMU

Registration No: D61/70620/2008

is a Master of Business Administration (MBA) student of the University of Nairobi.

He/she is required to submit as part of his/her coursework assessment a research project report on a management problem. We would like the students to do their projects on real problems affecting firms in Kenya. We would, therefore, appreciate if you assist him/her by allowing him/her to collect data in your organization for the research.

The results of the report will be used solely for academic purposes and a copy of the same will be availed to the interviewed organizations on request.

Thank you.

UNIVERSITY OF NAIROBI
SCHOOL OF BUSINESS
MBA OFFICE
P. O. Box 30197
NAIROBI

DR. W.N. IRAKI
CO-ORDINATOR, MBA PROGRAM

APPENDIX A

Group 1 - Liquidated Companies. (Source: Own)

1 Meru Mulika Lodge Ltd
2 African Tours & Hotels Ltd
3 Solar Hotel Ltd
4 Buffalo Springs Ltd
5 Milimani Hotel , Meru.
6 Marsabit Hotel Ltd
7 Mt.Elgon Lodge Ltd
8 Church Road Development Co. Ltd.
9 Kitui Tourist Hotel Ltd.
10 Kabarnet Hotel Ltd

Group 2 - Healthy Companies. (Source: Own)

1 Mombasa Beach Hotel Ltd
2 Voi Safari Lodge Ltd
3 Ngulia Safari Lodge
4 Hilton Hotel Ltd
5 Intercontinental Hotel Ltd
6 Bomas of Kenya Ltd
7 Garden Hotel Co. Ltd, Machakos.
8 Sunset Hotel Ltd
9 Hotel Big Five Ltd.
10 Golf Hotel Ltd
11 Jacaranda Hotel Ltd , Mombasa.
12 Farmview Hotel Ltd.
13 Sosa Cottages Ltd.
14 Cross Culture Craft Ltd.
15 Metro Enterprises Ltd.
16 Illusions Hotel Ltd.
17 Mountain Lodges Ltd
18 Proland Ltd
19 Maralal Safari Lodge Ltd
20 Ark Hotel Ltd.

