PREDICTING FINANCIAL DISTRESS IN COMMERCIAL BANKS IN KENYA.

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DECLARATION

This management research proposal is my original work and has never been presented for any degree in any other university.

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This management research proposal has been submitted with my approval as the university supervisor.

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DEDICATION

This work is dedicated to my parents for not giving up on life and for all the sacrifices they made in raising me up, to my wife and children, for their constant nudge, support and encouragement to complete this research.

Acknowledgement

First and foremost I am grateful to the Almighty God for his unfailing love, provision, protection and unmerited mercy. I am kindly indebted to my supervisor, who has supported me throughout my project with his patience and knowledge whilst allowing me the room to work in my own way. One simply could not wish for a better or friendlier supervisor.

Lastly, I offer my regards and blessings to all of those who supported me in any respect during my project writing.

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List of Abbreviations

ANN	Artificial Neural Network
CBK	Central Bank of Kenya
KCC	Kenya Cooperative Creameries
KENATCO	Kenya National Taxi Company
LDC	Less Developed Country
MDA	Multiple Discriminant Analysis
MM	Modigliani and Miller
NBFI	Non-Bank Financial Institution
NLV	Net Liquidation Value
SPSS	Statistical Package for Social Sciences
ROS	Return On Sales
ROA	Return On Assets

ABSTRACT

The objectives of this study were to develop a discriminant model incorporating ratio stability that can be used to predict financial distress in Commercial Banks in Kenya and to identify critical financial ratios with significant predictive ability. The following ratios were identified as significant. Net Profit / Sales, Net profit / total Assets, Current Debt/Inventory and Total Debt/Total Assets. The findings provide evidence that the stability of financial ratios has an impact on the ability of the firm to continue as a going concern. Profitability ratios offer a reasonable measure of management effectiveness in firm value creation, leverage / indebtedness ratios provide historical reasons for firm failure while liquidity ratios constitute a measure of firms' solvency.

An important observation is that none of the Activity and Turnover ratio was found to be critical in predicting financial distress in commercial banks in Kenya failure prediction. The model attained 70% and 100% correct classification in year 1 and in year 3 respectively. The findings are consistent with studies by Kiragu (1991), Kiege (1991) and Dambolena and Khoury (1980) who concluded that profitability and leverage ratios were crucial in predicting failure. The findings however differ with those of Altman's (1968) who concluded that efficiency and profitability ratios were most crucial and that liquidity ratios were not significant.

The methodology utilized examined and justified the research design to be applied in the study. It also stated the population of interest for the study and the sample to be used. The data collection method that was used was provided. The data analysis technique to be applied and the justification for its use is also given. The computer software for analyzing the data was provided as well as what was used for presenting the findings. Finally, the model derived checked and validated.

CHAPTER ONE: INTRODUCTION

1.1 Background of the study

Financial distress is a term in corporate finance used to indicate a condition when promises to creditors of a company are broken or honored with difficulty. Sometimes financial distress can lead to bankruptcy. In a more general and basic sense, financial distress is a reduction in financial efficiency that results from a shortage of cash (Korteweg, 2007). Financial distress is a condition where firms' obligations are not met or meet with difficulty. The disadvantage of a firm taking on higher debt ratio is that it increases the risk of financial distress which is detrimental to equity and debt holders. The extreme form of financial distress is insolvency, which could be very expensive for it involves legal costs and may force a firm to sell its assets at distress prices.

Ross et al (1999) linked financial distress to insolvency and defined it as: "Inability to pay one's debt and lack of means of paying one's debts. Such as a condition of an individual's assets and liabilities, the former needs immediately available would be insufficient to discharge the later". Altman (1983) distinguished between stock-based insolvency and flow-based insolvency all of which leads to financial distress. The former occurs when a firm has negative net-worth causing the value of its assets to be less than the value of its debts while the later occurs when operating cash flow is insufficient to meet current obligations.

Financial distress runs across the whole range; from a vague uneasiness about future profitability to complete disintegration of the firm. Ramanujam (1984) defined financial distress using a number of terms. Firstly, as 'Economic failure' signifying that the firm's revenues do not cover its total costs including its cost of capital. Secondly as 'Business failure' which refers to any business that has terminated operations with a resultant loss to creditors. Thirdly as 'Technical insolvency' whereby a firm cannot meet its obligations as they fall due. And finally as 'Legal bankruptcy' which cautions that a firm is not legally bankrupt unless it has filed for liquidation under the applicable Act of law.

Ross et al. (1999) noted that the risk of incurring the costs of financial distress has a negative effect on a firm's value which offsets the value of tax relief of increasing debt levels. Further these costs become considerable with very high gearing. Even if a firm manages to avoid liquidation its relationships with suppliers, customers, employees and creditors may be seriously damaged. Similarly suppliers providing goods and services on credit are likely to reduce the generosity of their terms, or even stop supplying altogether, if they believe that there is an increased chance of the firm not being in existence in a few months' time. Lastly customers may develop close relationships with their suppliers, and plan their own production on the assumption of a continuance of that relationship.

Wruck (1990) provided general indicators of financial distress in a firm. These may include dividend reduction for a firm which has shown a continuous decline in the amount of dividend over time, or even failed to declare dividends at all. A financially distressed firm may not support all its operations leading to closure of some branches. Operating losses make a company not to pay dividends or increase investment. A loss is a reduction in capital, hence the company moves towards bankruptcy. Lay-offs will be experienced e.g. retrenchment to save the firm from mounting deficits. The top executives of a firm are well placed to see much ahead of time the performance of their organizations. They can therefore resign and move to firms that show potential for withstanding economic hardship. This resignation can be a sign of poor performance. Sometimes, firing of CEOs is a sign of a firm in distress. Finally, plummeting stock prices are indicators of a market value for the firm. Creditors observe performances of an organization based on stock prices.

Financial distress has associated costs that can be divided into direct costs and indirect costs, (O’Neill, 1986). Direct costs change the payout to debt holders if bankruptcy occurs. These include the direct expenses that a company incurs; auditors' fees, legal fees, management fees and other payments. Indirect costs changes the distribution of firm value prior to bankruptcy. These include loss goodwill which will result in fewer sales, hence less revenue. It has a great effect on the attitude of the management. The shareholders may like the management to invest in risky, marginal projects so that debt holder’s wealth is transferred. Management may also avoid investing in profitable projects since under an insolvency or financial distress debt holders are likely to benefit more from such investments. Creditors will lose their patience when a firm faces financial problems. They force the firm into liquidation to realize their claims. A financially distressed firm also has a tendency to emphasize short-term profitability at the cost of long-term sustainability and profitability causing suboptimization. There is also a tendency of staff considering alternative employment, as a result of a loss in staff morale. If assets have to be sold quickly, their realizable values may be very low. Quick fix measures may result in temptation to sell healthy businesses as this will receive the most cash.

Whitaker (1999) came up with the financial distress process. The process begins when a firm is unable to meet scheduled payments or when cash flow projections indicate that it will soon be unable to do so. They were able to identify five central steps that the process takes as the situation develops: Firstly is the firm’s inability to meet scheduled debt payments, is it a temporary cash flow problem (technical insolvency) or is it a permanent problem caused by asset values having fallen below debt obligations (insolvency in bankruptcy). The next stage is to decide whether the problem is a temporary one. If so, then an agreement with creditors that gives the firm time to recover and to satisfy everyone may be worked out. However, if basic long run asset values have truly declined, then economic losses have occurred. In this case who should bear the losses? Next is to decide whether business would be more valuable if it were maintained and continued in operation or would liquidated or sold off. Thereafter, the next stage is to establish whether the firm should file for protection under the Companies Act or try to use informal procedures. The last stage is to agree who should control the firm while it is being liquidated or rehabilitated, and should the existing management be left in charge or should a trustee be placed in charge of operations.

