AN ANALYSIS OF THE DISCRIMINANT CORPORATE FAILURE PREDICTION MODEL BASED ON STABILITY OF FINANCIAL RATIOS

BY

SAMUEL KARANJA KOGI

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DECLARATION

This Management Research Project is my original work and has not been presented for a degree in any other University.

Signed: .... **Date:** 7th november 2003

Kogi, Samuel K.

This Management Research Project Has Been Submitted For Examination With My Approval As University Supervisor.

Signed: .... **Date:** 7th November, 2003

Winnie Nyamute (Mrs.)

Lecturer,

Department of Accounting,

University of Nairobi

DEDICATION

This Management Research Project is dedicated both to my loving mum, Phyllis Wangurwe Kogi and my fiancée, Elispher Nyambura. All that I am or hope to be, I owe my angel mother. It is God who gives success and guide in the straight path.

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ABSTRACT

The objectives of this study were to develop a discriminant model incorporating financial ratio stability that can be used to predict corporate failure, to identify critical financial ratios with significant predictive ability and to measure the improvement in the predictive ability achieved by incorporating a measure of stability of financial ratios to the discriminant failure model. The study, which covered the period between 1992 to 2000, was based on 20 companies; 10 failed and 10 non-failed. A failure prediction model that discriminates between failed and non-failed companies was developed using ratios alone and subsequently incorporating ratio stability using the standard deviation of the ratios.

The findings show that it is possible to predict corporate failure with up to 70 percent accuracy three years before its occurrence, using ratio stability discriminant model. Further validation of the findings suggest that the predictive accuracy was significantly better than chance. Net profit/Sales, Net profit/Total Assets, Current Debt/Inventory, and Total Debt/Total Assets were identified as critical financial ratios in predicting corporate failure. In general the liquidity, profitability and leverage ratios were found to be significant in company failure prediction. The ability of a firm to meet both short-term and long-term obligations was a key indicator of a company's failure path.

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CHAPTER ONE

INTRODUCTION

1.1 BACKGROUND OF THE STUDY

Various attempts have been made to predict the failure of companies. Beaver (1966, 1967) considered the predictive ability of individual financial ratios for this purpose. Altman (1968) used the multivariate discriminant analysis to combine several predictors into a model, which was more successful in predicting failure than models using only financial ratio one at a time. Deakin (1972) and Keige (1991) used a similar model based on financial ratios and obtained improved predictability up to two years prior to the date of failure. Ratios based on historical accounting information are often considered as benchmarks for evaluating the financial condition and performance of a firm. Financial ratios are used for all kinds of purposes including the assessment of ability of the firm to pay its debts, the evaluation of business and managerial success and even the statutory regulation of firm's a performance.

Business failure is costly to society, and its prediction is therefore beneficial. The reason ratios are used as opposed to absolute values, is a mathematical one, and is basically in order to facilitate comparison by adjusting for the size. However, this assumes that ratios possess the appropriate statistical properties for handling and summarizing data. Corporate failure has increased in intensity in the last two decades. The commercial banking for instance has been severely shaken in the past one and a half decade. The stability and financial integrity of the industry has been a subject of concern. Bankers and other regulators have come under severe pressure to strengthen and make public their efforts to identify and disclose potential failures, (Sametz 1997).

While Altman's (1968) work addresses the question of corporate failure, the treatment is far from adequate. It is the stability of every ratio over time that is relevant as this may be a pointer to a firm's financial stability, Dambolena and Khoury (1980). Pinches *et al* (1973) have empirically documented substantial changes in some of financial ratios overtime. This is problematic when industries differ with respect to factors of production, product life cycle, competitive structure and distribution mode, which cause industry differences in various measures of financial condition.

1.2 STATEMENT OF THE PROBLEM

The corporate failure literature contains a number of methodologies used to discriminate between failed and non-failed firms. The better-known multivariate studies use multiple discriminant analysis, Altman (1968) and Altman et *al* (1977). In business failure prediction, there are other models that use other basis than financial ratios to predict failure such as the catastrophe model. This model is useful where the path towards failure is not smooth and continuous, but is explosive, sudden and catastrophic, (Ho and Saunders, 1980).

The validation results testing the predictive ability of these models have been disappointing. Atman's (1977) work to some extent ignored the question of ratio stability. Wide and increasing downward shifts in some ratios can spell disaster for a firm. Corporate failure prediction models typically report out- of- sample classification results that are different from the models within- sample results. This disparity has been addressed by Platt and Platt (1990) and possible explanations of this phenomenon include instability of data overtime and different industry effects on corporate failure.

Corporate failure may be an indication of resource misallocation, which is undesirable from a social as well as economic point of view. The inclusion of stability of ratios in the analysis will considerably improve the ability of discriminant models to predict failure. Studies that have been conducted with a view of predicting failure have aimed at trying to identify possible failures as far ahead as possible in time. Thus far, we have seen that failure can be predicted accurately for two years prior to failure (Keige, 1991). This is too short a time for claim holders to extricate themselves from the failing firms without incurring considerable losses. It would be of interest to investigate whether the models could be improved to cover prediction for a period of over two years. Could the firms have avoided failure by being able to foresee it in advance?

1.3 OBJECTIVES OF THE STUDY

a) To identify critical financial ratios with significant corporate failure predictive ability.

b) To develop a multivariate discriminant model incorporating ratio stability that can be used to predict corporate failure.

c) To measure the improvement in the predictive ability achieved by incorporating a measure of stability to the discriminant failure model.

1.4 IMPORTANCE OF THE STUDY

The evidence provided by this study may be important to the following stakeholders.

Auditors: Business failure can result in costs to the auditors of the company as a result of lawsuits, legal fees and loss of revenue. The accountant has a special interest in the prediction of failure since external financial reports are generally prepared on a going concern basis.

Government: Government bodies may suffer loss of tax revenues and loss of part of the economic base of the community. Failure of companies leads to loss of jobs opportunities and may also send negative signals to potential businesses.