APPENDIX B: FINANCIAL INFORMATION

Group 2: Non failed sampled companies

Variables	NF 1	NF 2	NF 3	NF 4	NF 5	NF 6	NF 7	NF 8	NF 9	NF 10
YEAR 1	2003	2003	2003	2003	2003	2003	2003	2003	2003	2003
Current Assets:	264,978,000	123,150,000	5,869,400	60,249,086	62,200,160	31,546,271	51,538,295	49,349,015	177,392,000	4,536,183
Total Assets:	2,361,158,000	2,197,424,000	10,869,400	147,465,744	221,748,248	184,765,013	133,553,224	134,749,302	557,014,000	9,616,076
Current Liabilities:	49,020,000	20,208,000	7,353,000	26,307,793	11,033,269	17,663,583	15,330,470	19,119,855	364,582,000	21,860,548
Total Liabilities:	162,540,000	132,089,000	24,381,000	47,902,804	139,218,499	91,949,672	37,655,170	43,708,542	434,814,000	50,419,928
Retained Earnings:	974,781,000	841,498,000	9,856,000	30,752,686	764,369	5,802,841	27,640,605	24,987,092	(140,484,000)	(46,003,852)
Sales:	243,220,000	156,760,000	32,859,320	94,439,987	137,565,045	201,647,680	49,989,152	75,555,588	313,523,000	3,380,245
EBIT	168,157,000	108,748,000	25,223,550	26,396,792	12,388,697	(22,128,110)	2,057,061	1,025,003	22,719,000	78,852
Book value of Equity	219,861,800	89,567,500	55,200,000	99,562,939	82,529,785	92,815,341	129,104,600	91,040,760	122,200,000	33,559,380
YEAR 2										
Current Assets:	232,253,217	104,677,500	4,988,990	51,211,723	81,308,525	26,814,330	43,807,551	41,946,663	150,783,200	3,855,756
Total Assets:	2,069,554,987	2,307,295,200	11,412,870	154,839,031	245,313,320	194,003,264	140,230,885	141,486,767	584,864,700	10,096,880
Current Liabilities:	42,966,030	15,762,240	5,735,340	20,520,079	15,883,419	13,777,595	11,957,767	14,913,487	284,373,960	17,051,227
Total Liabtlities:	142,466,310	122,842,770	22,674,330	44,549,608	169,376,420	85,513,195	35,019,308	40,648,944	404,377,020	46,890,533
Retained Earnings:	854,395,547	715,273,300	8,377,600	26,139,783	(8,846,449)	4,932,415	23,494,514	21,239,028	(119,411,400)	(39,103,274)
Sales:	213,182,330	122,272,800	25,630,270	73,663,190	158,181,905	157,285,190	38,991,539	58,933,359	244,547,940	2,636,591
EBIT	147,389,611	84,823,440	19,674,369	20,589,498	(26,008,146)	(17,259,926)	1,604,508	799,502	17,720,820	61,505
Book value of Equity	192,708,868	94,045,875	57,960,000	104,541,086	75,936,900	97,456,108	135,559,830	95,592,798	128,310,000	35,237,349
YEAR 3										
Current Assets:	224,124,354	101,013,788	4,814,375	49,419,313	31,546,271	25,875,829	42,274,286	40,478,530	145,505,788	3,720,804
Total Assets:	1,997,120,562	2,226,539,868	11,013,420	149,419,665	184,765,013	187,213,149	135,322,804	136,534,730	564,394,436	9,743,489
Current Liabilities:	41,462,219	15,210,562	5,534,603	19,801,876	17,663,583	13,295,379	11,539,245	14,391,515	274,420,871	16,454,434
Total Liabilities:	137,479,989	118,543,273	23,808,047	42,990,371	91,949,672	82,520,233	33,793,632	39,226,231	390,223,824	45,249,364
Retained Earnings:	824,491,702	690,238,735	8,084,384	25,224,891	5,802,841	4,759,780	22,672,206	20,495,662	(115,232,001)	(37,734,660)
Sales:	205,720,948	117,993,252	24,733,210	71,084,978	201,647,680	151,780,209	37,626,835	56,870,691	235,988,762	2,544,310
EBIT	142,230,974	81,854,620	18,985,766	19,868,865	(22,509,350)	(16,655,828)	1,548,350	771,520	17,100,591	59,352
Book value of Equity	185,964,057	90,754,269	55,931,400	100,882,148	92,815,341	94,045,144	130,815,236	92,247,050	123,819,150	34,004,042
YEAR 4										
Current Assets:	157,538,255	114,529,500	5,458,542	56,031,650	36,909,137	29,338,032	47,930,614	45,894,584	164,974,560	4,218,650
Total Assets:	554,574,414	1,428,325,600	7,065,110	95,852,734	153,354,961	120,097,258	86,809,596	87,587,046	362,059,100	6,250,449
Current Liabilities:	370,380,564	11,114,400	4,044,150	14,469,286	14,660,774	9,714,971	8,431,759	10,515,920	200,520,100	12,023,301
Total Liabilities:	445,477,096	138,693,450	25,600,050	50,297,944	76,318,228	96,547,156	39,537,929	45,893,969	456,554,700	52,940,924
Retained Earnings:	795,634,493	782,593,140	9,166,080	28,599,998	4,816,358	5,396,642	25,705,763	23,237,996	(130,650,120)	(42,783,582)
Sales:	80,244,634	86,218,000	18,072,626	51,941,993	167,367,574	110,906,224	27,494,034	41,555,573	172,437,650	1,859,135
EBIT	8,584,657	59,811,400	13,872,953	14,518,236	(18,682,761)	(12,170,461)	1,131,384	563,752	12,495,450	43,369
Book value of Equity	194,548,714	83,297,775	51,336,000	92,593,533	77,036,733	86,318,267	120,067,278	84,667,907	113,646,000	31,210,223
YEAR 5										
Current Assets:	165,415,168	133,999,515	6,386,494	65,557,030	10,574,027	34,325,497	56,078,819	53,696,663	193,020,235	4,935,821
Total Assets:	582,303,135	1,185,510,248	5,864,041	79,557,769	37,697,202	99,680,725	72,051,964	72,697,248	300,509,053	5,187,873
Current Liabilities:	388,899,592	9,224,952	3,356,645	12,009,508	1,875,656	8,063,426	6,998,360	8,728,214	166,431,683	9,979,340
Total Liabilities:	467,750,951	115,115,564	21,248,042	41,747,294	23,667,145	80,134,139	32,816,481	38,091,994	378,940,401	43,940,967
Retained Earnings:	835,416,217	649,552,306	7,607,846	23,737,998	129,943	4,479,213	21,335,783	19,287,536	(108,439,600)	(35,510,373)
Sales:	84,256,866	71,560,940	15,000,280	43,111,854	23,386,058	92,052,166	22,820,048	34,491,126	143,123,250	1,543,082
EBIT	9,013,890	49,643,462	11,514,551	12,050,136	2,106,078	(10,101,482)	939,048	467,914	10,371,224	35,996
Book value of Equity	204,276,150	69,137,153	42,608,880	76,852,633	14,030,063	71,644,162	99,655,841	70,274,363	94,326,180	35,904,485