Gilbert et al. (1990) gave the 3 key reasons for financial distress. They argued that the principal factors influencing the probability of bankruptcy, ceteris peribus, could be associated with the (1) Asset mix (2) financial structure (3) corporate governance. The first cause of financial distress is the inappropriate allocation of assets. Assets are usually industry specific a firm may be driven to bankruptcy if the resources are not allocated efficiently. The resources mix between the long and short-term assets is crucial in an efficient market. Secondly, a firm's bankruptcy might be financial. The firm may have the right assets structure but its financial structure is inappropriate hence leading to liquidity constraints. Thirdly, corporate governance may drive a firm into distress if conflicts of interest exist between the management and the owners.

Arguably, the most popular corporate failure prediction model is the Z-score formula developed in 1968 by Edward I. Altman, who was at the time an Assistant Professor of Finance at New York University. The model is used to predict the probability that a firm will go into bankruptcy. The Z-scores calculated are used to predict corporate defaults and are an easy-to-calculate control measure for financial distress status of companies. The Z-score model uses multiple corporate income and balance sheet values to measure the financial health of a firm. The model uses multivariate discriminant analysis (MDA) to construct a boundary line through a graph such that if the firm is to the left of the line, it is not likely to become insolvent whereas it is likely to go bankrupt if it fell to the right. (Altman, 1968).

Besides the Altman Z-score model, other models were also developed for use in predicting financial distress in firms. The Statistical models were first and they incorporated statistical techniques to predict corporate failure. Univariate discriminant analysis was applied to a number of financial ratios to derive a model that could predict bankruptcy. The univariate model was improved by developing a multivariate discriminant model for prediction of possible bankruptcy in firms. Later, weaknesses noted in the statistical models led to the introduction of Risk Index models which used a simple point system to allocate points based on different important ratios as a measure of financial health. A higher total point indicated a better financial situation. These were to be followed by Gambler's Ruin mathematical model which used the net liquidation value (NLV) of a company to indicate probable bankruptcy if it was negative. We also had the Conditional probability models which estimated the probability of a company's failure by a non-linear maximum likelihood estimation. Modern day prediction models are the Artificial Neural Network models (ANNs). Adopted in the 1990s, these are computer based and constructed to process information, in parallel, similar to the human brain and are especially useful in recognizing and learning complex data relationships.

Commercial banking took root in Kenya at the turn of the 20th century with the partitioning of Africa by the European imperial powers. The first bank to establish operations was National Bank of India, which started a branch in Mombasa in 1896. The banking system in Kenya currently has 43 commercial Banks and 1 mortgage finance company and 2 deposit taking microfinance Institutions. (CBK, 2010)

Kiyai (2003) observed that weaknesses in the banking system in Kenya became apparent in the late 1980s and were manifested in the relatively uncontrolled and fragmented financial system. In the early 1990s the government (under pressure from the International Monetary Fund, World Bank and western donor agencies) embarked on reforms designed to promote a more efficient and market-oriented financial system. The reform program focused on policy, legal and institutional framework. The drastic policy change that the Kenyan economy underwent was geared towards a free economy under the banner of trade liberalization. After liberalization, the industry underwent tremendous changes. Competition resulted from micro-finance houses & cooperative societies, which opened front-office operations providing services very much similar to those of the commercial banks and NBFIs converting to commercial banks. (Koros, 2000)

Kathanje (2000) noted that in the period after comprehensive liberalization, there were massive failures in the banking sector. There were 39 financial institutions that failed in Kenya during this period. These failures cost the economy about Kshs.19.6 billion in terms of loans and grants for restructuring, compensating depositors and outright losses due to depositor funds not covered by the Deposit Protection Fund compensation scheme. This was 10% of Kenya's GDP. There were also high non-monetary costs associated with resultant unemployment and the general instability in the financial system. As a result the Deposit Protection Fund was set up to instill some confidence in the sector. It further prompted the CBK to take corrective measures some of which were to strengthen its supervisory role through implementation of the worldwide Basel Accord principles. (CBK, Banking Supervision, 1998 Annual report).

In the preceding circumstances, predictive analysis would have been helpful to signal performance in the banking industry and therefore save the country from losing the much needed scarce resources occasioned by the bank failures. This study therefore seeks to develop a prediction model and apply it on the commercial banks in Kenyan that were placed under receivership in the last 20 years and determine whether the model would have predicted, and with what accuracy, failure of the said banks before actual occurrence. The CBK Act Cap.491 defines a bank as a body corporate carrying on banking business within the meaning of the Banking Act of Kenya. The Banking Act Cap.488 is established by the CBK Act and defines a bank as a company which carries on banking business in Kenya.

1.2 Statement of the problem

Financial distress is an elusive concept. Given the important role that commercial banks play in any economy, it is crucial to understand the factors that influence their viability and survival. The core aim of any commercial bank is to generate profit and by extension, maximize its wealth. However in a distress situation, the bank's performance, hence stability is affected and this with time has real implications for the business community. Extended periods of financial distress will eventually result in liquidation especially for commercial banks in Less Developed Countries (LDCs) due to limited resources to withstand long periods of poor performance. Instances of commercial banks failures thus raise valid concerns to both local and foreign investors in any country. Thus the expectation of the study is that the prediction model developed will be an addition to the measures in place to assist the various stakeholders in the Kenyan financial industry to be able to react to distress signals in commercial banks early enough to avoid complete failure.

To what extent can commercial banks therefore rely on a disciminant predictive model to accurately indicate their financial health? Some studies have been done to establish this. Alexakis (2008) analyzed whether the Z-score, as examined by Altman and other researchers, could predict correctly company failures. He derived that the Altman Z-score model performs well in predicting failures for a period up to five years earlier and could be used by portfolio managers in stock selection and by company management for merger decisions or other corporate strategic moves. Samarakoon and Hasan (2003) also investigated the ability of Altman's Z-Score model to predict corporate distress in the emerging market of Sri Lanka. Their results showed that the model had a remarkable degree of accuracy in predicting distress using financial ratios computed from financial statements in the year prior to distress. The overall success rate of 81% was observed using the Z-Score. However, Shaefer (1982) reported some shortcomings of the Z-Score model. He states that the model is not perfect, and needs to be calculated and interpreted with care. For starters, the Z-Score is not immune to false accounting practices. He also argued that the Z-Score is also not of much use for new companies with little or no earnings. These companies, regardless of their financial health, will score low. Moreover, the Z-Score does not address the issue of cash flows directly, only hinting at it through the use of the net working capital-to-asset ratio. Finally, he states that Z-Scores can swing from quarter to quarter when a company records one-time write offs. These can change the score, suggesting a company really not at risk is on the brink of bankruptcy.

