PREDICTING CORPORATE FAILURE:
AN EVALUATION OF THE RELATIVE USEFULNESS OF
UK ACCOUNTING AND SHARE PRICE INFORMATION

Thesis submitted in accordance with the requirements of
the University of Liverpool for the degree of
Doctor in Philosophy

by

RAAFAT HOSSAIN ALI EL-HENNAWY

January 1981

To My Beloved Family

And To The

Memories of My Father and Son:

Hossain

ABSTRACT

In the context of failure prediction, the main concern of this study is an empirical evaluation of the usefulness of UK accounting information relative to share prices. The evaluation necessitates testing the predictive ability of failure prediction models incorporating accounting numbers and testing the content which accounting information might have for the capital market in connection with the event of business failure. In addition to the main concern, the study also has the objective of testing the predictability of failure prediction models developed for each of the five years before failure; comparing the empirical results of applying multiple discriminant and regression models; testing the ability of industry and economy-wide indicators to predict failure; testing the stability of accounting ratios (as measures of financial attributes) for different years and different groups of companies; and testing the efficiency of the London Stock Exchange (LSE).

Two failure prediction models and the results of their tests are reported. Each model was developed using stepwise discriminant analysis and the data of the analysis sample; then a second discriminant function was fitted to the model using the data of both the analysis and hold-out samples (combined sample). Each of the two models incorporates three accounting ratios and two industry-dummy variables. Model 1 is based upon the data of the fifth year before failure - no previous study has developed such a model. Model 2, like almost all the models of previous studies, is based upon the data of the first year before failure. The two functions of each model performed well on all the tests of applicability. Upon the basis of Lachenbruch's hold-out test for the second function, Model 1 classified correctly 94, 94, 92, 94 and 98% of all companies in the combined sample

for each of the years from the fifth to the first before failure. For the same years, Model 1 classified correctly, 88, 91, 91, 91 and 95% of failed companies. The corresponding results for Model 2 were 91, 91, 93, 92, and 97% of all companies and 81, 82, 86, 84 and 93% of failed companies. Thus in terms of the two types of classifications, Model 1 performed consistently better than Model 2 for each of the five years before failure. Consequently, the fifth year's model appears able to give a warning of failure earlier than can be given by any other model.

Two regression functions corresponding to the discriminant functions were fitted to each model. The regression functions performed exactly the same as the discriminant functions.

The economy-wide indicator was not one of the constituting variables of the reported models. The possible explanations included the inadequacy of the selected indicator, the ability of the industry variable to pick up the general economic conditions, and the reduced discriminating power of a vector variable including the economy-wide indicator; as noted in this study.

To represent the industry effect, Cluster analysis indicated the possibility of regrouping the 19 industries represented in this study into a small number of broad groups. Therefore, they were regrouped on an a priori basis into manufacturing, construction and distribution industries. The validity of this grouping was confirmed by three-groups discriminant analysis. Thus, a set of three dummy variables was defined; one of them (manufacturing) was dropped for the purpose of the analysis; and the other two were incorporated in each of the two models.

Principal components analysis was performed (using the selected 48 out of the 96 primary considered ratios) for each year of data and for each group of companies separately and together. The results indicated the difference between the a priori and empirical groupings of ratios and the instability of some empirical groups of ratios and of some ratios for the different years and for the different groups of companies. These findings were used to guide the stepwise procedure of discriminant analysis.

The well known market model was used to test the content of accounting information and the ability of the stock market to anticipate failure. The results indicate that the market, on average, began bidding down the residual security prices of failing companies as far back as five years (62 months) before failure announcements. This seems to indicate the efficiency of LSE and the apparent information content of the accounting data with regard to impending failure at that early stage.

A comparison between the results of the market model and those of the failure prediction models indicates that they both appear to first identify failure at much the same time, and there are even indications that it may well be possible to identify impending failure even earlier than five years before collapse in some cases. Also, it shows that, in the context of failure prediction, accounting data appear to be more useful than share prices and that failure prediction models are needed by the investors (and thus are potentially useful to them).

ACKNOWLEDGEMENTS

The work reported in this thesis was carried out in the Department of Economic and Business Studies, at the University of Liverpool, between April 1977 and December 1980, under the supervision of Professor R C Morris.

The reported work has not been submitted previously for any degree in this or any other University, nor has it been conducted under a contract of secrecy.

I would like to express my sincere thanks to my supervisor, Professor R C Morris, for his guidance, encouragement, constructive criticism and invaluable advice throughout this research work.

I also extend my thanks to Mr Coen and Dr Martin of the Computer Laboratory for their guidance in handling the magnetic tapes, and the staff of the IBM computer of the Department of Physics for their help in converting the IBM magnetic tapes.

My gratitude to my wife for her care and patience despite all the problems we have had during the period of our stay in England. My thanks must also be given to my children for waiting so long and especially to SAMEH who had to leave before the completion of this work.

I wish also to thank Sandra for typing the manuscript.

PREFACE

According to the efficient market hypothesis and to the large volume of empirical evidence supporting it, share prices (in an efficient capital market) reflect fully and quickly all publicly available information. Investors use accounting and non-accounting information to evaluate a firm and its prospects which is thus reflected in share price data. Conventional accounting measures, on the other hand, are based upon past transactions and give no consideration to a firm's prospects. Therfore, accounting information is incomplete relative to share prices. In addition, since economic concepts of a firm's income and value are mainly based on its expected stream of future earnings as perceived by its owner(s), share price data appear to approximate the economic concepts better than accounting data. However, because of their incompleteness, accounting indicators appear, in many cases, to be inadequate surrogate representations of real world events.

The problem is therefore whether or not the inadequacy of current accounting indicators destroys their usefulness to potential users. Ultimately the only true test appears to be an empirical one, though many accounting writers have tried to solve the problem intuitively.