APPENDIX B: FINANCIAL INFORMATION

Group 2: Non failed sampled companies continued

Variables	NF 11	NF 12	NF 13	NF 14	NF 15	NF 16	NF 17	NF 18	NF 19	NF 20
YEAR 1	2003	2003	2003	2003	2003	2003	2003	2003	2003	2003
Current Assets:	264,978,000	123,150,000	5,869,400	60,249,086	62,200,160	31,546,271	51,538,295	49,349,015	177,392,000	68,042,745
Total Assets:	2,361,158,000	2,197,424,000	10,869,400	147,465,744	221,748,248	184,765,013	133,553,224	134,749,302	557,014,000	73,122,638
Current Liabilities:	49,020,000	20,208,000	7,353,000	26,307,793	11,033,269	17,663,583	15,330,470	19,119,855	364,582,000	21,860,548
Total Liabilities:	162,540,000	132,089,000	24,381,000	47,902,804	139,218,499	91,949,672	37,655,170	43,708,542	434,814,000	50,419,928
Retained Earnings:	974,781,000	841,498,000	9,856,000	30,752,686	764,369	5,802,841	27,640,605	24,987,092	(140,484,000)	(46,003,852)
Sales:	243,220,000	156,760,000	32,859,320	94,439,987	137,565,045	201,647,680	49,989,152	75,555,588	313,523,000	3,380,245
EBIT	168,157,000	108,748,000	25,223,550	26,396,792	12,388,697	(22,128,110)	2,057,061	1,025,003	22,719,000	548,965
Book value of Equity	2,198,618,000	89,567,500	55,200,000	99,562,939	82,529,785	92,815,341	129,104,600	91,040,760	122,200,000	33,559,380
YEAR 2										
Current Assets:	225,231,300	104,677,500	4,988,990	51,211,723	52,870,136	26,814,330	43,807,551	41,946,663	150,783,200	57,836,333
Total Assets:	2,479,215,900	2,307,295,200	11,412,870	154,839,031	232,835,660	194,003,264	140,230,885	141,486,767	584,864,700	76,778,770
Current Liabilities:	38,235,600	15,762,240	5,735,340	20,520,079	8,605,950	13,777,595	11,957,767	14,913,487	284,373,960	17,051,227
Total Liabilities:	151,162,200	122,842,770	22,674,330	44,549,608	129,473,204	85,513,195	35,019,308	40,648,944	404,377,020	46,890,533
Retained Earnings:	828,563,850	715,273,300	8,377,600	26,139,783	649,714	4,932,415	23,494,514	21,239,028	(119,411,400)	(39,103,274)
Sales:	189,711,600	122,272,800	25,630,270	73,663,190	107,300,735	157,285,190	38,991,539	58,933,359	244,547,940	2,636,591
EBIT	131,162,460	84,823,440	19,674,369	20,589,498	9,663,184	(17,259,926)	1,604,508	799,502	17,720,820	428,193
Book value of Equity	2,308,548,900	94,045,875	57,960,000	104,541,086	86,656,274	97,456,108	135,559,830	95,592,798	128,310,000	35,237,349
YEAR 3										
Current Assets:	217,348,205	101,013,788	4,814,375	49,419,313	51,019,681	25,875,829	42,274,286	40,478,530	145,505,788	55,812,062
Total Assets:	2,392,443,344	2,226,539,868	11,013,420	149,419,665	224,686,412	187,213,149	135,322,804	136,534,730	564,394,436	74,091,513
Current Liabilities:	36,897,354	15,210,562	5,534,603	19,801,876	8,304,742	13,295,379	11,539,245	14,391,515	274,420,871	16,454,434