Researchers and scholars: The findings from this study will pique the curiosity of scholars and researchers and motivate them to explore new complexities of modern corporate finance- improvement in the conceptual framework of models for predicting corporate failure.

Management and investors: An early warning signal (whistle blowing) of probable failure will enable both management and investors to take preventive measures, operating policy changes, reorganization of financial structure and even voluntary liquidation which shorten the length of time losses are incurred and therefore improve resource allocation.

CHAPTER TWO

LITERATURE REVIEW

2.1 FINANCIAL DISTRESS

Financial distress is an emerging field steeped in confusion and complexity (Wruck, 1990). Some of the confusion can be resolved by understanding the diverse nature of financial distress and an appreciation that it is not synonymous with corporate death. Firms in distress face a variety of situations having very different effects on their values and claim holders. This diversity in conjunction with conflicts of interest among claim holders lead to an information problem that makes valuing a distress firm very difficult.

Financial distress has both benefits and costs. Financial distress is often accompanied by comprehensive organization changes in management, governance and structure. This organization restructuring can create value by improving the use of resources. Financial distress is defined as a situation where cash flow is insufficient to cover current obligations. These obligations can include unpaid debt to suppliers and employees, actual or potential damages from litigation and missed principal or interest payments under borrowing agreements (Wruck, 1991).

Some confusion arises when the word insolvent is used as a synonym for financial distress. Insolvency can be interpreted as pertaining to stock and flows. For example, Webster's New World Dictionary defines insolvency; first as 'not enough to pay all debts' and then as unable to pay debts as they become due. A stock based definition describes as insolvent a firm with a negative economic net worth; the present value of its cash flows is less than its total obligations (Wruck, 1990). A firm in financial distress is insolvent on a flow basis, if it is unable to meet current cash obligations (Altman, 1983).

The information problem faced by a distressed firm claim holder is how to obtain reliable data to determine whether the firm is insolvent on a stock as well as on a flow basis. The value maximizing ways to resolve distress differs between claim holders. Even if all claimholders accurately predict future cash flows, there would still be conflict over the best way to resolve distress, because different reorganization policies distribute wealth across managers, creditors and shareholders differently (Wruck 1991). Therefore reorganization policies are advocated both out of concern for value maximization and out of self-interest. Where the two differ, there is potential for value destroying behavior.

The most reliable estimate of future cash flows can be obtained when managers and claim holders share accurate information. Managers generally have better information about the firm's internal operations than outside investors, but may lack the ability or incentives to make the best use of that information. A management team committed to a poor strategy or to preserving its control over the firm is using its superior information about the firms operations to make poor and sub-optimal decisions.

Financial distress is resolved in an environment of imperfect information and conflict of interest. Distress is not synonymous with corporate death. To bridge the mismatch between hard and soft contracts, the firm can take the following actions.

First, asset restructuring - the asset size of the balance sheet is restructured in order to generate sufficient cash to meet the requirements of hard contracts. Wruck (1990) defines assets restructuring as the divestiture, or spin off of a subsidiary or division, the sale of a substantial part of a firm operating or non – operating asset, the discontinuance of operations in a division, line of business or geographical region or the restructuring of operations through closing or consolidating plants or regional headquarters. Assets restructuring is not without problems such as illiquid secondary market which increases the costs as prices are adversely affected as well as the poor or weak condition of the seller that weaken his bargaining position.

Second, management change - poor management decision-making and weak governance may be the cause of financial distress. Incumbent management may be a stumbling block to the acquisition of requisite expertise. Gilson (1989, 1990) document changes in composition of top management after distress and reports that non-distressed firms have 12-19% rate of annual turnover while distressed firms experience 52%. This is consistent to the idea that impending distress acts as a catalyst for organization change.

Third, Divided cuts - DeAngelo and DeAngelo (1990) investigated the link between dividend policy and financial distress in a sample of 80 financial distressed firms from 1980-1985 in the US. They found out that dividend growth during the pre distress period was high approximately 11%; but managers drastically reduced dividends during distress period. Besides, managers reduce dividends quite early in reaction to the onset of distress.

Fourth, infusion of new capital – where a firm in distress has positive net present value (NPV) projects available, one alternative to enhance firm value is to attract new investment capital. In order to attract capital, however, the firm has to deal with under-investment problem described by Myers (1977), which arises because a disproportionate amount of economic gain from incremental investment accrues to the pre-existing financial claimants.

Previous studies on financial distress focus on the costs and ignore the possibility that distress can result in beneficial outcomes. This stems in part from widely accepted model of firms capital structure decisions. Brealey and Myers (1995) present the formula for the value of levered firm as,

Value of firm = Value of equity + PV of tax shield

- PV cost of financial distress.

According to this formula, the firm balances the tax benefits of leverage against the cost of an increased probability of financial distress. This analysis ignores both the non-tax benefits of leverage and the benefits of financial distress. Leverage provides discipline and monitoring not available to an all equity firm. According to free cash-flow hypothesis, it creates value by imposing a discipline on organizations that reduce agency costs. When liquidation or reorganization is the firm's highest valued alternative, default creates value by providing an event that triggers change. Financial distress gives creditors the right to demand restructuring because their contracts have been breached. Leverage can therefore lead to value maximization by triggering liquidation.

Changes in Management and Governance- Poor management decision making and weak governance can lead to financial distress. Incumbent managers and directors can also inhibit a firm's ability to recover if new or special skills are required to turn the firm around. Gilson (1989, 1990) documents changes in top management and board of directors following financial distress. The non-distressed firms have a 19% annual turnover in top management. Gilson found out that within four years after the onset of financial distress, only 47% of old directors still hold their seats. 8% of the firms replace their entire board. He also found out that boards of directors are restructured following financial distress. For 60% of his sample firms, the size of the board is reduced following distress and consistent with loss of reputation; departing directors subsequently serve on fewer boards.