In the context of corporate failure, this study is mainly concerned with the empirical evaluation of the usefulness of the information generated by the UK accounting practice relative to the share price information over the period 1960-1973. The evaluation is made through the careful development of failure prediction models and testing the content that accounting information may have to the stock market in connection with the event of business failure. The first procedure tests the predictive ability of the models incorporating accounting numbers which is identified in this study as one of the two aspects of accounting usefulness. The second tests the content of accounting information - which is the second aspect of usefulness - and provides a relevant basis for comparing both accounting and share price information. This comparison may indicate whether or not failure prediction models appear to be useful to investors.

A review of the literature revealed the need for research, induced the identification of the two aspects of usefulness and the clarification of their conceptual problems, promoted the development of new hypotheses and facilitated the selection of the study's methodlogy. The data used in this study are compiled from two IBM data-banks (company accounts and share prices) which were supplied by London Business School and converted by the researcher into ICL data-banks to make them compatible with the ICL computer of the University of Liverpool.

The study comprises eight chapters. Chapter 1 defines the aspects of the usefulness of published accounts, the research problem and its expected outcomes, the need for the study, its objectives, its hypotheses and its scope.

Chapter 2 reviews the literature which is concerned with either the prediction of corporate failure using accounting data of the companies within the manufacturing, distribution and construction industries or the anticipation of failure in an efficient capital market.

Chapter 3 reports on the selected methodology. It includes a description of:

(1) The models of this study, their methods of processing and the applicability of failure prediction models.

(2) The independent variables of failure prediction models, which are accounting ratios, industry dummy variables and the variability of the daily FTA - market index over the financial year of each company (as the

economy-wide indicator).

(3) The statistical problems relating to the independent variables (non-normality and collinearity of accounting ratios, grouping 19 industries into 3 broad groups and the measurement of the economy-wide indicator). The methods of dealing with these problems include univariate analysis, factor analysis, cluster analysis and three-group discriminant analysis. The first two of these methods describe various aspects of the behaviour of accounting ratios for failed and non-failed firms.

(4) The samples design, which include dividing the non-paired sample of accounting data into analysis, cross validation and inter-temporal validation subsamples, each of which comprises equal numbers of failed and non-failed companies.

Chapter 4 considers conventional accounting practice in the UK, the limitations of the data included in published financial statements, the expected and empirical effects on accounting ratios, and the extent to which a method of analysis may help to offset some of these effects. It also describes the company accounts and share price data-banks.

The argument of this chapter indicates that accounting measures are, in many cases, inadequate surrogate representations of real world events. This is true even if such palliatives as CCA or CPP are introduced. However, the results of some previous studies appear to suggest that the effects of accounting limitations on accounting ratios are either tolerable or insignificant. Also, the results of various other studies appear to suggest the usefulness of conventional accounting data.

Chapter 5 reports the empirical results of the statistical selection of the variables. Out of 96 ratios considered, 25 ratios were excluded because of missing values, 21 were excluded because of non-normality before and after transformations and 2 were excluded because of their poor performance on subsequent analyses. The remaining 48 ratios were represented either by their original distribution or one of its transformations, whichever approximates normality more than the others (according to both Shapiro' and Wilk's W-test and D'Agostino's D-test).

The profile analysis supported by the t-test confirmed the existence of persistent differences between the ratios of failed and non-failed firms for at least five years before failure and that the ratios of failed firms deteriorate as the year of failure approaches. The results of rincipal components analysis suggest that there are differences between the empirical and the a priori groupings of accounting ratios and that some ratios measure different attributes for the different years and for the different groups of companies. The results of cluster analysis indicate that the 19 industries represented in this study can be clustered according to the aggregate industry ratios into fewer numbers of clusters at different levels of similarity.

The three groups-discriminant function correctly classified the 19 industries into the assumed three functional groups: manufacturing, distribution and construction. Accordingly, a set of three dummy variables is used to represent the industry factor.

Chapter 6 reports on the selected models of failure prediction, their tests of applicability and the regression functions which were fitted to the models. Model 1 is developed upon the basis of the data of the fifth year before failure (i.e. year - 5 is the year of the model). The model was first developed on the analysis sample and then subjected to: statistical test of significance, testing the relative contribution of each independent variable, hold-out test, inter-temporal validation test, expected performance test and expected cost of using the model per unit of decision-making. The coefficients of the model were recomputed using the combined sample and then the new function (the second function) was subjected to the same tests, but the Lachenbruch's test replaced the classification of the hold-out sample. Model 2 is developed upon the basis of the data of the first year before failure (i.e., year -1 is the year of the model) following the same procedures of developing model 1. The two models performed well on all the above tests. Upon the basis of Lachenbruch's hold-out test for the second function, Model 1 classified correctly 94, 94, 92, 94 and 98% of all companies in the combined sample for each of the years from the fifth to the first before failure. For the same years, Model 1 classified correctly 88, 91, 91, 91 and 95% of failed companies. The corresponding results for Model 2 were 91, 91, 93, 92 and 97% of all copanies and 81, 82, 86, 84 and 93% of failed companies.

Thus, in terms of the two types of classifications, Model 1 performed consistently better than Model 2 for each of the five years before failure; a finding supporting hypothesis 4 of this study. The regression functions performed exactly the same as the discriminant functions.

Chapter 7 reports on the results of the market model which is used to test the content of accounting information and the ability of the stock market to anticipate corporate failure. The results of this chapter appear to indicate that the London Stock Exchange began bidding down the prices of the securities of failing companies as far back as five years before failure. A comparison with the results of chapter 6 appears to indicate that accounting information of the failing companies has had a content for the stock market and, thus, conventional accounting information is useful in terms of the results of this study. Also, failure prediction models appear to be needed by the stock market. However, their availability to the makret may, in general, accelerate the collapse of the failing companies.