Total Liabilities:	145,871,523	118,543,273	21,880,728	42,990,371	124,941,642	82,520,233	33,793,632	39,226,231	390,223,824	45,249,364
Retained Earnings:	799,564,115	690,238,735	8,084,384	25,224,891	626,974	4,759,780	22,672,206	20,495,662	(115,232,001)	(37,734,660)
Sales:	183,071,694	117,993,252	24,733,210	71,084,978	103,545,209	151,780,209	37,626,835	56,870,691	235,988,762	2,544,310
EBIT	126,571,774	81,854,620	18,985,766	19,868,865	9,324,972	(16,655,828)	1,548,350	771,520	17,100,591	413,206
Book value of Equity	2,227,749,689	90,754,269	55,931,400	100,882,148	83,623,305	94,045,144	130,815,236	92,247,050	123,819,150	34,004,042
YEAR 4										
Current Assets:	246,429,540	114,529,500	5,458,542	56,031,650	57,846,149	29,338,032	47,930,614	45,894,584	164,974,560	63,279,753
Total Assets:	1,534,752,700	1,428,325,600	7,065,110	95,852,734	144,136,361	120,097,258	86,809,596	87,587,046	362,059,100	47,529,715
Current Liabilities:	26,961,000	11,114,400	4,044,150	14,469,286	6,068,298	9,714,971	8,431,759	10,515,920	200,520,100	12,023,301
Total Liabilities:	170,667,000	138,693,450	25,600,050	50,297,944	146,179,424	96,547,156	39,537,929	45,893,969	456,554,700	52,940,924
Retained Earnings:	906,546,330	782,593,140	9,166,080	28,599,998	710,863	5,396,642	25,705,763	23,237,996	(130,650,120)	(42,783,582)
Sales:	133,771,000	86,218,000	18,072,626	51,941,993	75,660,775	110,906,224	27,494,034	41,555,573	172,437,650	1,859,135
EBIT	92,486,350	59,811,400	13,872,953	14,518,236	6,813,783	(12,170,461)	1,131,384	563,752	12,495,450	301,931
Book value of Equity	2,044,714,740	83,297,775	51,336,000	92,593,533	76,752,700	86,318,267	120,067,278	84,667,907	113,646,000	31,210,223
YEAR 5										
Current Assets:	288,322,562	133,999,515	6,386,494	65,557,030	67,679,994	34,325,497	56,078,819	53,696,663	193,020,235	74,037,311
Total Assets:	1,273,844,741	1,185,510,248	5,864,041	79,557,769	119,633,180	99,680,725	72,051,964	72,697,248	300,509,053	39,449,663
Current Liabilities:	22,377,630	9,224,952	3,356,645	12,009,508	5,036,687	8,063,426	6,998,360	8,728,214	166,431.683	9,979,340
Total Liabilities:	141,653,610	115,115,564	21,248,042	41,747,294	121,328,922	80,134,139	32,816,481	38,091,994	378,940,401	43,940,967
Retained Earnings:	752,433,454	649,552,306	7,607,846	23,737,998	590,016	4,479,213	21,335,783	19,287,536	(108,439,600)	(35,510,373)
Sales:	111,029,930	71,560,940	15,000,280	43,111,854	62,798,443	92,052,166	22,820,048	34,491,126	143,123,250	1,543,082
EBIT	76,763,671	49,643,462	11,514,551	12,050,136	5,655,440	(10,101,482)	939,048	467,914	10,371,224	250,603
Book value of Equity	1,697,113,234	69,137,153	42,608,380	76,852,633	63,704,741	71,644,162	99,655,841	70,274,363	94,326,180	25,904,485