Changes in Organizational Strategy and Structure. Firms in financial distress undergo dramatic organizational changes, refocusing their strategy and undertaking restructuring. Often some assets are sold, while others are reorganized and re staffed. Financial distress forces a change in the firm's economic activities and the way these activities are organized. These same reorganizations probably would have created value before financial distress but the impetus for change provided by distress was absent when firm value deteriorates as a result of poor management or when firm value is highest in liquidation and management refuses to liquidate, financial distress create value. However the process of recovering from distress can create value even if events leading to distress are out of management's control (Wruck, 1991).

There are two types of costs associated with financial distress. First, there are out of pocket costs. The out of pocket or direct costs are the easiest to measure. They include legal, advisory and administrative fees paid by the company. Gilson, John and Lang (1990) present evidence on direct costs of private workouts. They found out that the medium out of pocket cost is 0.32% of total assets. Warner (1979a), Altman (1984) and Weiss (1990), all measured direct costs as a percentage of market value of the firm one year before bankruptcy. They found out that direct costs are quite small, averaging between 3% and 4.5% of market value. The maximum out of pocket costs are 6.6% of the market value in Weiss sample and 9.8% in Warner's sample.

Second, there are the indirect costs - These are opportunity costs imposed on the firm because financial distress affects its ability to carry out business as usual. For instance, the business loses the right to make certain decisions without approval, reduced demand for the firm's product and increase in its production costs. Demand falls if the value of the product to consumer depends on the firm's future performance. Worried about the distressed firm ability to pay its debts, suppliers often charge a risk premium through increased prices; tighten credit terms or poorer service. Suppliers begin to view their relationship with the firm as a short term one.

Moreover, management spends considerable time resolving financial distress and this time could have been spent more productively elsewhere. Estimating the indirect cost is difficult because the costs represent lost opportunities. Available evidence is mixed. Altman (1984) estimates the unexpected loss in profits for three years before failure for eleven retailing and five industrial firms and uses this as measure of the indirect costs of financial distress. The interpretation is problematic because it is impossible to tell whether the loss in profits is caused by financial distress or whether financial distress is caused by the loss in profits. He found out that the sum of direct and indirect cost (loss in profits) averages 8.7% of market value for retailing and 15.0% for the industrial firm one year before failure. It is not surprising that the loss in profits should be smaller in retailing firms. Industrial firms are more likely to be selling products for which the future availability of service, guarantees, parts, support and warranties is important.

2.2 TRADITIONAL RATIO ANALYSIS

In order to gauge accurately the financial health of a corporation, it becomes necessary to undertake further analysis and regrouping of the figures contained in conventional financial statements. Analysis may be in two directions. First, analysis of financial statements over a number of years – in such case trend is important and second analysis of position of a corporation at a particular date – here the detailed position disclosed by one set of financial statements is sought to be examined. Needless to mention, financial ratios can be of significant help in the task. . Based on a sample of 41 companies in the Nairobi Stock Exchange. Aduda (1993), found out that financial ratios are not normally distributed, either in raw or in transformed form. The evidence also indicated that ratios are positively skewed. In discriminant models however the financial ratios are assumed to be normally distributed.

Ratio is a fraction whose numerator is the antecedent and denominator the consequent. It is simply an expression of one number in terms of another (Paul, 1997). It may also be defined as the relationship or proportion that one amount bears to another, the first number being the numerator and the later denominator. Another explanation of the ratio may be the relation of the latter to the earlier amount and computed by dividing the amount for the later date or period by the amount of the earlier date or period.

The detection of company operating and financial difficulties is a subject, which has been particularly susceptible to financial ratio analysis. Quantitative measures of company performance developed from agencies that had been established to supply qualitative information assessing the credit worthiness of merchants. Smith Winakov (1985) concluded that failing firms exhibit significantly different ratio measurements than continuing entities. Studies have been carried on ratios of large asset size corporations that experienced difficulties in meeting their fixed indebtedness obligations. Observed evidence for five years prior to failure was cited as conclusive that ratio analysis can be useful in the prediction of failure. The studies mentioned imply a definite potential of ratios as predictors of failure. In general ratios measuring profitability, solvency and liquidity prevailed as the most significant indicators.

The interrelationship that exists among the different items appearing in the financial statement is revealed by financial ratios. Ratios are the best tools for measuring management efficiency, profitability, solvency and liquidity. The importance of ratio analysis is discussed here under. It helps analyze the probable causal relationship among different items after analyzing and scrutinizing the past result.

Secondly, it helps to take time dimension into account by trend analysis i.e. whether the firm is improving or deteriorating over a number of years. Besides ratio throws light on the degree of efficiency of management and utilization of the assets and that is why it is called survey of efficiency. Ratio help to make inter firm comparison either between two firms employed in the identical types of business or between the same firms at two different dates. Other reasons for using ratios are to control the size of the financial variables being examined. Although Lev (1974) touched on these, it was not until Saunder (1979) that the full ramifications were examined. They found out that the use of ratios was necessarily based on hypothesis (either explicitly specified or implicitly assumed) about the relationship between the numerator variable and the denominator size variable.

Ratios aid comparison between a subject firm and its industry. In practical analysis, a firm's ratio will be compared with industry norm and inferences about the firm's performance based on the difference between the firm's ratios and the industry norm. There is considerable debate in financial literature as to which ratios are most useful and in particular for assessing the likelihood of failure. The focus originated on liquidity as an indication of both current and future cash flows. It is well known fact that one cannot arrive at a definite conclusion about the financial health of an enterprise simply by studying and scanning of the absolute figures contained in the conventional form of financial statements, (Aduda 1993). The same is only possible when the absolute figures are analyzed further in terms of ratios that one can assess the financial health properly. Ratio analysis is not free from snags. First, comparison between two variables proves worth provided their basis of valuation is identical. In reality, however, it is not possible, such as, method of inventory valuation, depreciation and so on. Moreover, ratios depends on figures appeared on the financial statements. But in most cases, the figures are window dressed especially when a corporation is in financial problems. As a result the correct picture cannot be drawn up by ratios.