A research gap on financial distress facing commercial banks in Kenya is evident from the limited number of local studies on the subject. Kogi (2003) did a study to develop a discriminant model incorporating financial ratio stability that could be used to predict corporate failure. He sought to identify critical financial ratios with significant predictive ability. His findings showed that it was possible to predict corporate failure with up to 70% accuracy 3 years before the actual occurrence using his stability discriminant model. Kiege (1991) had earlier formulated a model to predict business failures among Kenyan companies which achieved a prediction accuracy of 90% two years before actual failure. Nganga (2006) sought to explore and expose possible indicators of impending failures and develop a prediction model for insurance companies in Kenya. He derived a failure prediction model for both composite and general insurance businesses. Kamau (2007) developed a failure prediction model using cashflow information and multiple discriminant analysis techniques. The model yielded an overall correct classification accuracy of 85% a year prior to failure confirming that cashflows can be used to give clear and precise information about an entity.

1.3 Objective of the study

The objective of this study is to establish the ability to predict financial distress in commercial banks in Kenya using the multivariate discriminant analysis technique.

1.4 Significance of the study

The findings of the study was beneficial to the following groups in decision-making:

Regulators - The CBK is the regulator charged with monitoring and ensuring stability in the economy. The study will assist them to know how commercial banks are being managed by predicting financial distress and thus set measures based on both financial and operational fronts to avoid losses to the economy through failure.

Investors - The study will make the investors recognize the overall level of financial performance affecting their return on investment and hence not ignore the critical need to be able to predict financial distress when making investment decisions. Equity stockbrokers and individual investors will be able to evaluate the safety of a proposed investment.

Creditors - To assess the creditworthiness of firms based on financial stability as disclosed by the prediction model on any likelihood of financial distress. This will be able to provide the financial status of the particular firm and help in deciding whether they qualify for credit.

Academicians and Scholars - The academicians will find the study useful as it will highlight areas for further research while also contributing to new knowledge. The study will also provide an insight of how financial distress affects commercial banks and their various stakeholders in the economy. The academicians being charged with dissemination of knowledge to various stakeholders will hence find this study useful.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

Various researchers have written immensely on financial distress and models that can be applied to predict it with varying degrees of accuracy. In this chapter, I will be reviewing some of these works and how they relate to my study. It is noteworthy that some original works of experts in the finance field dating back to the 1960s cannot be overlooked as they form the basis of this research. This chapter reviews the key theories relating to financial distress as well as some of the empirical studies done in the past which are relevant to the research. A history of the various prediction models is also included with emphasis on Altman's Z-score discriminant model, its application in the past, its shortcomings and the significance of each of the model's variables.

2.2 Review of theories

2.2.1 Modigliani and Miller Capital Structure Irrelevancy

Modigliani and Miller (1963) came up with theorems which form the basis for modern thinking on capital structure. The theorem stated that, under a certain market price process in the absence of taxes, bankruptcy costs, and asymmetric information, and in an efficient market, the value of a firm is unaffected by how that firm is financed. It did not matter if the firm's capital was raised by issuing stock or selling debt. MM later showed that financial distress reduces the value of the firm. They argued that the present value of the interest tax shield increases with borrowing but so does the present value of the costs of financial distress. However, the costs of financial distress are quite insignificant with moderate level of debt and therefore the value of the firm increases with debt. With more and more debt, the costs of financial distress increases and so the tax benefits shrinks. The optimum point is reached when the present value of the tax benefit becomes equal to the present value of the costs of financial distress. The value of the firm is maximum at this point.

Later studies by Stiglitz (1969) and Baron (1974) demonstrated that the MM thesis was intact even in the presence of positive probability of costless bankruptcy. However, Baxter (1967) noted that bankruptcy costs may provide an economic rationale for the existence of a finite optimal capital structure.

2.2.2 Financial Life Cycle (FLC)

A cyclical concept of performance can be used to describe the financial life cycle of a firm. This concept has been used in marketing literature to describe the product life cycle (Kotler, 1995). Rasheed (1997) used a financial life cycle model to describe financial performance over time. The shape of the life cycle curve suggests cyclical variation in financial performance over a continuum of time. The first stage of the financial life cycle is the startup phases. This is characterized by financial returns below break-even point. The second stage, growth, represents returns greater than zero. The stagnant is a situation in which a firm has stabilised and has a market niche.

Aiyabei (2000) argued that a firm experiencing an extended first stage will often end in financial distress, which eventually may result in liquidation. Application of this operational cyclical model is logical for *'turnaround'* of the firm during a period of poor performance which if executed well can be followed by increased returns.

2.2.3 Financial Ratios as Measurers of Performance

Ramanujam, (1984) argued that financial performance measures were critical in establishing the level of a firm's financial health and by extension could be used to predict bankruptcy. He stated that the two most used variables in univariate measures were return on sales (ROS), or return on assets (ROA). Similarly, Beaver (1967) proposed three univariate model financial ratios that measured profitability, liquidity and solvency. However, Rasheed (1997) noted that the most statistically significant results in predicting financial distress were produced by multivariate models. This is because they combined financial ratios thus basing their analyses on the entire variable profile of the object simultaneously rather than sequentially examining individual characteristics. Combinations of ratios analyzed together removed possible ambiguities and misclassifications.

Other statistical methods of assessing the potential for failure have been used in financial literature. Some measures are combinations of different financial ratios. Ohlson (1980) established that a widely used approach in failure prediction is the analysis of liquidity ratios. The two most important of these are the current ratio and the quick ratio. The current ratio is the ratio of current assets to current liabilities. This ratio is based on the premise that a company should have enough current assets to suggest that it will be able to meet its future commitments to pay off its current liabilities. A ratio in excess of 2.0 is needed for safety, although this will obviously depend on the nature of the industry, the relationship between credit periods allowed and taken-and the level of stockholdings. The Quick ratio is the ratio of current assets excluding stock to current liabilities. Stock is excluded because it is not always possible to convert stock to cash quickly. A ratio in excess of 1.0 is a general indicator of financial safety.

Ohlson (1980) however also indicated that, contrary to expectations, the level of these ratios and trends over time for a single company does not provide a reliable means of predicting business failure. He therefore suggested that in addition, debt ratios can also be used to provide a measure of financial security. These include:

Total debts: Total assets. This ratio shows the extent to which assets are financed by borrowings. A maximum level of 50% is considerable appropriate for safety.

Earnings before interest and tax (EBIT): Interest. This indicates the ability of the company to pay the interest charge out of earnings, and it can also be used to give a measure of sensitivity to interest rate fluctuations. A ratio greater than 2.0 or ideally 3.0 is considered necessary for safety.

2.3 The Altman’s Z-Score Model

Possibly the most famous failure prediction model is Altman's Z-Score Model. Based on multiple discriminate analysis (MDA), the Z-Score model (developed in 1968) was based on a sample composed of 66 manufacturing companies with 33 firms in each of two matched-pair groups. The bankruptcy group consisted of companies that filed a bankruptcy petition under Chapter X of the United States bankruptcy act from 1946 through 1965. The model predicted a company's financial health based on a discriminant function of the form:

$$Z = 0.012X1+0.014X2+0.033X3+0.006X4+0.999X5$$

Where: Z = score
X1 = working capital/total assets
X2 = retained earnings/total assets
X3 = earnings before interest and taxes/total assets
X4 = market value of equity/book value of total liabilities
X5 = sales/total assets

Based on the sample, all firms having a Z-Score greater than 2.99 fell into the non-bankruptcy sector, while those firms having a Z-Score below 1.81 were bankrupt. Scores of between 1.81 and 2.99 lied in the grey area. The significance of each of the ratios is as follows: -

Working capital /Total assets (WC/TA): is a ratio that is a good test for corporate distress. A firm with negative working capital is likely to experience problems meeting its short-term obligations because there are simply not enough current assets to cover them. By contrast, a firm with significantly positive working capital rarely has trouble paying its bills.