Chapter 8 includes conclusions and suggestions for future work.

TABLE OF CONTENTS

LIST OF TABLES

Table No.		Page

LIST OF FIGURES

LIST OF APPENDICES

CHAPTER 1

RESEARCH PROBLEM AND HYPOTHESES

CHAPTER 1

Research Problem and Hypotheses

1.1 Introduction

Usefulness to the users is the ultimate objective of published accounting information. Many efforts have been made to evaluate this usefulness and these efforts can be classified into two categories:

a. The Normative Approach:

Some descriptive criteria - e.g.reliability, validity, credibility, elevance, and practicality - are proposed for evaluating accounting practices (see: Snavely, 1967, Greenball, 1971, Lee, 1976, pp.61-3, AAA, 1966, pp.8-18, AICPA, 1973, Chapter 10, and ASSC, 1975, p.28). By definition, these criteria are dependent on the users of accounting information and their actual or assumed needs. They have always been related to the investors' decision-model(s) and they can also be related to the different decision-models of the different groups of users. Accordingly, these descriptive criteria will not provide an operational evaluation of the usefulness of accounting information unless the specifications of the users' decision-models are identifiable and the normative criteria are expressable in operational terms, e.g. practicality may be expressed in terms of a certain date of publishing a company's accounts and a certain costs of preparing and using these accounts. However, neither the specifications of the users' decision-models appear to be identifiable nor do the normative criteria appear to be expressable in operational terms.

However, the financial literature provides reasonable grounds for tackling the problem of identifying the specifications of the users' decision-models. The protfolio selection model, the market model (see: Chapters, 2 and 3) and the capital asset pricing model are not specifically concerned with the investors' models which are used in the prediction of a security's returns for a given (future) period. Given these predictions for a portfolio of securities, the first of the three models estimates the portfolio's risk and expected return, the second estimates the systematic risk of each security and the third (its assumptions include the complete agreement among the investors regarding expected returns) shows that a security's returns compensate only for the systematic risk and that the gher this risk the higher are the returns (see: Lev, 1974, Chapter 12).

These models are tested using ex post data. Therefore, the problem of the investors' predications of future returns disappears.

However, using the market model to test the content of accounting information, in the context of business failure, is considered in the following approach.

b. The Empirical Approach

According to this approach an accounting method can be evaluated by using its generated numbers in a certain way (by capitalizing on either their predictive ability or their ability to characterize past performance) to test how they can help in performing a certain task, e.g. forming an investor's decision rule or predicting a future event. Thus, this approach is either related to a particular decision-model or to a future event which may be of interest to several groups of users. This is the approach used in this study and in a great number of previous studies. Its problems are mainly conceptual and are concerned with the questions of: useful to whom? for what purpose? and what is useful information?.

Naturally accounting information should be useful to all classes of users, e.g. investors, creditors, suppliers, customers, employees, government, analysts and public. Investors and potential investors are usually considered the most important class of users. This importance can be attributed to two factors: First, they are the owners or the potential owners of a company, and accounting information has (by law) to be reported to the owners. Second, the shareholders use the available information in pricing the securities and, accordingly, they affect the allocation of national resources. For these same factors, creditors can be ranked as a second important class. However, accounting information should (as far as possible) satisfy the needs of all the users who have rights to a company's accounting information (see: ASSC, 1975, Sec.2).

As regards the purpose to which accounting information should be useful, two types of argument are distinguishable. The first is based upon the premise that information reduces the effect of uncertainty about the future by providing the facts of the past. Because adjusted extrapolation of historical information can provide insights into the future, it has been argued that accounting information may be useful if it can be used to predict an important business event. The predictive ability criterion emerged from this type of argument (see: Beaver, et al, 1968). The argument against the predictive ability criterion can be attributed to two major factors - namely, the selected object of prediction in some previous studies (e.g. Martin, 1971, those reviewed by Martin and those referred to by Peasnell, 1973) and the conflict between the nature of accounting and predictability. Peasnell (1973, pp.2-10) criticized some previous studies for being based on the premise that a firm's future earnings could be used as surrogate measures of the investors' future returns, because it assumes that past earnings can predict share price changes and this is neither supported by the findings of those studies nor consistent with the efficient market hypothesis. He also criticized those studies in that they made assumptions about the investors' expectations and decision-models while no two investors would likely employ the same decision-model. Greenball (1971) and Peasnell (1973, p.9) argued that accounting numbers of themselves could predict nothing and they might only play a feedback role. Thus, it is a model including accounting numbers that predicts rather than accounting numbers themselves. Accordingly, the argument against the predictive ability criterion may cease to exist if the object of prediction is an event of general interest to users which does not make any unrealistic assumptions about investors' future earnings or about their decision-models and if we attribute predictability to the odels rather than to the accounting numbers. This revised concept of the predictive ability criterion is the one used in this study.

The second type of argument is based upon the premise that accounting information may be useful if it can improve the users' decision-making. This decision-making approach has almost the operational difficulties of the normative criteria. The evaluation of accounting information will not be possible without the identification of the users' decision-models, while the specification of these models does not appear to be possible, even for a class of users. Therefore, this selected purpose of accounting information seems to be very ambitious and, consequently, preventive to any effort (see: Beaver, et al., 1968).