Thirdly, ratios are computed on past results. Corporate failure is futuristic. It therefore does not help properly predict future and significantly it is difficult to ascertain a standard ratio in order to make proper comparison because, it differs from firm to firm, industry-to-industry and even between different seasons of the same industry. Financial ratios have been used as inputs for advanced statistical models to forecast many kinds of business events and to identify financial and other characteristics. Notable studies include Pinches and Mingo (1973) who used multivariate discriminant analysis, to predict published corporate bond rating by means of individual ratios.

However, the main focus has been on testing multivariate statistical models, which use financial ratios to predict corporate failure. These were based on the original work of Beaver (1966) and Altman (1968). Altman *et al* (1977) developed and marketed a "second generation" model called "Zeta analysis" which is essentially the same as the Z score model but takes into account changes in the financial reporting standards (lease capitalization). Most widely used measures of financial ratio stability are the standard deviation, standard error of estimate and the coefficient of variation (Dambolena and Khoury 1981). There are also the balance sheet decomposition measures, which reflect the extent to which the asset and liability structures of companies have changes over the previous years.

Lev (1969) found out that firms adjusted their financial ratios to conform to their industry's average. Etabari and Horrigan (1987) suggested that indeed the industry average of a financial ratio is the optimal level for companies in that industry. This suggests that a company's financial ratios reflect capital structure and revenue/expense patterns specific to its industry. Consequently, when companies which form several industries are analyzed, the sample mean financial ratios and the sample variability depend not only on chance selection of companies but also upon the distribution of companies across industries and the cyclical level of each industry. Altman and Izan (1984) proposed using company to industry financial ratios (industry relative ratios) to control for industry variation within their sample of Australian companies. Industry – relative ratios may also provide better metric of company financial health.

2.3 INSTABILITY OF FINANCIAL DATA

The instability of financial data overtime is not a new idea. Pinches, Mingo and Caruthers (1973) documented time – series changes in some ratio values for 221 industrial firms over the period 1951 – 1969. Scott and Martin (1975) and Platt (1989) reported evidence of systematic time series changes in aggregate industry financial ratios.

Dambolena and Khoury (1980) found out that data instability is greatest for firms about to fail.

The consequence of data instability on predicting model is that the observed range of values may shift from estimation to forecast periods. Dambolena and Khoury (1980) and Betts and Behlhoul (1987) used the variation in financial ratios to measures the stability of the financial ratios. Perhaps a more promising method to effectively deal with data instability is to create industry – relative variable by relating the same ratio for a firm to that of the average firm in its industry. The industry relative ratio essentially measures the relative position of an individual company within the distribution of all companies in its industry. An industry – relative ratio is defined as the ratio of a firm's financial ratio relative to the mean value for that ratio in the firms industry at a point of time, (Platt and Platt 1990). Thus industry relative variable may also ameliorate the data instability problem and still allow for changes within the industry. A model based on these ratios should therefore produce more efficient forecasts than a model using unadjusted ratios.

Platt and Platt (1990) defines a stable variable as one in which the mean does not change across estimation and forecast time period as shown in the equation.

$(X_{i\,E}) = \text{Mean}\ (X_{i\,F})$

Where X = a financial ratio

i = ratio 1, ... n

E = the estimation period

F = the forecast period.

Furthermore, a relatively stable variable is one which exhibit the least change in the mean value from estimation to forecast period. Univariate methodologies placed emphasis on individual signals of impeding problems and thus ratio analysis presented in this fashion is susceptible to faulty interpretation and is potentially confusing, Altman (1968). For example a company with poor profitability and / or solvency record may be regarded as a potential failure, but because of its above average liquidity; the situation may not be considered serious.

Ratios have been used to predict corporate failure. Keige (1991) found out that the types of ratios, that would best discriminate between failed companies and successful ones differ from place to place. From his study of Kenyan companies, he found out that the Current ratio, Fixed asset 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 two years before it occurs. Using an initial sample of 15 ratios from financial statements of 20 companies in Kenya that failed between 1980 and 1990, Keige (1991) study resulted in the following discriminant function.

$$Z = -0.3671X_1 + 0.16603X_7 + 13.258X_8 + 2.8216X_{10} - 0.65541X_{11} + 0.01818X_{13} + 1.02299X_{15} - 2.72963$$

The result showed that it is possible to predict failure with up to 90% accuracy two years before the event. Kiragu (1991) sought to build a model to predict corporate failure using accounting data adjusted for price level changes. From a sample of 10 failed and 10 non-failed companies, Kiragu (1991) found out that nine ratios had a high corporate failure predictive ability. These ratios in order of their importance were Time interest earned coverage, Fixed charge coverage, Quick ratio, Current ratio, Equity to total assets, Change in monetary liabilities, Total debt to total assets and Inventory turnover. The most critical ratios were the liquidity and debt service ratios.

The results however differed from earlier study by Altman (1968) who concluded that liquidity ratios were not of any significance in failure prediction. Both concluded that efficiency and profitability ratios were most crucial. The analytical studies on the general macro economic causes of corporate failure was begun by Altman (1968). Failure was significantly linked to prevailing monetary policy, the investor's expectations about economic conditions and the state of economy. On the micro level, Altman (1968) found that the age of the firm has a significant impact on its chance of failure.

Dambolena and Khoury (1980), collected data on 68 firms, half of them failed and half of them non-failed. The companies were paired by industry and a final sample of 46 firms was examined for failure between 1969- 1975 period. They used (1) the standard deviation of the financial ratio, (2) their standard error of estimate, and (3) their coefficient of variation to measurer the stability of the financial ratios. These measures of ratio stability showed remarkable differences between failed and non-failed firms. One of the most striking examples is perhaps that of the standard deviation of the Profit/net worth ratio on the year prior to failure measured over the past years. For the twenty-three non-failed firms, the standard deviation has values in the range 0 to 0.06, with a relatively uniform spread over that range. For the failed firm, on the other hand, only four of the twenty three values are 0.06 or less, whereas twelve of the values - that is those of more than half of the failed firms – exceed 0.50, (Dambolena and Khoury, 1980).