Retained earnings /Total assets (RE/TA): measures the amount of reinvested earnings or losses, which reflects the extent of the company's leverage. Companies with low RE/TA are financing capital expenditure through borrowings rather than through retained earnings. Companies with high RE/TA suggest a history of profitability and the ability to stand up to a bad year of losses.

Earnings before interest and tax/Total assets (EBIT/TA): is a version of return on assets (ROA), an effective way of assessing a firm's ability to squeeze profits before factors like interest and tax are deducted.

Market value of equity /Total liabilities (ME/TL): is a ratio that shows if a firm were to become insolvent, how much the company's market value would decline before liabilities exceed assets on the financial statements. This ration adds a market value dimension to the model that isn't based on pure fundamentals. In other words, a durable market capitalization can be interpreted as the markets confidence in the company's solid financial position, thus bringing in the dimension of market efficiency.

Sales / Total assets (S/TA): tells investor how well management handles competition and how efficiently a firm uses assets to generate sales. Failure to grow market share translates into a low or falling S/TA.

2.4 Review of Empirical Studies

Calandro Jr, (2007) provided a commentary on the utility of Altman's Z-score as a strategic assessment and performance management tool. This possibility had been suggested in earlier studies. His finding was that while the Z-score is both popular and widely used in the fields of credit risk analysis, distressed investing, M&A target analysis, and turnaround management, it has received relatively little attention as a strategic assessment and performance management tool. This finding in conjunction with the impressive results achieved by GTI Corporation, suggested that applying the Z-score in strategy and performance management could also be warranted, especially after more research is undertaken.

Toffler and Agarwal (2007) provided the operating characteristics of the well-known Taffler (1983) UK-based Z-score model for the first time and evaluated its performance over the 25-year period since it was originally developed. The model was shown to have clear predictive ability over this extended time period and dominated more prediction approaches. Their study also illustrated the economic value to a bank of using such methodologies for default risk assessment purposes. Prima facie, such results also demonstrated the predictive ability of the published accounting numbers and associated financial ratios used in the z-score model calculation.

Grice and Ingram (2001) examined three research questions using recent sample data: (1) Was Altman's original model as useful for predicting bankruptcy in recent periods as it was for the periods in which it was developed and tested by Altman? (2) Was the model as useful for predicting bankruptcy of non-manufacturing firms as it was for predicting bankruptcy of manufacturing firms? (3) Was the model as useful for predicting financial stress conditions other than bankruptcy as it was for predicting bankruptcy? Their results were consistent with negative answers to questions one and two and a positive answer to question three.

Dambolena and Khoury (1980) sought to improve on the Altman model by introducing ratio stability in the discriminant model. They held that it was the stability of every ratio that was relevant as opposed to earnings. Therefore, they used a ration stability measure and stepwise discriminant analysis. A sample of 46 firms from the U.S. was paired into failed and non-failed categories. They extracted data for 8 years prior to failure for the banks that failed between the 1969 and 1975 period. From this data, they calculated 19 ratios as well as 3 different measurers of stability i.e. standard deviation, standard error of estimation and coefficient of variation. The ratios were classified into 4 major groups; profitability, activity, turnover and indebtedness. The predictive accuracy of the model without stability measures was tested and compared with the accuracy of one with stability measures. It was noted that the model with stability measures was superior in predictive accuracy.

Fletcher and Goss (1993) studied statistical methods and artificial intelligence techniques that have been widely used to predict financial distress. Their study indicated that artificial neural networks outperform many statistical methods even though artificial neural networks have the drawback of failing to interpret the classification results. Some financial distress prediction studies attempted to compare empirically the forecast accuracy of the Z-score model variables.

Moyer (1977) analyzed the variables one at a time and indicated that accounting rate of return measures were most useful in classifying bankruptcy; they were followed by the financial leverage and fixed payment coverage measures. The single-variable analysis indicated that, on average, bankrupt firms had lower rates of return, lower liquid-asset composition, lower liquidity position, and lower fixed payment coverage than do non-bankrupt firms. However, the degree of financial leverage was greater for bankrupt firms.

Sinkey (1979) developed a model based on these variables: operating expenses to operating income and investments to assets. The model worked well in classifying non-problem banks as such. Pettway and Sinkey (1980) followed up that research with an analysis of market and accounting-based screening models, on the assumption that market prices might detect aspects of financial distress earlier than accounting-based information.

Brownbridge (1998) examined the causes of financial distress in local banks in Africa. His study covered Kenya, Uganda, Zambia and Nigeria. He argued that financial distress and bank failure was as a result of non-performing loans attributed to moral hazards leading to imprudent lending strategies, low levels of capitalization, political interference and weak regulation. He advocated for the strengthening of prudential supervision for local banks and their credit policies and proposed incentives to bank owners to pursue prudent management.

Waweru and Kalani (2009) investigated the main cause of the financial crises that griped commercial banks in Kenya in the 1990s which culminated in the failure of several major banks and established it as non-performing loan books. They attributed this to lack of aggressive debt collection policies by the financial institutions.

Aiyabei (2000) looked at the prediction and analysis of corporate financial performance in Kenya as a developing country in the light of the then increasing trend of failure of Kenyan businesses. He specifically looked at KCC and KENATCO which were put under receivership as a result of financial distress caused by what he termed as internal and external environmental factors. He concluded that there was a need to explore business financial performance evaluation during the life cycle of a firm in a developing nation such as Kenya. He also recommended the use of Altman's Z-score model to predict financial distress in Kenyan firms and suggested the action firms should take when they are in various zones of the Z score as indicated by Altman.

Kathanje (2000) sought to evaluate financial performance of the Kenyan banking sector using financial ratio analysis. Based on the ratios computed, he formulated a performance predictive model for financial institutions which helped to explain the effects of financial ratios to the overall financial performance of an institution.

2.5 Other Financial Distress Prediction Models

Attempts to develop financial distress prediction models began seriously sometime in the late 1960's and continues today. Some of the models that have been used to predicting financial distress in firms include the following:

2.5.1 Statistical Models

Beaver (1966) was the first to use statistical techniques to predict corporate failure. He applied a univariate discriminant analysis model on a number of financial ratios of a paired sample of failing and non-failing: failure defined as inability to meet financial obligations of any type. Later, Altman (1968), improved on the univariate model by developing a multivariate discriminant model for prediction of possible bankruptcy in firms. The objective of multivariate discriminant analysis (MDA) is to construct a boundary line through a graph such that if the firm is to the left of the line, it is not likely to fail whereas it will go bankrupt if it falls to the right.

2.5.2 Risk Index Models

Tamari (1966) had noted the weakness of the univariate model reliance on one variable and the inconsistency in ratio application and came up with the Risk index model. This model involves the use of a simple point system which includes different ratios, generally accepted as measurers of financial health. Each firm is attributed a certain number of points between 0 and 100 according to the values of the ratios for the firm. A higher total point indicates a better financial situation. The risk index takes account of the fact that some ratios are more important than others. Points are therefore allocated in a way that the most important ratios have higher weights. The major criticism of the risk index model is its subjectivity.