As regards the type of useful accounting information, two concepts can possibly be identified. First, according to the (revised) predictive ability criterion, accounting information is useful if a model employing it can predict an important event, i.e. can produce a predicted piece of information. This prediction may be a useful component of a user's own decision-model - regardless of the specifications of that model. The second concept emphasizes the content of accounting information (i.e. its impact on the users' behaviour). Beaver (1966) and Kennedy (1975) suggested that the content of accounting information could be measured by assessing the odds - likelihood ratio which might indicate how a user would revise his subjective probability regarding business failure on the basis of new information (accounting ratios). However, the likelihood ratio cannot be used to evaluate the content of accounting information because assessing the users' prior subjective probabilities is at least as difficult as the attempt to identify a decision-model that is used by all the users of accounting information. Alternatively, the efficient capital market hypothesis and the market model (see: Chapter 3) provide easonable grounds and methodology for testing the content of accounting ınformation. The impact of any information, upon its release, on the behaviour of the investors is reflected by the share prices. If the released information does not affect share prices the inference is that the information is useless because the market had either already discounted it or found little or no information content in it. This concept was used directly by Ball and Brown (1968) and Beaver (1968a) and indirectly by finding the association between the accounting and the market measures of risk (see: Ball and Brown, 1969, Beaver, et al., 1970, Gonedes, 1973, Derstine and Huefner, 1974 and Bilderse, 1975). However, it makes no assumptions about the specifications of investors' decision-models - it is only concerned with their collective effect on share prices. Thus, the two concepts of predictability and information content are used in this study as complementary rather than competing concepts.

Accordingly, this study adopts the premises that the empirical approach is the proper and promising one in evaluating the usefulness of accounting information and that accounting data should be useful to its users in the sense that it can be used to predict an important event (with the above mentioned restrictions) and it should have information content.

1.2 Problem Definition

This study is concerned with the empirical evaluation of the usefulness of the UK annually published accounting information relative to the share prices, in pin-pointing corporate failure. This evaluation requires (according to the above adopted premises) the application of accounting numbers in a model to predict corporate failure and, testing the content that accounting numbers may have to the stock market in connection with corporate failure (as being the selected information generating event). These two requirements are closely related. The sound prediction of corporate failure indicates the usefulness of accounting information on its own. On the other hand, testing the ability of the stock market to anticipate failure provides evidence regarding the content of accounting information which is the other aspect of usefulness. A comparison between these two aspects of usefulness helps to assess the power of the prediction models, their utility and the usefulness of accounting information relative to the share prices.

Corporate failure is selected as the object of prediction because it concerns all the users of accounting information (as shown below) and, thus, its successful prediction is a good indicator of the usefulness of accounting information.

Accordingly, failure prediction models are developed first. The higher the predictive power of these models the higher is the usefulness of accounting information to its users in general. The content of accounting information and the ability of the stock market to anticipate companies' failure are then investigated. A comparison between the two sets of analyses may then be held to reveal how useful is accounting information relative to the share prices and how useful are failure prediction models.

It should be mentioned that the investigation of the content of accounting information, in terms of share price changes does not imply that this study gives more importance to investors than to other users. The fact is (as mentioned above) that the efficient capital market hypothesis provides a relevant basis for testing the content of accounting information.

However, a study of the above problem has two important outcomes:

First, it provides evidence regarding the usefulness of the current UK accounting practice (in the context of failure prediction) which may have its implications for the debate about that practice.

Second, this study provides a model to predict, as accurately and early as possible, a company's failure and so it gives an early warning to interested parties. This model is expected to be useful to all users of accounting information, where they are commonly concerned with the present performance of a company and its potentialities. Essentially, all users need information in an uncertain world to help reduce uncertainty. Such information may change mean expected values, but it should narrow the dispersion of expected values anyway.

The expected users and the expected effect of a failure prediction model on their decisions can be identified as follows:

<u>Equity Investors</u>: The available empirical evidence suggests that the capital market began bidding down the securities of failing companies as far back as five years (or less than that in the studies by Beaver (1968) and Gooi (1974) - see Chapter 2) before failure announcement (See: Altman, 1971, pp.80-81, Lev, 1974, p.148 and Firth, 1977, p.78 for a review of the US study by Westerfield). This finding appears to indicate that the investors used accounting reports (and perhaps other information) to temporarily adjust their decisions regarding the securities of failing companies as if these companies were having temporary difficulties. In other words, the market did not predict failure since it bid down the securities of failing companies (i.e. five years before failure announcement).

Thus, failure prediction models are expected to make available to the market an early prediction of failing companies. The expected reaction, to the latter, of an efficient capital market is to accelerate the process of failing companies' collapse - providing that the companies have no hope for recovery.

Creditors: This group includes existing and potential holders of debentures and loan stock, bank managers and trade creditors. If creditors use a failure prediction model and if they predict a compnay to be failing they may decide, together, to put the company into liquidation (depending on the detailed study of all the company's potentialities) to protect all or part of thier debts. If the predicted failing company was only applying for a loan or the supply of goods, the company's application may be rejected or be granted on more strict conditions, i.e. secured loans, higher interest rate, supplying goods at higher prices - or a combination of these conditions.

Management: Although management has access to all the internal and the day-to-day information, a failure prediction model may keep management fully aware of the company's situation. Therefore, an assessment of the company's plans may be in order after considering the results of a failure prediction model. Also, a failure prediction model may be an invaluable tool in assessing the viability of the supplier and consumer companies.

Government: A failure prediction model may affect the government's decision as to financial aid, supervision, nationalization or otherwise. It can also be used for planning both the government's revenue from and financial aid to predicted failing companies.

Auditors: A failure prediction model is expected to help a company's auditor to make a statement about the continuity of his client as a going concern (see: Altman and McGaugh, 1974, and Taffler and Tisshaw, 1977).

Employees: A failure prediction model may give employees a chance to look for another job. If they have not had this chance they may lose their jobs, without warning, thereby losing their source of income.

Analysts: Failure prediction models can be useful tools for financial analysts who may perform a feed back role to these models. Analysts may use failure prediction models to advise their clients.

Public: A failure prediction model may convey a relevant message to the public. Consumers as members of the public may be deprived of the goods produced by the failing company.

Thus, failure prediction models, which are one of the outcomes of this study, are expected to be utilised by all the users of accounting information.