Dambolenas work (1980) lies not only in the superior predictive power of the model, but also in the improvement in the conceptual framework of models for predicting corporate failure. The standard deviation of ratios over time appeared to be the strongest measure of ratio stability. The other measures, namely standard error of estimate and coefficient of variation were found to be inferior to those obtained with the standard deviation. Dambolenas (1980) model which included the ratios of Net profit to sales, Net profits to total assets, Fixed assets to net worth, Debt to net working capital, Total debt to total assets, and the Standard deviations of inventory to net working capital, and of Fixed assets to net worth was found to predict failure for 5 years with 83% accuracy.

Altman (1968) developed a model from a sample of 66 companies with thirty-three firms in each of the two groups. The bankrupt group consisted of manufacturers that filed a bankruptcy petition under chapter X of the US National Bankruptcy Act during the period 1946 – 1965. The mean asset size of these corporations was £6.4 Million with a range of between $0.7 Million and $25.9 Million. Group 2 consisted of a paired sample of manufacturing firms chosen on a stratified random basis. The firms were stratified by industry and by size with asset range restricted to between $1 - $25 Million.

An important issue in Altman's work was to determine the asset size group to be sampled. He observed that the decision to eliminate both the small firms (under $1 million in total assets) and the very large companies from initial sample was essentially due to the range in the firms in group 1. In addition the incidence of bankruptcy in the large asset – size firms is quite rare even today (except in fraudulent activities) while the absence of comprehensive data negated the represèntation of small firms. The final discriminant function identified Working capital/total assets, Retained earnings/total assets, EBIT/total assets, Market value of equity/book value of debt and Sales/total assets as discriminant ratios. A Z score less than 2.675 indicates that a company has a 95 percent chance of becoming bankruptcy within one year. However Altman (1968) result show that in practice the area between 1.81 and 2.99 should be thought as a gray area. Altman (1968) further showed that failed firms and non-failed firms have very different financial profiles one year before failure.

CHAPTER THREE

RESEARCH DESIGN AND METHODOLOGY

3.1 POPULATION OF THE STUDY

The population of interest consisted of those companies in the register of the Registrar of Companies in the period between 1992 - 2000. The population was split into two groups. The first group consisted of those companies that failed while the second group comprised of those that did not fail. In the context of this study, failed companies refer to those that were placed under receivership during the period of interest.

3.2 THE SAMPLE

The intention was to select a sample composed of sixty companies with thirty companies in each of the two groups (failed and non-failed.) However because of data unavailability, twenty companies were studied in pair. The sample was similar to Kiragu (1991) and Keige (1991) studies. The failed group was identified first and then matched with a similar company in the non-failed group. The average total asset range was restricted from Ksh 300 Millions to 950 Millions. No sampling of the failed companies was undertaken because only ten companies had a complete data set. Both very small companies and very large companies were eliminated essentially due to range of asset size and from the fact that the incidence of failure in large asset size firms is quite rare (except in the case of fraudulent activities) and absence of data from very small companies.

3.3 DATA COLLECTION

All data used in this study was secondary. The annual accounts for six years prior to failure were collected for both the failed and non-failed companies. Specifically items in the Income statement and Balance sheet of every company in the sample were collected.

3.4 DATA ANALYSIS

From the data for each company and each year, the 19 ratios (see Appendix 1) were computed. The above ratios were selected on the basis of having been used elsewhere in business failure prediction studies, their reasonableness and general acceptability of the ratios in relation to their intended use - the development of a discriminant function and the development of a comprehensive set of ratios by types: profitability, activity, liquidity and indebtedness ratios. These types of ratios have shown considerable merit in financial analysis and in the measurement of financial well being of companies.

The statistical tool used in this study was the multivariate discriminant analysis. This was used to identity the ratios, which can reliably discriminate between failed and non-failed companies. The discriminant statistical tool was used since, the criterion variable in dichotomy (failed and non-failed), which makes discriminant analysis fairly appropriate.

The general form of a discriminant function is,

$$Z = V_1 X_1 + V_2 X_2 + \ldots\ldots\ldots\ldots + V_n X_n$$

Where

$V_1 V_2 + \ldots\ldots V_n$ = Discriminant coefficient

$X_1 X_2 + \ldots\ldots X_n$ = Independent variables

Z=Discriminant score.

The ' best' linear discriminant function was developed using stepwise procedure. The predictor variables were the ratios and their standard deviations. The stability of ratios was measured by the standard deviation. The analysis begun with the desire to statistically distinguish between two or more prior defined groups namely, failed and non-failed. These groups are defined for each particular research question. To distinguish between the groups the researcher selects a collection of discriminating variables that measures characteristics on which the groups are expected to differ with the objective of weighing and linearly combining the discriminating variables is such a manner that the groups are forced to be as statistically distinct as possible.

In the case of a two – group discriminant analysis, the function is one. However, if there are more than two groups, it is possible to get more than one function. The maximum number of functions, which can be derived, is either one less the number of groups or equal to the number of discriminating variables. A researcher may be faced with what he may consider to be too many variables. He may be interested only in a certain number of variables, which passes a specified level of significance in the function. The variables can be ranked using the initial discriminant function coefficients or the variables can be screened by way of linear multiple regression (Chirchir, 1989).