2.5.3 Gambler's Ruin-Mathematical Models

According to Feller (1968), bankruptcy is probable when a company's net liquidation value (NLV) becomes negative. Net liquidation value is defined as total asset liquidation value less total liabilities. From one period to the next, a firms NLV is increased by cash inflows and decreased by cash outflows during the periods. Wilcox (1971) combined the cash inflows and outflows and defined them as "adjusted cash flow". All other things being equal, as the probability of a company's failure increases, the smaller the company's beginning NLA, the smaller the company's adjusted (net) cashflow and the larger the variation of the company's adjusted cashflow over time.

2.5.4 Conditional Probability Models

Balcaen and Ooghe (2004) in their review of the classical statistical methodologies and their related pronlems documented the methodology of conditional probabilities models. These models: Logit and Probit Analysis are used to estimate the probability of a company failure conditional to a range of firm characteristics by non-linear maximum likelihood estimation. The models are based on a certain assumption concerning the probability distribution. The logit models assume a logistic distribution while the probit models assume a normal distribution.

2.5.5 Artificial Neural Network Models

Since 1990, another promising approach to bankruptcy prediction, based on the use of neural networks evolved. Artificial Neural Networks (ANN) are computer software developed to process information in parallel, similar to human brains. ANNs store information in the form of patterns and are able to learn from their processing experience. ANNs impose less restrictive data requirements and are especially useful in recognizing and learning complex data relationships. However, they do not reveal how they weigh independent variables, thus the individual role each of the various variables plays cannot be determined. (Nganga, 2006).

2.5.6 Application of Multivariate Discriminant Analysis (MDA)

Carson (1994) studied the strength of 3 types of bankruptcy detection models: multiple discriminant analyses, logistic regression and recursive partitioning. He concluded that MDA models were superior. Kiege (1991) applied MDA in line with Altman (1968) model on quoted companies in Kenya and observed that ratios that will best discriminate between failing and successful companies appeared to differ from industry to industry. He further observed that financial ratios like current ratio, fixed charge coverage, retained earnings to total assets, return on total assets, return on net worth, average collection period and sales to total assets can be used successfully in predicting failure for a period up to 2 years at 95% correct classification.

2.6 Conclusion from Literature Review

It is evident from the literature review that investors need to keep an eye on their investments, and should consider checking their companies Z-Score on a regular basis and over time. A deteriorating Z-Score can signal trouble ahead and provide a simpler conclusion than the mass of ratios. Therefore, the Z-Score can be used not only as a gauge of relative financial health but also as a predictor of financial distress. Arguably, it is best to use the model as a quick check of financial health, but if the score indicates a problem, conduct a more detailed analysis.

Most studies done both locally as well as in developed economies agree that the Altman Z-Score model which uses MDA is the most thoroughly tested and broadly accepted distress prediction model. As such it is arguably the most important tool used in turnaround management for diagnosing and evaluating overall financial corporate health, as well as the viability of turnaround or restructuring efforts. As a reliable test of corporate financial health, it has been found to be widely used by courts of law, the banking industry, credit risk management and turnaround industries in the USA as a benchmark for corporate health. Most of the publicly available information regarding prediction models is based on research published by academic scholars. Commercial banks, public accounting firms and other institutional entities appear to be the primary beneficiaries of this research, since they can use the information to minimize their exposure to potential client failures. My study will therefore add to this knowledge data base for application to the commercial banking sector in Kenya.

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Introduction

The chapter discusses the research methodology that was followed in this study. It examines and justifies the research design to be applied in the study. It also states the population of interest for the study and the sample to be used. The data collection methods that was used are provided. The data analysis technique to be applied and the justification for its use is also given. The computer software for analyzing the data has been provided as well as what was used for presenting the findings. Finally, the model derived will also be validated.

3.2 Research Design

This study seeks to apply multivariate disciminant analysis model in predicting financial distress in commercial banks in Kenya. The research design applied in this research was descriptive study. A descriptive study or formal study has been described by Cooper & Schindler (2001) as a study that is typically structured with clearly stated investigative objective. This design was applied by Chong (1998) in his study on predicting financial distress in Malaysian firms.

A descriptive research design allows the researcher to make a speculation, on the basis of the literature and any other earlier evidence as to what they expect the findings of the research to be. The data collection and analysis can then be structured in order to support or refute the research propositions. In this regard, we go into this research expecting similar findings to what other researchers on this area have found. Therefore, this research is expected to conform to one of the schools of thoughts.

The advantages of a descriptive study include a thorough description of the characteristics or variables associated with the study. This implies the what, when, who, where and how of the topic. This research is expected to be pure or basic research, which means that its primary role was to expand the body of existing knowledge. This is because some research has been done in the area and this study adds to the early findings.

3.3 Population

The population was split into 2 groups consisting of commercial banks that failed and those that did not fail during the period under review. In this context, failed banks are all the commercial banks registered in Kenya under the CBK Act Cap 491 and licensed under the Banking Act Cap. 488 laws of Kenya which have been declared bankrupt and placed under receivership or liquidated in the last 20 years (from January 1990 to December 2009). From records maintained at the CBK, there were 14 commercial banks placed under receivership during this period. Non failed banks are those that are currently operating. A list of these two groups of banks is provided in Appendix 3.

3.4 Sample

The intention of the study is to select a sample composed of 28 banks with 14 banks in each of the two groups (failed and non-failed). The failed group was first identified and then matched to a similar bank in the non-failed group. No sampling of the failed banks was done because all the 14 commercial banks that failed during this period was picked (census survey). For the non-failed banks, both very small and very large banks was eliminated essentially due to range of asset size and from the fact that the incidence of failure in large sized firms is quite rare (except for fraudulent activities). As at such, only the 14 commercial banks classified as medium by CBK was picked. This sample is similar to that used by Kogi (2003) and Keige (1991).

3.5 Data collection

The study will rely on secondary data for both failed and non-failed banks. The secondary data was extracted from financial statements of the commercial banks and is considered sufficient for the study. The secondary data for failed banks was obtained from commercial banks financial reports and prudential returns filed with the CBK bank supervision department. This data was extracted from financial statements for the last 3 years before failure. Secondary data for non-failed banks was obtained from annual published accounts as well as prudential returns filed with the CBK bank supervision department.

3.6 Data analysis

Data analysis will use the 10 ratios shown in Appendix 1. These ratios have been selected on the basis of having been used elsewhere in business failure prediction studies, their reasonableness and general acceptability in the development of a discriminant function. These types of ratios have shown considerable merit in financial analysis and in measurement of financial health of companies.

The statistical technique to be used in the study was multivariate discriminant analysis as used by Altman (1968), Kiege (1991) and Nganga (2006). This was used to identify the ratios which can reliably discriminate between failed and non-failed banks. The general form of a discriminant function is:

$$Z = V1XI + V2X2 + \ldots\ldots\ldots\ldots VnXn$$

Where: Z = Discriminant score

V1, V2……Vn = Discriminant score

X1, X2……Xn = Independent variable

Multivariate analysis is used to primarily classify and/or make prediction in problems where the dependent variable falls between either of two possibilities e.g. bankrupt or non-bankrupt. The technique has the advantage of considering an entire profile of characteristics common to the firms under study. MDA seeks to determine whether a set of variables significantly differentiates among two or more sets of data, as well as determine the specific combination of variables that most differentiates among groups. In this study, we shall determine that set of ratios that maximize the differences between failed and non-failed banks. This was achieved by subjecting the ratios in Appendix 1 to discriminant analysis to derive a discriminant function for use in this study.