APPENDIX C : Z SCORE CALCULATION

Group 2 : Non Failed Companies

	NF1	NF2	NF3	NF4	NF5	NF6	NF7	NF8	NF9	NF10
YEAR 1										
X_1	0.091	0.047	-0.136	0.230	0.231	0.075	0.271	0.224	-0.336	-1.802
X_2	0.413	0.383	0.907	0.209	0.003	0.031	0.207	0.185	-0.252	-4.784
X_3	0.071	0.049	2.321	0.179	0.056	-0.120	0.015	0.008	0.041	0.008
X_4	1.353	0.678	2.264	2.078	0.593	1.009	3.429	2.083	0.281	0.666
X_5	0.103	0.071	3.023	0.640	0.620	1.091	0.374	0.561	0.563	0.352
Z_1	**1.837**	**1.234**	**13.145**	**3.046**	**1.442**	**1.436**	**3.097**	**2.364**	**0.110**	**-8.082**
YEAR 2										
X_1	0.091	0.039	-0.065	0.198	0.267	0.067	0.227	0.191	-0.228	-1.307
X_2	0.413	0.310	0.734	0.169	-0.036	0.025	0.168	0.150	-0.204	-3.873
X_3	0.071	0.049	2.321	0.179	0.056	-0.120	0.015	0.008	0.041	0.008
X_4	1.353	0.766	2.556	2.347	0.448	1.140	3.871	2.352	0.317	0.751
X_5	0.103	0.053	2.246	0.476	0.645	0.811	0.278	0.417	0.418	0.261
Z_2	**1.837**	**1.156**	**12.387**	**2.949**	**1.368**	**1.216**	**3.159**	**2.292**	**0.183**	**-6.251**
YEAR 3										
X_1	0.091	0.039	(0.065)	0.198	0.075	0.067	0.227	0.191	(0.228)	(1.307)
X_2	0.413	0.310	0.734	0.169	0.031	0.025	0.168	0.150	(0.204)	(3.873)
X_3	0.071	0.037	1.724	0.133	(0.122)	(0.089)	0.011	0.006	0.030	0.006
X_4	1.353	0.766	2.349	2.347	1.009	1.140	3.871	2.352	0.317	0.751
X_5	0.103	0.053	2.246	0.476	1.091	0.811	0.278	0.417	0.418	0.261
Z_3	**1.837**	**1.114**	**10.293**	**2.797**	**1.429**	**1.317**	**3.146**	**2.286**	**0.149**	**(6.258)**
YEAR 4										
X_1	(0.384)	0.072	0.200	0.434	0.145	0.163	0.455	0.404	(0.098)	(1.249)
X_2	1.435	0.548	1.297	0.298	0.031	0.045	0.296	0.265	(0.361)	(6.845)
X_3	0.015	0.042	1.964	0.151	(0.122)	(0.101)	0.013	0.006	0.035	0.007
X_4	0.437	0.601	2.005	1.841	1.009	0.894	3.037	1.845	0.249	0.590
X_5	0.145	0.060	2.558	0.542	1.091	0.923	0.317	0.474	0.476	0.297
Z_4	**2.006**	**1.413**	**12.298**	**3.084**	**1.513**	**1.384**	**3.142**	**2.459**	**0.117**	**(10.407)**
YEAR 5										
X_1	(0.384)	0.105	0.517	0.673	0.231	0.263	0.681	0.619	0.088	(0.972)
X_2	1.435	0.548	1.297	0.298	0.003	0.045	0.296	0.265	(0.361)	(6.845)
X_3	0.015	0.042	1.964	0.151	0.056	(0.101)	0.013	0.006	0.035	0.007
X_4	0.437	0.601	2.005	1.841	0.593	0.894	3.037	1.845	0.249	0.590
X_5	0.145	0.060	2.558	0.542	0.620	0.923	0.317	0.474	0.476	0.297
Z_5	**2.006**	**1.452**	**12.677**	**3.372**	**1.442**	**1.505**	**3.414**	**2.716**	**0.340**	**(10.075)**