Statistical significance of discriminant function can be tested using a variety of methods such as F-ratio or correlation coefficient. However an indirect and most widely used approach to test the significance of the discriminant function is Wilks' Lamda. This was the approach used in this study. To measure the discriminant power not already accounted for by the model, the Wilks' Lambda associated with each step in the model was calculated. Wilks' Lambda, also called the *U* statistics, is available for testing the equality of group centroids. It is a multivariate analysis of variance test statistics that varies between 0 and 1. Small values indicated that the groups differ and hence preferable. This was calculated such that values of Lamda near zero indicate high discrimination; and when it is equal to its maximum value of unity, the groups are equal, and thus there is no discrimination. Wilks' Lamda can also be transformed by approximation, into a chi square statistic. To measure the relative importance of the model, the Eigen values were calculated. Eigen value is a ratio of the between groups sum of squares to the within groups or error sum of squares. To measure the discriminating power already in the model, canonical correlations were computed. Canonical correlation measures the association between the discriminant scores and the groups.

The discriminant analysis is based on two major assumptions: First, the variables being used are assumed to have a multivariate normal distribution. The effects of departure from this assumption are unclear although the procedure is still appropriate even when multivariate normality is absent. Second, the variables are assumed to have equal variance – covariance matrices within each group. When the dispersion matrices are not equal, a quadratic discriminant function should be fitted (Belhoul and Betts, 1987) Multivariate discriminant analysis classifies an observation into one of several a priori grouping dependent upon the observations individual characteristics. It is used to primarily classify and/or make prediction in problems where the dependent variable appears in a qualitative form, for example, bankrupt or no bankrupt, successful or not successful. Multivariate discriminant analysis attempts to derive a linear combination of the characteristics which "best" discriminates between the groups. If a particular object for instance a corporation has characteristics (financial ratios), which can be quantified for all the companies in the analysis, the multivariate discriminant analysis determines a set of discriminant coefficients. The technique has the advantage of considering an entire profile of characteristics common to the relevant firms as well as the interaction of these properties.

CHAPTER FOUR

DATA ANALYSIS AND FINDINGS

4.1 MODEL DEVELOPMENT

This section on model development started with discriminant function for one, three and five 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.

Year 1 (See Appendix 2 and 5)

The discriminant function using the ratios was:

$$Z = 7.116X_4 - 3.407X_{10} - 2.444X14 + 1.709X_{18} + 4.789$$

Introducing the standard deviation, the following function was obtained.

$$Z = 2.622X_4 + 0.425.$$

The Wilks' lambda using the ratios alone was 0.003 while using the standard deviation; the Wilks' lambda was 0.794. Although Wilks' lambda increases by 0.791, 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 1 using ratios alone has Eigen value of 293.322 while using the standard deviation, the Eigen value was 0.259. This means the relative importance of the function in year 1 using the standard deviation diminishes significantly. This decline was also supported by canonical correlation, which decreased from 0.998 to 0.453 using ratios and deviations respectively.

Year 3 (See Appendix 3 and 6)

The discriminant function using the ratio was;

$$Z = 0.367X_3 + 1.057X_{13} - 2.768.$$

Introducing the standard deviation the function was;

$$Z = 0.130X_1 + 4.028X_5 + 0.216X_{13} + 10.079X_{19} - 4.083$$

There was much improvement in Wilks' lambda from 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 10.669. 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 0.956. In both year 1 and year 3, both models show conflicting percent correct classification.

In year 1, ratios show 100% correct classification while standard deviation show 70% correct classification. In year 3, ratios show a decline in correct classification to 80% while standard deviation show marked improvement in percent correct classification of 100%. The results imply that standard deviations of ratios are better predictors of failure than using the average of the same ratios alone..

Year 5 (See Appendix 5 and 7)

Using the ratios alone as the independent variables, only 50% of the cases were valid and at least 50% of discriminating variables were found missing and out of range. A maximum 38 steps were executed and at each step, the variable that maximizes the 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. 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 0.912 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 100%.

Thus, the model for year 3 using standard deviation emerged as the "best" discriminant function. The function was;

$$Z = 0.13X1 + 4.028X5 + 0.216X13 + 10.079X19 - 4.083$$

Where Z = Discriminant score

X_1 = Net Profit/Sales

X_5 = Net Profit/Total Assets

X_{13} = Current Debt/Inventory

X_{19} = Total Debt/Total 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 a 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 in 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 uncollectibility 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 meet 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 3 and year 5 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 was 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

CONCLUSIONS AND RECOMMENDATIONS

5.1 CONCLUSIONS

The objectives of this study were to develop a discriminant model incorporating ratio stability that can be used to predict corporate failure 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 corporate 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, leverage 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 findings of this study imply that companies in Kenya companies fail due inefficient and ineffective financial decision making by those in control of company's resources.

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 project that adds 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 fixed 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.

Other management decisions are dysfunctional to the overall functioning of the company. For a value-maximizing manager, high liquidity may be 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 corporate control 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_9 (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 firms could not be undertaken on stratified basis, as information on private owned companies is not publicly available.

The study has focused on financial analysis of corporate failure. 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 FOR FURTHER RESEARCH

This study present a model on corporate failure 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.

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APPENDICES

APPENDIX 1.

INDEX OF RATIOS USED IN THE ANALYSIS

Profitability Measures

X_1. Net profit/Sales

X_2. Net profit/ Net worth.

X_3. Net profit/Net working capital

X_4. Net profit/Fixed Assets

X_5. Net profit/Total Assets

Activity and Turnover Measures

X_6. Sales /Net worth

X_7. Sales/Net working capital

X_8. Sales /Inventory

X_9. Cost of sales/Inventory

Liquidity Measures

X_{10}. Current Ratio

X_{11}. Acid Test Ratio

X_{12}. Inventory/Net working capital

X_{13}. Current debt/Inventory

Indebtedness Measures

X_{14}. Fixed Assets/Net worth

X_{15}. Current Debt/Net worth

X_{16}. Total Debt/Net worth

X_{17}. Time Interest Earned

X_{18}. Total Debt/Net working capital

X_{19}. Total Debt/Total assets

APPENDIX 2

DISCRIMINANT RESULTS FOR YEAR 1-USING RATIOS.