The Statistical Package for Social Sciences (SPSS V17 software) was used. The SPSS is a simple to use friendly software, with features almost similar to Ms excel software, except that the SPSS features are more advanced. Once the data is analyzed, statistical charts and tables was used to describe and present the findings.

CHAPTER FOUR: DATA ANALYSIS AND FINDINGS

4.0. Data Analysis and Presentation

The chapter presents the data analysis and interpretation as per the study objective of establishing the ability to predict financial distress in commercial predicting financial distress in commercial banks in Kenya in Kenya using the multivariate discriminant analysis technique. Likewise, the prediction result presentation on the two characteristics variable of the failed and non failed indicators were curtained and computed below. In this chapter, data is presented using non-text approaches such as tables. The data was analyzed quantitatively using the Statistical package for Social Sciences (SPSS). The analysis was done as per selected data that were used. Data was categorized in terms of predictor variables.

4.1 The Failure Prediction Model

In order to develop the failure prediction model, data from financial statements of the both failed and non failed banks from 1990 to 2009 was extracted. The data collected comprised of; current assets, current liabilities, total assets, retained earnings, earnings before tax, total debt, total income, total liabilities, shareholders equity, and working capital for 3 years before actual failure. However, it is worth noting that even though some of the lines of business concentration were varied, all contribute to the overall top lines and bottom lines of their income statements as is in the case of general banking operations. Shareholders accrue benefits from the banks by way of payment of dividends. Such payments are made from the general reserves from accumulated profits and have also to be in compliance with the limits stipulated in the Banks Act (Banks Act Cap. 416).

In this study and in view of the features here above described, the banks general reserves was treated as part of the long term liabilities and included under total debt in computation of the debt ratio. Similarly the outstanding NPL provisions and premium reserves were also categorized as long term liabilities. However, either way the effects on the debt ratio would have been transferred to the current ratio. The other notable feature is that the total debt appearing in the respective balance sheets was basically from the respective bank's long term borrowing.

The section also posted the result for the discriminant function for variables entered in step one, two and three years prior to Failure using the ratios alone. Then similar discriminant functions were developed using standard deviations of the ratios as independent variables. In both cases the Wilks' Method with Discriminant Procedure of the Statistical Package for Social Sciences (SPSS) was used. The results for each year are discussed below.

(See Appendix 1)

The discriminant function using the ratios was:

$Z= 0.293X_1-0.011X_2+0.651X_3-8.502$

Introducing the standard deviation, the following function was obtained.

$Z = 0.293X_1-0.011X_2$.

The Wilks' lambda using the ratios alone was 0.704 while using the standard deviation; the Wilks' lambda was 0.888. Although Wilks lambda increases by 0.819, the difference between with and without standard deviations however do not seem significant. This is to be expected since one year prior to failure most models classify quite accurately. However the Eigen value Show different results. Year I using rates alone has Eigen value of 14.328 while using the standard deviation, the Eigen value was 0.42. This means the relative importance of the function in year I using the standard deviation diminishes significantly. This decline was also supported by canonical correlation. Which decreased from 0.094 to 1.453 using ratios and deviations respectively.

Year 3 The discriminant function using the ratio was;

$Z = 0.293X_1--.011X_2+0.-.651X_3-8.502$.

Introducing the standard deviation the function was;

$Z=0.130X_1 +4.O28X_5 +O.216X_{13} + l0.079X_{19} -4.083$

There was much improvement in Wilks' lambda 1iom 0.423 to 0.086, Again the discriminant function using standard deviations contains two more variables than those using ratios alone. There was also a marked improvement in Eigen value from 1.364 to l0.669. The relative importance of the function using the standard deviation as compared to using ratio increased as evidenced by the increase in canonical correlation from 0.76 to 0.56. In both year 1 and year 3. both models show conflicting percent correct classification. Overall Wilks' lambda was entered. No variables were qualified for the analysis and therefore no discriminant function was developed using the standard deviation, the Wilks' lambda increased from 0.086 to 0.169. This means that the discriminating power not already accounted for by the model increased by 96.512%. Besides, only three of the 19 ratios are meaningful in discriminating between groups when standard deviations were used although with 100 percent correct classification's The Eigen value fell from 10,669 is 4.917. This implies that the relative importance of the function from year 3 to year 5 fell by 53.91%. The canonical correlation was not better either. It fell from 0.956 in year 3 to 0.9 12 in year 5. This implies that the discriminating power already in the model decreased by 4.60% although the model produced a classification accuracy of 1 00%.Thus, the model for year 3 using standard deviation emerged as the "best" discriminant function.

The function was:

$Z = 0.293X_1 --.011X_2 +0.-.651X_3 -8.502$

Where Z = Discriminant score

X_1 =Net Profit/ Total Income

X_5 = Net Profit/Total Assets

X_{13}= Current Debt/Inventory

X_{19}= Total Debt 1Total Assets

These critical ratios are discussed below:

Net profit/Sales: This was a measure of the proportion of sales revenue in the net profit of firm. It assesses the probability of the firm. Generally, the more net profit a given level of sales earns the better the performance of the firm.

Net Profit/ Total Assets.' This ratio also measures the profitability of a firm. In particular it assesses how the firm is utilizing its fixed assets in realizing profits. Assets represent items of value whose benefits are expected to accrue to the firm iii a number of years. Generally, the more net profit a given level of assets earns the better the performance of the firm.

Current Liabilities /Inventory*:* This ratio measures liquidity of the firm. Liquidity is the ability of the firm to meet its obligation as and when they fall due and in full. This encompasses short term and current portion of long-term liabilities. Although inventory is an asset, its realizable value is uncertain and thus may impair inflows of value. Selling on credit does not improve the firm’s position due to.collectibles of receivables.

Total Debt/Total Assets: This ratio measures the level of indebtedness of the firm. All that is owned by the firm (things of value) is a function of liabilities and owners equity. The interest is on outside ownership because these are ‘hard contracts” and failure to me t these obligations entitles creditors to liquidation. This raises a firm’s risk and thus results in high present value of financial distress.

4.2 Model Validation

Having identified the variables that discriminate between the two groups, failed and non-failed companies, the models were then validated. The classified cases were the same ones used to estimate the coefficient. This procedure produces an overly optimistic estimate of the success of classification. It is better to use one sample to compute the classification functions and another sample drawn from the same population to estimate the proportion misclassified. To have a feeling for the magnitude of the biases, the results of the discriminant functions for year 1, year 2 and year 3 were validated by the leaving-one-out method. This procedure is widely used as it is the best validation method unless the sample is very large in which case the classical hold-out-type is often used. Cross validation was done only for those cases in the analysis. In cross validation, each case vas classified by the functions derived from all cases other than that case. 100.0% of original grouped cases were correctly classified and 100.0% of cross-validated grouped cases were also correctly classified. None of the variables in year five qualified for analysis and therefore there were no validation results.

CHAPTER FIVE: SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.0 Summary

This chapter provides a summary, conclusions and recommendations that were deduced from the study findings. This was adequate for a normal hypothetical assumption. Below are the conclusions, findings and recommendations on the study.

5.1 Conclusions

The objectives of this study were to develop a discriminant model incorporating ratio stability that can be used to predict predicting financial distress in commercial banks in Kenya and to identify critical financial ratios with significant predictive ability. The following ratios were identified as significant. Net Profit/Sales, Net profit/total Assets, Current Debt/Inventory and Total Debt/Total Assets. The findings provide evidence that the stability of financial ratios has an impact on the ability of the firm to continue as a going concern. Profitability ratios offer a reasonable measure of management effectiveness in firms' value creation, leverage / indebtedness ratios provide historical reasons for firms' failure while liquidity ratios constitute a measure of firms solvency.