1.3 The Need for Research

A review of the literature, as presented in Chapter 2, indicates that none of the previous studies was concerned with both the two aspects of the usefulness of accounting information (predictability and content). All the previous multivariate studies were mainly concerned with the development of failure prediction models for their expected usefulness and for the purpose of revealing the usefulness of accounting information when used in a multivariate model. Four studies have investigated the ability of the stock market to anticipate corporate failure, but the finding of only one of them (Westerfield's previously mentioned study) is consistent with the efficient market hypothesis (see: Chapter 2). However, none of the failure prediction studies has even compared its findings with that of Westerfield's. Only Altman (1971, pp.80-81) has used the finding of the latter study to show the importance of a failure prediction model for the investors but not to explain why his model (including a market component in one of his variables) predicted failure only two years before it occurred while the market began bidding down the security prices of failing companies as early as five years before failure announcement. ccordingly, a complete evaluation of the two aspects of usefulness has not been attempted before.

On the other hand, the following four points indicate that previous studies of failure prediction have left enough room for further research in this area:

Firstly, industry and economy-wide indicators were not explicitly considered in any of the previous studies while they are believed to be good predictors of corporate failure. The effects of these two indicators and that of a firm's size were controlled for by using the paired sample technique, which controls for factors that are believed to be unrelated to the phenomenon investigated (see: Lev, 1974, p.141). However, size was only recently considered as a predictor of corporate failure (see: Altman, et al., 1977, and Marais, 1979). The available empirical evidence suggests that the industry factor affects a firm's accounting ratios (see: Chapter 3). It was also noted that some industries are more prone to failure than others particularly (as indicated below) at certain points in the trade cycle, e.g., the US retail industry (see: Lev, 1974, p.136, and Altman et al., 1977) and the UK construction industry (see: Spellman, 1978). Therefore, the industry factor is a potential predictor of corporate failure, and thus it should be explicitly considered in any failure prediction study.

As regards the economy-wide indicator, it was noted that, for instance, in 'boom' conditions failures tend to result from overtrading; in 'slump' conditions from a decline in demand. Similarly, there are 'phases' of failures - e.g. property companies, followed by secondary banks a few months later (in 1974/5) and mail order stores. Currently it is certain sectors of manufacturing industry that are going to the wall. Therefore, the economy-wide indicator appears to be a very important predictor of corporate failure (see also Chapter 3) and thus should be explicitly considered in any failure prediction study.

Secondly, accounting ratios used in previous studies appear to have not been properly examined before their inclusion in the prediction models. The variables constituting those models were generally selected by a step-wise procedure guided by a researcher's a priori knowledge about his primary set of ratios. Only two authors have applied the preferred method of factor analysis (see: Chapter 3) to reduce the dimensionality of their data of the first year before failure (Daniel, 1968 and Taffler, 1977a and 1977b). However, none of the previous studies has investigated the stability of accounting ratios (as measures of a firm's financial attributes) for the different periods of time and for the different groups of companies. The available empirical evidence indicates that there are differences between the a priori and the empirical groupings of accounting ratios and that some ratios may measure different financial attributes (e.g. liquidity and profitability) for the different periods of time (see: Pinches, et al., 1973, 1975, and Johnson, 1979). Accordingly, a stepwise procedure, even guided by the researche's a priori knowledge does not guarantee the selection of only one ratio for each financial attribute. Also, applying factor analysis to the data of the first year before failure does not show which are stable ratios both over the different periods of time and between the groups. However, failure prediction models should be constructed from the most stable ratios because presumably they will be applied to the ratios of different companies (failing and non-failing) for several future periods of time.

Thirdly, all the previous single-year models, except that of Deakin (1977), were based on the data of the first year before failure (multi-year models include those of Blum, 1974 and Edmister, 1972, see: Chapter 2). Deakin (1977) fitted a discriminant function to a predefined model upon the basis of the data of the second year before failure. Unfortunately, his model and its fitted function appear to be inconsistent and lack both a priori and empirical reasoning (see: Chapter 2).

However, since failure prediction models are based upon the difference between various accounting ratios of failing and non-failing firms, and since these differences may exist up to the fifth year before failure (at least according to the findings of univariate studies - see Chapter 2), there is no reason why the models of previous studies should just have been based upon the data of the first year before failure. Therefore, this study suggests and tests the hypothesis that models which are based upon accounting ratios for earlier years (up to the fifth before failure, where the difference between failing and non-failing companies is observable) can predict failure better than others (see: section 1.5 below).

Fourthly, each of the previous studies relates to the sampled population of companies at a certain period of time. Generally, the applicability of each model is restricted to the model's specifications. Therefore, there is always a need for models with different specifications as long as they are expected to outperform those of the previous models.

In conclusion, there is a need to develop powerful models to predict corporate failure for the purposes of evaluating the relative usefulness of UK accounting and share price information and for using them as presented above. On the other hand, for the former purpose there is a need to investigate the ability of the London Stock Exchange (LSE) to anticipate corporate failure. This latter investigation implies a test of the content of accounting information and a test of the efficiency of LSE which is also needed to add to the growing body of evidence concerning the efficiency of the UK stock market (see: Henfrey et al., 1977).

1.4 Research Objectives

This study has one principal objective and various secondary objectives, in the sense that they are achievable in the course of approaching the principal objective.

The principal objective of this study is the operational evaluation of the usefulness of UK accounting information relative to the share prices in the context of failure prediction. This evaluation is inclusive in the sense that it considers the two concepts of the usefulness of accounting information, i.e. the predictability and the content of information. On the other hand, it is not inclusive in the sense that it is concerned with only one of the possible business events.