Discriminant

Analysis 1

Stepwise Statistics

Variables Entered/Removed

	Entered	Wilks' Lambda							
		Statistic	df1	df2	df3	Exact F			
Step						Statistic	df1	df2	Sig.
1	X18	.444	1	1	6.000	7.517	1	6.000	.034
2	X14	.146	2	1	6.000	14.654	2	5.000	.008
3	X4	.010	3	1	6.000	137.326	3	4.000	.000
4	X10	.003	4	1	6.000	219.991	4	3.000	.000

At each step, the variable that minimizes the overall Wilks' Lambda is entered.

a Maximum number of steps is 36.

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	Wilks' Lambda
1	X18	1.000	7.517	
2	X18	.227	29.254	.998
	X14	.227	10.229	.444
3	X18	.022	249.075	.608
	X14	.018	146.666	.362
	X4	.079	56.623	.146
4	X18	.006	220.456	.253
	X14	.005	208.995	.240
	X4	.039	57.890	.069
	X10	.136	5.491	.010

Wilks' Lambda

	Number of Variables	Lambda	df1	df2	df3	Exact F			
Step						Statistic	df1	df2	Sig.
1	1	.444	1	1	6	7.517	1	6.000	3.366E-02
2	2	.146	2	1	6	14.654	2	5.000	8.108E-03
3	3	.010	3	1	6	137.326	3	4.000	1.728E-04
4	4	.003	4	1	6	219.991	4	3.000	4.941E-04

Eigen values

Function	Eigen value	% of Variance	Cumulative %	Canonical Correlation
1	293.322	100.0	100.0	.998

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

Standardized Canonical Discriminant Function Coefficients

	Function
	1
X4	4.916
X10	-2.181
X14	-13.939
X18	12.821

Canonical Discriminant Function Coefficients

	Function
	1
X4	7.116
X10	-3.407
X14	-2.444
X18	1.709
(Constant)	4.789

Unstandardized coefficients

Classification Results

			Predicted Group Membership		Total
		V1	Failed companies	Non-failed companies	
Original	Count	Failed companies	7	0	7
		Non-failed companies	0	3	3
	%	Failed companies	100.0	.0	100.0
		Non-failed companies	.0	100.0	100.0
Cross-validated	Count	Failed companies	7	0	7
		Non-failed companies	0	3	3
	%	Failed companies	100.0	.0	100.0
		Non-failed companies	.0	100.0	100.0

a Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

b 100.0% of original grouped cases correctly classified.

c 100.0% of cross-validated grouped cases correctly classified.

APPENDIX 3

DISCRIMINANT RESULTS FOR YEAR 3-USING RATIOS

Discriminant

Analysis 1

Stepwise Statistics

Variables Entered/Removed

	Entered	Wilks' Lambda							
		Statistic	df1	df2	df3	Exact F			
Step						Statistic	df1	df2	Sig.
1	X13	.658	1	1	8.000	4.150	1	8.000	.076
2	X3	.423	2	1	8.000	4.774	2	7.000	.049

At each step, the variable that minimizes the overall Wilks' Lambda is entered.
a Maximum number of steps is 38.
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	Wilks' Lambda
1	X13	1.000	4.150	
2	X13	.912	4.489	.694
	X3	.912	3.896	.658

Summary of Canonical Discriminant Functions

Eigen values

Function	Eigen value	% of Variance	Cumulative %	Canonical Correlation
1	1.364	100.0	100.0	.760

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

Canonical Discriminant Function Coefficients

	Function
	1
X3	.317
X13	.433
(Constant)	-1.157

Unstandardized coefficients

Classification Results

			Predicted Group Membership		Total
		X0	Failed companies	Non-failed companies	
Original	Count	Failed companies	8	0	8
		Non-failed companies	3	4	7
	%	Failed companies	100.0	.0	100.0
		Non-failed companies	42.9	57.1	100.0
Cross-validated	Count	Failed companies	7	1	8
		Non-failed companies	5	2	7
	%	Failed companies	87.5	12.5	100.0
		Non-failed companies	71.4	28.6	100.0

a Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

b 80.0% of original grouped cases correctly classified.

c 60.0% of cross-validated grouped cases correctly classified.

APPENDIX 4

DISCRIMINANT RESULTS FOR YEAR 5-USING RATIOS

Discriminant

Analysis 1

Stepwise Statistics

Variables Entered/Removed

Step

At each step, the variable that minimizes the overall Wilks' Lambda is entered.

a Maximum number of steps is 38.

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.

e No variables are qualified for the analysis.

Wilks' Lambda

Step

a No variables are qualified for the analysis.

APPENDIX 5

DISCRIMINANT RESULTS FOR YEAR 1-USING STANDARD DEVIATIONS.

Discriminant

Analysis 1

Stepwise Statistics

Variables Entered/Removed

	Entered	Wilks' Lambda							
		Statistic	df1	df2	df3	Exact F			
Step						Statistic	df1	df2	Sig.
1	X4	.794	1	1	18.000	4.659	1	18.000	.045

At each step, the variable that minimizes the overall Wilks' Lambda is entered.

a Maximum number of steps is 38.

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
1	X4	1.000	4.659

Wilks' Lambda

	Number of Variables	Lambda	df1	df2	df3	Exact F			
Step						Statistic	df1	df2	Sig.
	1	.794	1	1	18	4.659	1	18.000	4.464E-02

Eigen values

Function	Eigen value	% of Variance	Cumulative %	Canonical Correlation
1	.259	100.0	100.0	.453

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

Canonical Discriminant Function Coefficients

	Function
	1
X4	2.622
(Constant)	.425

Unstandardized coefficients

Classification Results

			Predicted Group Membership		Total
		V1	Failed companies	Non-failed companies	
Original	Count	Failed companies	4	6	10
		Non-failed companies	0	10	10
	%	Failed companies	40.0	60.0	100.0
		Non-failed companies	.0	100.0	100.0
Cross-validated	Count	Failed companies	4	6	10
		Non-failed companies	0	10	10
	%	Failed companies	40.0	60.0	100.0
		Non-failed companies	.0	100.0	100.0

a Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

b 70.0% of original grouped cases correctly classified.

c 70.0% of cross-validated grouped cases correctly classified.