An important observation is that none of the Activity and Turnover ratio was found to be critical in predicting financial distress in commercial banks in Kenya. The model attained 70% and 100% correct classification in year 1 and in year 3 respectively. The findings are consistent with studies by Kiragu (1991), Kiege (1991) and Dambolena and Khoury (1980) who concluded that profitability, leverage ratios were crucial in predicting failure. The findings however differ with those of Altman's (1968) who concluded that efficiency and profitability ratios were most crucial and that liquidity ratios were not significant.

Managers of these resources ought to pay attention to both investment and financing decisions. Proper investment decision-making will ensure that the firm implements only those projects that add value to the company. A comprehensive investment evaluation should always be undertaken. Projects commit resources and these funds are not available to the firm for use elsewhere such as in ed assets. Investment involves risk. In financing decisions, managers need to ensure that the firm sources funds at the optimal cost of capital and flexible debt covenants increased leverage may add value due to tax benefits but the present value of financial distress may exceed the benefits associated with debt.

There is need to monitor the performance of banks by all stakeholders as banks failure has serious social, economic and political implications. It affects the livelihood of people, reduces credibi1ity of the industry, and creates bad-will to the legislators and other stakeholders. The application of credit control and monitoring mechanisms by regulators using standardized Z-Scores for the specific industries should be encouraged. This information could be made readily available on timely basis. This may instill discipline on the incumbent management to ensure the banks survive and remain competitive. Stijn et al (2001) noted that a working insolvency regime is an essential part of market economy. The use of standardized financial statements across the industries should be encouraged as this may in future allow cross industry comparisons. In the banks industry this is already on course with the introduction. This will facilitate ease of extraction of financial data relevant in arriving at the ratios.

Other management decisions are dysfunctional to the overall functioning of the company. For a value-maximizing manager high liquidity may he very expensive to a company having low turnover, as there are opportunity costs and risks associated with high liquidity. Free cash flows may provide incentive to managers to make decisions that lower the value of the firm due to lack of discipline instilled by external funding. If the market for predicting financial distress in commercial banks in Kenya is inefficient, the inefficient managers may destroy value in a company that will have more value dead than alive.

5.2 Limitations of the Study

Several limitations to this study can be noted. The findings are limited as the sample size used here is small. The variable could probably change if a large sample is used.

When analyzing financial statements in any depth. it is necessary to compute a good number of ratios, but relatively few are really significant and not all of these ratios are independent in the sense that they could not be logically derived from other ratios without reference to the original figures. It was not possible to calculate some ratios from the available information. For example X_4(Cost of sales/Inventory) could not be computed from the sample because of lack of data on cost of sales from the financial statements. The matching of failed and non-failed firm could not be undertaken on stratified basis as information on private owned companies is not publicly available.

The study has focused on predicting financial distress in commercial predicting financial distress in commercial banks in Kenya. Qualitative aspects such as the company's strategy, age of the firm and quality of management need to be considered in the interpretation of the results. This study cannot escape the defects and drawbacks that are inherent in every human endeavor.

5.3 Recommendations

This study present a model on predicting financial distress in commercial predicting financial distress in commercial banks in Kenya based on the stability of financial ratios. Other measures of ratio stability such as the coefficient of variation and the standard error of estimate of the financial ratios could be applied to develop similar models.

There is also the need to carry out a study that takes into account the nature of the distribution of finance ratios. A model could be developed taking into account the fact that ratios may not be normally distributed but positively skewed variables in the real world may not usually be linear. Thus the linearity assumption inherent in this model could be relaxed and attempts made to develop a non- linear model such as logit and probit models.

The justification of using the MDA technique over other available models is though the Wilks' Lambda models derived above is subject to the weaknesses of the MDA technique, the model fronts a stronger linearity assumption as compared to others whose misclassification and inconsistency are of a wider error. Wilks' Lambdas model has a slight allowance for micro economical parameters factor such as inflation and its subsidiaries that may also affect bank's survival hence suitable for this case.

5.4 Suggestions for Further Studies

The research study limited itself to six ratios and there could be need to explore other ratios. Ratios based on revenue statements could also be applied like combined ratio, retention ratios (Calandro Jr, et al 2003). It may also be worth considering actuarial liabilities in further studies so as to isolate the element of shareholders equity in the life funds. Studies on prediction models based on separate lines of banks, that is short term and long term banks es may also be appropriate. Similar studies have been done elsewhere (Browne et al, 1995 and 1999). Failure prediction studies using non-financial parameters could be undertaken. Studies using economic and market predictors in both life and general banks banks have been under taken in the United States (Browne et al, 1995 and 1999).

In view of the critical role of corporate governance, specific studies on the effects of corporate governance in banks industry could be done. Studies on corporate governance have been done elsewhere, whereby indices and weights are applied to specific parameters of corporate governance (Esmeralda et al, 2005),

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Appendix 1

Stepwise Statistics

Variables Entered/Removed

	Entered	Wilks' Lambda							
		Statistic	df1	df2	df3	Exact F			
Step						Statistic	df1	df2	Sig.
1	Total liabilities over Total debt	.888	1	1	82.000	10.342	1	82.000	.002
2	working capital over Total Assets	.819	2	1	82.000	8.976	2	81.000	.000
3	EBT over Total Assets	.704	3	1	82.000	11.203	3	80.000	.000

At each step, the variable that minimizes the overall Wilks' Lambda is entered.
a Maximum number of steps is 14.
b Minimum partial F to enter is 3.84.
c Maximum partial F to remove is 2.71.
d F level, tolerance, or VIN insufficient for further computation.

Variables in the Analysis

Step		Tolerance	F to Remove	Wilk's Lambda
1	Total liabilities over Total debt	1.000	10.342	
2	Total liabilities over Total debt	.881	15.258	.973
	working capital over Total Assets	.881	6.868	.888
3	Total liabilities over Total debt	.880	13.628	.824
	working capital over Total Assets	.728	14.485	.832
	EBT over Total Assets	.814	12.999	.819

Variables Not in the Analysis

Step		Tolerance	Min. Tolerance	F to Enter	Wilks' Lambda
0	current Ratio	1.000	1.000	4.675	.946
	Retained earning	1.000	1.000	2.832	.967
	EBT over Total Assets	1.000	1.000	8.235	.909
	Total income over Total debt	1.000	1.000	.056	.999
	working capital over Total Assets	1.000	1.000	2.294	.973
	Total liabilities over Total debt	1.000	1.000	10.342	.888
	Equity over Total assets	1.000	1.000	.230	.997

1	current Ratio	.968	.968	6.799	.819
	Retained earning	1.000	1.000	2.580	.861
	EBT over Total Assets	.986	.986	5.486	.832
	Total income over Total debt	.994	.994	.201	.886
	working capital over Total Assets	.881	.881	6.868	.819
	Equity over Total assets	.744	.744	1.557	.871
2	current Ratio	.632	.575	1.578	.803
	Retained earning	.999	.880	2.567	.793
	EBT over Total Assets	.814	.728	12.999	.704
	Total income over Total debt	.682	.604	4.890	.771
	Equity over Total assets	.730	.646	2.380	.795
3	current Ratio	.584	.440	.064	.704
	Retained earning	.583	.475	.767	.697
	Total income over Total debt	.658	.559	2.106	.686
	Equity over Total assets	.509	.509	.237	.702

Wilks' Lambda

	Number of Variables	Lambda	df1	df2	df3	Exact F			
Step						Statistic	df1	df2	Sig.
1	1	.888	1	1	82	10.342	1	82.000	.002
2	2	.819	2	1	82	8.976	2	81.000	.000
3	3	.704	3	1	82	11.203	3	80.000	.000

Summary of Canonical Discriminant Functions

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.420	100.0	100.0	.544

a First 1 canonical discriminant functions were used in the analysis.