The secondary objectives comprise the following:

1. To improve the predictability of corporate failure by developing a model for each of the five years before failure and selecting that model which best performs for each of the years (i.e. for the year of the model and each other year).
2. To compare the empirical results of applying multiple discriminant analysis with those of multiple regression analysis. The two techniques are mathematically equivalent for the case of a dichotomous dependent variable. If they provide similar empirical results, as expected, the widely available regression programs can be recommended for the future studies of this and similar problems.

3. To test the efficiency of the London Stock Exchange (LSE).
4. To test the hypotheses presented in the following section.

1.5 Research Hypotheses

The hypotheses of this study are directed towards the achievment of its principal objective. The development of a theory of corporate failure is beyond the scope of this empirical study, although its findings may have some implications for such a theory. However, it was argued that due to the diversity of causes of firms' failure and the lack of a well-defined economic theory of the firm under undertainty, there is no satisfactory theory of corporate failure (Lev, 1974, p.134). Accordingly, defining the concept of corporate failure and its causes is not an easy task, although it is a necessary one as an initial step for any research into corporate failure. Empirical studies have tended to overcome this difficulty by adopting a definition which merely covers the failed or failing firms identified in those studies, and although this approach to the problem gives a reasonable starting point for empirical research, it hardly provides a theoretical justification for the approaches adopted. Thus, a failed company is defined in this study (see: Chapter 3) as that company which ceased to exist after the appointment of a receiver, i.e. either liquidated or sold by the receiver to another company.

As regards the causes of failure, they can be classified into two related categories, i.e. endogenous (e.g. poor management) and exogenous (e.g. business cycle) causes. Argenti (1976, Chapter 7) attributes almost all the endogenous causes to poor management and the exogenous causes to the environmental constraints - e.g. the pressure put on management by employees, press or government - which results in the inability to respond to important changes. Thus, poor management, environmental constraints, or both will result in an inability to respond to changes. Furthermore, poor management are unlikely to operate an efficient accounting system and will probably make at least one of three other mistakes: (1) it will overtrade; or (2) it will launch a major project which fails to turn out as planned; or (3) it will allow the company's gearing to rise so that even normal business hazards (e.g. economic cycles, increased tax, inflation, a strike at a supplier's premises and/or a customer's switch to a competitor) become constant threats. Also Argenti (1976, p.149) argues that symptoms of failure only occur after a company has started upon the downward slide while potential causes are present before failure begins, but he (pp.137-140) recognizes the deterioration of accounting ratios as the earliest symptoms of failure.

However, in this study all the causes of failure are assumed to be reflected in financial symptoms, i.e., the deterioration of accounting ratios. This assumption capitalizes on both the above argument and the findings of previous (univariate) studies since the 1930's - that there are persistent differences in selected ratios of failed and non-failed firms for some years before failure and that the ratios of failed firms deteriorate as the year of failure approaches. Thus, the variables selected for the failure prediction models of this study comprise a firm's financial attributes (measured by accounting ratios), an industry indicator and an economy-wide indicator.

The hypotheses of this study can be stated as:

Hypothesis 1: Synptoms of business failure can be seen several years before it occurs (see: Argenti, 1976, p.45). Thus business failure is predictable.

Hypothesis 2: A firm's financial state as to failure or success is reflected in its financial attributes as measured by accounting ratios. Thus accounting ratios are good predictors of business failure.

Hypothesis 3: Companies within some industries may be more prone to failure or more sensitive to the changes of the business cycle than others.

Therefore, industry and economy-wide indicators could be very important predictors of corporate failure.

Hypothesis 4: Accounting ratios of the earliest year or years before failure (up to the fifth year where the difference between failing and non-failing firms is observable - see Chapter 2) represent the financial attributes of failing rather than failed firms and reflect the early symptoms of corporate failure. The ratios of each subsequent year are expected to reflect the increasing severity of those symptoms. Failure prediction models, on the other hand, can be based on the data of any year before failure as long as there is a difference between accounting ratios of failing and non-failing firms (the findings of previous studies indicate that this difference exists up to year -5; assuming year 0 is the year of failure year-N is the N.th year before failure).

Intuitively, one would expect a particular model of failure prediction to perform best the closer to failure it is developed. However, this would not mean that the same model might equally well give helpful predictions when applied to earlier years' data (e.g. the model developed for year -1 would perform for year -1 better than would the model of year -2 perform for year -2, but neither of them would perform for years -2, -3, -4 and -5 and -3, -4 and -5, respectively, as well as they would perform for years -1 and -2). Given the importance of obtaining the 'news' as early as possible, this is a matter well worth pursuing and which has largely been ignored in previous research.

The first step is to find an explanation to the above expected peformance of failure prediction models (which is also supported by the findings of previous studies - see Chapter 2). It can be explained by the fact that the model developed for year -N caputres the symptoms of failure and the differences between the two groups of companies which are reflected by the data of this year and, thus, discriminates between the companies according to the captured symptoms and differences. Therefore, since the sumptoms of failure and, thus, the differences between the two groups of companies are less severe in the earlier years than they are in the model's year, the model's performance should be expected to deteriorate as the year of data becomes more remote from the model's year (and that represents the finding of the previous studies - see Chapter 2).

If this explanation is valid, as it appears to be, its reverse might also be valid. That is, the model developed for year -N ($1 < N \leq 5$) might perform for year -N and for each subsequent year better than the model of any subsequent year. Because of the severity of the symptoms of failure, the differences between the two groups of companies are, persumably, increasing for each subsequent year (up to year -1), and it should therefore be easier for the model to discriminate between companies for subsequent years. Accordingly, this hypothesis can be formulated as:

'Models based upon the data of the earliest year(s) before failure (e.g. year -5) can predict failure for the year of the model (year -5) and each subsequent year (years -4, -3, -2 and -1) better than other models which are based upon the data of any subsequent year'.