APPENDIX C : Z SCORE CALCULATION

Group 2 : Non Failed Companies continued

	NF11	NF12	NF13	NF14	NF15	NF16	NF17	NF18	NF19	NF20
YEAR 1										
X_1	0.091	0.047	-0.136	0.230	0.231	0.075	0.271	0.224	-0.336	0.632
X_2	0.413	0.383	0.907	0.209	0.003	0.031	0.207	0.185	-0.252	-0.629
X_3	0.071	0.049	2.321	0.179	0.056	-0.120	0.015	0.008	0.041	0.008
X_4	13.527	0.678	2.264	2.078	0.593	1.009	3.429	2.083	0.281	0.666
X_5	0.103	0.071	3.023	0.640	0.620	1.091	0.374	0.561	0.563	0.046
Z_1	**9.142**	**1.234**	**13.145**	**3.046**	**1.442**	**1.436**	**3.097**	**2.364**	**0.110**	**0.347**
YEAR 2										
X_1	0.075	0.039	-0.065	0.198	0.190	0.067	0.227	0.191	-0.228	0.531
X_2	0.334	0.310	0.734	0.169	0.003	0.025	0.168	0.150	-0.204	-0.509
X_3	0.071	0.049	2.321	0.179	0.056	-0.120	0.015	0.008	0.041	0.008
X_4	15.272	0.766	2.556	2.347	0.669	1.140	3.871	2.352	0.317	0.751
X_5	0.077	0.053	2.246	0.476	0.461	0.811	0.278	0.417	0.418	0.034
Z_2	**10.033**	**1.156**	**12.387**	**2.949**	**1.279**	**1.216**	**3.159**	**2.292**	**0.183**	**0.434**
YEAR 3										
X_1	0.075	0.039	(0.065)	0.198	0.190	0.067	0.227	0.191	(0.228)	0.531
X_2	0.334	0.310	0.734	0.169	0.003	0.025	0.168	0.150	(0.204)	(0.509)
X_3	0.053	0.037	1.724	0.133	0.042	(0.089)	0.011	0.006	0.030	0.006
X_4	15.272	0.766	2.556	2.347	0.669	1.140	3.871	2.352	0.317	0.751
X_5	0.077	0.053	2.246	0.476	0.461	0.811	0.278	0.417	0.418	0.034
Z_3	**9.973**	**1.114**	**10.417**	**2.797**	**1.231**	**1.317**	**3.146**	**2.286**	**0.149**	**0.428**
YEAR 4										
X_1	0.143	0.07	0.20	0.43	0.36	0.16	0.46	0.40	(0.10)	1.08
X_2	0.591	0.55	1.30	0.30	0.00	0.04	0.30	0.27	(0.36)	(0.90)
X_3	0.060	0.04	1.96	0.15	0.05	(0.10)	0.01	0.01	0.03	0.01
X_4	11.981	0.60	2.01	1.84	0.53	0.89	3.04	1.84	0.25	0.59
X_5	0.087	0.06	2.56	0.54	0.52	0.92	0.32	0.47	0.48	0.04
Z_4	**8.473**	**1.41**	**12.30**	**3.08**	**1.43**	**1.38**	**3.14**	**2.46**	**0.12**	**0.45**
YEAR 5										
X_1	0.209	0.11	0.52	0.67	0.52	0.26	0.68	0.62	0.09	1.62
X_2	0.591	0.55	1.30	0.30	0.00	0.04	0.30	0.27	(0.36)	(0.90)
X_3	0.060	0.04	1.96	0.15	0.05	(0.10)	0.01	0.01	0.03	0.01
X_4	11.981	0.60	2.01	1.84	0.53	0.89	3.04	1.84	0.25	0.59
X_5	0.087	0.06	2.56	0.54	0.52	0.92	0.32	0.47	0.48	0.04
Z_5	**8.552**	**1.45**	**12.68**	**3.37**	**1.63**	**1.50**	**3.41**	**2.72**	**0.34**	**1.10**