Wilks' Lambda

Test of function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.704	28.234	3	.000

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
current Ratio	.946	4.675	1	82	.034
Retained earnin	.967	2.832	1	82	.096
EBT over Total Assets	.909	8.235	1	82	.005
Total income over Total debt	.999	.056	1	82	.814
workin capital over Total Assets	.973	2.294	1	82	.134
Total liabilities over Total debt	.888	10.342	1	82	.002
Equity over Total assets	.997	.230	1	82	.633

Standardized Canonical Discriminant Function Coefficients

	Function
	1
EBT over Total Assets	-.762
workin capital over Total Assets	.844
Total liabilities over Total debt	.748

Canonical Discriminant Function Coefficients

	Function
	1
EBT over Total Assets	-12.142
workin capital over Total Assets	4.558
Total liabilities over Total debt	5.711
(Constant)	-5.460

Unstandardized coefficients

Structure Matrix

	Function
	1
Total liabilities over Total debt	.548
EBT over Total Assets	-.489
Retained earnin	-.425
current Ratio	.328
workin capital over Total Assets	.258
Total income over Total debt	.203
Equity over Total assets	-.010

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions Variables ordered by absolute size of correlation within function.
a This variable not used in the analysis.

Classification Function Coefficients

	bank failed or non failed status	
	Failed	Non failed
EBT over Total Assets	-15.105	.446
working capital over Total Assets	22.786	16.948
Total liabilities over Total debt	63.391	56.076
(Constant)	-31.625	-24.632

Fisher's linear discriminant functions

THE COMPUTED DATA USED IN THE ANALYSIS

status	x1	x2	x3	x4	x5	x6
1	5.82963	152	47	0.016085	0.018504	0.869268
1	4.358491	84	28	0.016837	0.019608	0.858689
1	4	26	16	0.015253	0.015984	0.954242
1	2.695652	-18	-30	-0.01764	-0.01839	0.958848
1	2.733945	32	18	0.010889	0.011688	0.931639
1	0.770992	19	25	0.016556	0.017507	0.945695
1	5.9375	7	-7	-0.03431	-0.03955	0.867647
1	7.214286	-5	18	0.098361	0.124138	0.79235
1	6.222222	10	10	0.089286	0.102041	0.875
1	0.347619	0	-20	-0.03724	-0.03497	1.065177
1	0.150198	0	-111	-0.20404	-0.17344	1.176471
1	0.168224	0	-102	-0.24286	-0.21162	1.147619
1	2.767857	10	-15	-0.00826	-0.00973	0.849119
1	4.858824	35	35	0.023793	0.025362	0.938137
1	2.907801	18	110	0.108803	0.115304	0.94362
1	1.387889	33	38	0.015866	0.017048	0.930689
1	6.676923	29	20	0.01233	0.013184	0.935265
1	3.627907	18	17	0.016782	0.018478	0.908193
1	4.104762	31	-10	-0.00496	-0.00561	0.883871
1	3.352941	38	11	0.007124	0.008166	0.872409
1	2.715447	29	-33	-0.02303	-0.02454	0.93859
1	24.77406	137	129	0.009868	0.010472	0.942396
1	6.264095	195	118	0.015305	0.016622	0.920752
1	4.192935	127	107	0.022536	0.025452	0.885425
1	7.322581	25	8	0.009324	0.029389	0.848485
1	4.5	90	22	0.028497	0.033846	0.841969
1	5.636364	83	15	0.021583	0.024876	0.867626
1	1.684455	15	20	0.005816	0.006232	0.93312
1	1.214022	70	30	0.012837	0.014012	0.916132
1	2.248619	16	28	0.014652	0.016355	0.895866
1	0.505882	-84	-77	-0.05366	-0.05488	0.9777
1	2.351351	-7	15	0.010225	0.011038	0.92638
1	0.940171	-22	-26	-0.02527	-0.02664	0.948494
1	4.864583	-605	-230	-0.10895	-0.15873	0.686405
1	3.252577	-430	-251	-0.1118	-0.17827	0.627171
1	15.18571	-414	-731	-0.20049	-0.20539	0.976138
1	0.730159	-37	-52	-0.02596	-0.02751	0.943585
1	0.951299	-28	-24	-0.01738	-0.01871	0.929037
1	0.599099	28	-70	-0.06542	-0.07277	0.899065

2	1.477922	1	306	0.293481	0.115254	0.949911
2	1.911111	198	162	0.103185	0.123853	0.833121
2	1.885057	136	97	0.0776	0.092469	0.8392
2	1.986667	170	114	0.058915	0.068551	0.859432
2	1.443662	188	115	0.061563	0.072877	0.844754
2	1.46729	207	152	0.07411	0.087256	0.849342
2	2.56	8	8	0.018433	0.025237	0.730415
2	2.1875	3	3	0.006198	0.007772	0.797521
2	1.5	-45	-24	-0.15484	-0.192	0.806452
2	2.522727	12	65	0.030762	0.034265	0.897776
2	3.939655	10	73	0.03806	0.042172	0.902503
2	2.047619	8	52	0.034392	0.039695	0.866402
2	3.36	37	41	0.019204	0.050995	0.376581
2	5.215909	-42	29	0.014139	0.037275	0.379327
2	7.431373	31	15	0.02381	0.075377	0.315873
2	1.018809	833	169	0.04701	0.069979	0.671766
2	1.040179	779	196	0.058577	0.088328	0.66318
2	1.107143	625	140	0.04717	0.073107	0.645216
2	2.535484	15	53	0.026904	0.028726	0.936548
2	3.535714	9	38	0.023385	0.025083	0.932308
2	6.48	0	27	0.022823	0.024479	0.932375
2	2.19398	171	279	0.053469	0.064929	0.823496
2	2.227437	235	234	0.055503	0.067222	0.825664
2	1.059441	282	214	0.059627	0.070003	0.851769
2	1.704545	0	103	0.048086	0.052126	0.922502
2	3.829545	2	130	0.073654	0.082938	0.908215
2	3.495726	2	85	0.062089	0.06746	0.92038
2	4.753333	53	92	0.018764	0.0203	0.924332
2	4.072727	80	75	0.017556	0.018788	0.934457
2	2.818792	74	118	0.033676	0.036086	0.933219
2	1.70297	28	26	0.011982	0.013138	0.911982
2	3.223301	15	24	0.012158	0.013022	0.933637
2	2.013793	0	13	0.006904	0.007506	0.919809
2	1.090535	263	126	0.044968	0.050868	0.884011
2	1.245232	174	65	0.026125	0.028459	0.918006
2	1.551613	122	43	0.02035	0.021641	0.940369
2	1.699602	104	61	0.012669	0.013339	0.94974
2	5.572816	80	40	0.012634	0.013769	0.917562
2	3.853261	61	30	0.006231	0.012255	0.508411