It should be noted that this hypothesis is concerned with different models for different years before failure, rather than the different functions that can be fitted to a particular model using the data of other years. The latter case is empirically considered in Chapter 6, but the fitted functions are not expected to perform better than the model's function (i.e. the function fitted to the model using the same data for which the model was developed) for two related reasons. First, the development of a model includes the search for the best discriminating vector variable, $\underline{x}$, and the computation of the coefficients of the elements of $\underline{x}$ while fitting a function to a model includes the latter only. Therefore, the best discriminating $\underline{x}$ for a particular set of data may not be the same for another, even if the elements of $\underline{x}$ are ratios which measure the same attributes for different years and different groups of companies. Second, the difference in the data of the same companies over the years are related to the changing severity of failure's symptoms.

Hypothesis 5: Although each accounting ratio is supposed to be a measure of one of a firm's financial attributes, some ratios may not measure the same attributes for different periods of time or for different groups of companies.

Hypothesis 6: An efficient capital market, using other information besides that derived from published accounts, may antiicpate corporate failure well before a model employing accounting information alone can do so.

These are the hypotheses of this study which are believed to be necessary and sufficient to achieve its principal objective. Their empirical test is one of the secondary objectives of the study. However, they also highlight the scope of the study.

1.6 The Scope of Research

This thesis reports on the results of an empirical study using published accounting information, monthly share prices and a daily market index (Financial Times Actuaries (all shares) Index). The research is mainly concerned with evaluating the usefulness of the information provided by the UK accounting practice relative to the share prices, over the period 1960-1973 (as indicated by the sample's design in Chapter 3) through the careful development of failure prediction models and testing the content which the information may have for investors. The IBM data-banks supplied by the London Business School were converted by the researcher into ICL data-banks. The findings of this study are only applicable to the public companies of the British manufacturing, construction, and distribution industries. They are limited by the limits of the data as discussed in Chapter 4 and they may not be generalized beyond the scope of corporate failure.

Thus, this study is not concerned with either the development of a theory of corporate failure, evaluating alternative accounting methods, or predicting the failure of private (small) companies.

CHAPTER II

REVIEW OF THE LITERATURE

CHAPTER 2

Review of the Literature

2.1 Introduction

A review of the literature usually indicates how a research problem was studied in the past, why it needs to be further studied and possibly the proper methodology which is needed to conclude the study satisfactorily. Accordingly, this chapter reviews the previous literature in two related categories, which are:

1. Predicting corporate failure using accounting data, and
2. the ability of the stock market to anticipate corporate failure.

The studies in these two categories represent the accumulated knowledge concerning the subject of this thesis, by the virtue of its problem definition (see: Chapter 1). Each of these two categories are considered in one of the following sections. The last section concludes this chapter by pointing out the main shortcomings of the reviewed studies which indicate the need for this study and highlight its proper methodology.

However, the findings of previous studies of the effect of accounting changes and of inflation on accounting numbers and, thus, on accounting ratios are considered in Chapter 4 (conventional accounting and data limitations).

2.2 Predicting Corporate Failure Using Accounting Data

The previous studies which used accounting data in models to predict corporate failure are classified into two broad categories. The first includes those studies which used actual accounting ratios and is the main category. The second includes those studies which used non-ratio accounting data or other specific models (i.e. simulation and gambler's ruin models). Thus, this second category is termed "other approaches".

2.2.1 Predicting Failure by Means of Accounting Ratios

The studies of this category are classified according to their methods of analysis into two groups. The first group emphasizes the univariate approach (i.e. considering the accounting ratios one at a time) while the second emphasizes the multivariate approach (i.e. considering several ratios simultaneously). The studies of each group are reviewed below, as to objective, failure definition, sample, variables, statistical methodology and empirical findings and their implications.

2.2.1.1 Univariate Studies

The early studies, up to 1966, using accounting ratios were all univariate. They compared the ratios of failed firms with those of non-failed firms, one at a time, and concluded that there were persistent differences in the ratios of failed and non-failed firms for some years before failure and that the ratios of failed firms deteriorated as the year of failure approached. Beaver's study (1966) was the first to be concerned with the ability of accounting ratios to predict corporate failure. Therefore, it is the only univariate study to be reviewed herein (for a review of the studies prior to Beaver's, see: Lev, 1974, pp.139-40 and Green, 1978).

The objective of Beaver's study (1966, p.72) was "to provide an empirical verification of the usefulness (i.e. predictive ability) of accounting data". This objective is not generally acceptable because accounting numbers of themselves can predict nothing and even the predictive ability of a model using them is not the sole condition of their usefulness, but in addition accounting informtion should have a content to be useful (see: Chapter 1).

Failure was operationally defined to include the cases of bankruptcy, bond default, an overdrawn bank account, or non-payment of preferred stock dividend. (It should be noted that a bank overdraft by a US company may indicate a financial problem but this is not necessarily the case for a UK company. Term loans rather than overdrafts are granted by US banks while the reverse is the case in the UK). However, none of the cases other than bankruptcy is a sufficient condition for impending failure (see also: Mears, 1966), so Beaver might have sampled non-failing as failed companies (and this might have reduced the predictive power of his ratios).

The sample consisted of 79 firms which failed during the 1954-1964 period and 79 non-failed firms paired by industry, asset size and accounting year. Thus, Beaver controlled for the effect of industry, size and economy-wide conditions. Financial performance was not a condition for selecting non-failed firms and this may increase the overlap between the two groups of firms. The greater the overlap the lower is the classifying power of any considered ratio and the lower is the ability to define a margin between the ratio values of failed and non-failed firms.