APPENDIX 6

DISCRIMINANT RESULTS FOR YEAR 3-USING STANDARD DEVIATIONS.

Discriminant

Analysis 1

Stepwise Statistics

Variables Entered/Removed

	Entered	Wilks' Lambda							
		Statistic	df1	df2	df3	Exact F			
Step						Statistic	df1	df2	Sig.
1	X19	.479	1	1	18.000	19.618	1	18.000	.000
2	X1	.220	2	1	18.000	30.073	2	17.000	.000
3	X13	.118	3	1	18.000	39.770	3	16.000	.000
4	X5	.086	4	1	18.000	40.009	4	15.000	.000

At each step, the variable that minimizes the overall Wilks' Lambda is entered.

a Maximum number of steps is 38.

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	Wilks' Lambda
1	X19	1.000	19.618	
2	X19	.212	56.976	.959
	X1	.212	19.915	.479
3	X19	.155	70.014	.636
	X1	.170	25.390	.306
	X13	.728	13.817	.220
4	X19	.122	86.639	.581
	X1	.151	27.552	.243
	X13	.517	21.951	.211
	X5	.662	5.697	.118

Wilks' Lambda

	Number of Variables	Lambda	df1	df2	df3	Exact F			
Step						Statistic	df1	df2	Sig.
1	1	.479	1	1	18	19.618	1	18.000	3.239E-04
2	2	.220	2	1	18	30.073	2	17.000	2.610E-06
3	3	.118	3	1	18	39.770	3	16.000	1.207E-07
4	4	.086	4	1	18	40.009	4	15.000	7.807E-08

Eigen values

Function	Eigen value	% of Variance	Cumulative %	Canonical Correlation
1	10.669	100.0	100.0	.956

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

Canonical Discriminant Function Coefficients

	Function
	1
X1	.130
X5	4.028
X13	.216
X19	10.079
(Constant)	-4.083

Unstandardized coefficients

Classification Results

			Predicted Group Membership		Total
		V1	Failed companies	Non-failed companies	
Original	Count	Failed companies	10	0	10
		Non-failed companies	0	10	10
	%	Failed companies	100.0	.0	100.0
		Non-failed companies	.0	100.0	100.0
Cross-validated	Count	Failed companies	9	1	10
		Non-failed companies	0	10	10
	%	Failed companies	90.0	10.0	100.0
		Non-failed companies	.0	100.0	100.0

a Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

b 100.0% of original grouped cases correctly classified.

c 95.0% of cross-validated grouped cases correctly classified.

APPENDIX 7

DISCRIMINANT RESULTS FOR YEAR 5-USING STANDARD DEVIATIONS.

Discriminant

Analysis 1

Stepwise Statistics

Variables Entered/Removed

	Entered	Wilks' Lambda							
		Statistic	df1	df2	df3	Exact F			
Step						Statistic	df1	df2	Sig.
1	X19	.483	1	1	18.000	19.302	1	18.000	.000
2	X1	.233	2	1	18.000	27.930	2	17.000	.000
3	X13	.169	3	1	18.000	26.226	3	16.000	.000

At each step, the variable that minimizes the overall Wilks' Lambda is entered.

a Maximum number of steps is 38.

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	Wilks' Lambda
1	X19	1.000	19.302	
2	X19	.204	51.541	.941
	X1	.204	18.159	.483
3	X19	.173	57.998	.782
	X1	.183	20.300	.383
	X13	.838	6.090	.233

Wilks' Lambda

	Number of Variables	Lambda	df1	df2	df3	Exact F			
Step						Statistic	df1	df2	Sig.
1	1	.483	1	1	18	19.302	1	18.000	3.505E-04
2	2	.233	2	1	18	27.930	2	17.000	4.242E-06
3	3	.169	3	1	18	26.226	3	16.000	2.047E-06

Eigen values

Function	Eigen value	% of Variance	Cumulative %	Canonical Correlation
1	4.917	100.0	100.0	.912

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

Canonical Discriminant Function Coefficients

	Function
	1
X1	-.263
X13	.078
X19	8.960
(Constant)	-2.696

Unstandardized coefficients

Classification Results

			Predicted Group Membership		Total
		V1	Failed companies	Non-failed companies	
Original	Count	Failed companies	10	0	10
		Non-failed companies	0	10	10
	%	Failed companies	100.0	.0	100.0
		Non-failed companies	.0	100.0	100.0
Cross-validated	Count	Failed companies	9	1	10
		Non-failed companies	0	10	10
	%	Failed companies	90.0	10.0	100.0
		Non-failed companies	.0	100.0	100.0

a Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

b 100.0% of original grouped cases correctly classified.

c 95.0% of cross-validated grouped cases correctly classified.

APPENDIX 8.

SUMMARY OF DISCRIMINANT ANALYSIS RESULTS

Percent Correct Classification

Ratios alone	Year prior to failure	Variables in the model	Failed	Non failed	Total	Wilks' lambda	Eigen value	Canonical correlation
	1	X_4 X_{10} X_{14} X_{18}	100	100	100	0.003	293.322	0.998
	3	X_3 X_{13}	100	57.1	80	0.423	1.364	0.760
	5	No variable qualified for the analysis	-	-	-	-	-	-
Ratios and Standard deviation	1	X_4	40	100	70	0.794	0.259	0.453
	3	X_1 X_5 X_{13} X_{19}	100	100	100	0.086	10.669	0.956
	5	X_1 X_{13} X_{19}	100	100	100	0.169	4.917	0.912