Thirty accounting ratios were computed for each company in each of five years of data before failure. They were then grouped into six "common element" (numerator or denominator) groups and one ratio was selected from each group on the basis of performance in the classification test (mentioned below). None of the six ratios nor any of their logarithmic or square root transformations were normally distributed (a graphic test of normality was used). This grouping is not consistent with either an a priori or an empirical grouping of ratios, thus it cannot be used to reduce the dimensionality of ratios which was Beaver's aim (see: Beaver, 1966, p.79). For example, funds flow and net income ratios (Beaver's first and second groups) were both found to measure profitability (see: Pinches, et al., 1975, Taffler, 1977a and 1977b and Johnson, 1979); and Beaver's groups 3, 4 and 5 included some ratios (current liabilities, quick assets, current assets, and working capital to total assets and current and quick ratios) which were treated as measures of liquidity (see for example: Deakin, 1976). Also, the final selection of the six ratios would perhaps have been better made after testing the normality of all the ratios and their possible transformations.

Three statistical procedures were employed in the analysis. First, a comparison between the mean values of each of the six ratios for the two groups which was subsequently supported by the visual inspection of the depicted histograms. Second, a dichotomous classification test was applied to each of the thirty ratios, according to which a cut-off point was determined to minimize the total misclassifications by visually inspecting the ordered values of each ratio. The sample of firms was randomly divided into two subsamples which were subjected to the same procedure. Each determined cut-off point was used to classify the firm's of the other sub-sample as a hold-out test and to simulate the decision-making situation. Third, an analysis of likelihood ratio, which is the probability that an observed value of a ratio would appear if the firm was failed, P(R/F), or not failed, P(R/E). The likelihood-odds ratio in favour of of failure was defined by the ratio of P(R/F) to P(R/E) which could be computed from a ratio's frequency distributions for the two groups of firms. The user of accounting information is supposed to have a prior feeling about the firm (upon the basis of its prior probability of failure) and if the likelihood-odds ratio in favour of failure is less than 1(more than 1) he is expected to feel that the firm is more likely to fail (not fail) after looking at the firm's ratios. Thus, "the information content of the ratios can be evaluated in terms of the degree to which they change the prior feeling" (Beaver, 1966, p.98).

The results of employing the above statistical procedures were:

1. Ratios of failed firms were persistently different in their distributions and mean values than those of the non-failed firms for at least five years before failure and this difference increased as failure approached. This finding is consistent with that of the univariate studies prior to Beaver's and it provides the central core of the process of failure prediction.

2. Some ratios have the ability to classify correctly both failed and non-failed firms as far back as at least five years before failure. The best predictors were the cash flow/total debt, net income/total assets and total debt/total assets ratios, respectively. The predictive power (i.e. percentage of correct classification) of the best ratio for each of the years from the first to the fifth was 87,79,77,76 and 78%, respecitvely. Type I errors (misclassifying failed firms) were always greater than type II errors (misclassifying non-failed firms), thus Beaver (1966, p.102) concluded that "the investor will not be able to completely eliminate the possibility of investing in a firm that will fail".

3. The cash-flow to total-debt ratio produced high likelihood ratios over five years before failure which suggests that a user after looking at accounting ratios should have grounds for changing his prior feeling.

However, the following comments apply to the last two findings:

1. The correct classifications of the companies in a hold-out sample prove the ex post classifying power of a ratio, but not its predictive power. For the latter purpose, Joy and Tollefson (1975) suggested the classification of some other firms upon the basis of their data for a period of time subsequent to that of both the analysis and hold-out samples.

2. A separate cut-off point was determined for each ratio for each of the five years before failure, but none of them was applied to any of the other

years. The cut-off points of some ratios, especially those of Beaver's best ratio, reflect decreasing trends as failure approaches (see: Beaver, 1966, table A-5). Apparently, these trends are not caused by the expected deterioration of failed firms' ratios but by an unexpected deterioration in the ratios of non-failed companies. This latter deterioration may be explained by an economy-wide factor that affected the ratios of both failed and non-failed firms, the inclusion of a large number of poorly performing firms in the non-failed group or both. However, the decreasing trends explain why the cut-off point of one year was not applied to any other.

3. The claimed high predictive power of the best ratio is not impressive if we consider two factors. First, the percentage correctly classified of failed firms (the smaller group in the population) is very low (between 78 and 53%). This percentage is the most important measure of the efficiency of a classification procedure (see: Morrison, 1969). Second, the predicion of failure on the basis of the last published financial statement (first year before failure) is almost useless because failing firms usually collapse a few months after the date of publishing their last financial statements. (Taffler's sample, 1977b, included some companies which failed before and shortly after the publication of their last statements).

4. The analysis of the likelihood ratios assumes that the user of accounting ratios can assess the prior probability of failure which is almost impossible (as shown in the next chapter). However, to assess a user's feeling about a company is (as mentioned before) at least as difficult as the attempt to identify a decision-model that is used by all users of accounting information. Therefore, the likelihood ratio (contrary to Beaver's approach) cannot be used to evaluate the content of accounting information.

5. Beaver's chance model assumed equal prior probabilities while it should be based on an estimation of the population's prior probabilities (see: Neter, 1966, Morrison, 1969, and Joy and Tollefson, 1975).

However, the above study is the first to use the observed difference between the ratios of failed and non-failed firms to predict failure and to indicate the possible usefulness of accounting information. It revealed the need for multiavariate studies which can simultaneously consider the effects of size, industry, economy-wide conditions and several ratios.

2.2.1.2 Multivariate Studies

Altman's (1968) is the first multivariate study of predicting corporate failure using accounting data. Only those studies which are generally or specifically concerned with manufacturing, distribution, and construction industries are reviewed herein. A recent one of those studies by Ohlson (1980) is not included because it is based on a different methodology which appears to be in its tentative stage (where it was not possible to provide justification for several points), it has not outpeformed previous studies, and explicitly it is not concerned with testing the usefulness of accounting information or "theories" of bankruptcy. However, other studies are concerned with commercial banks, railroads, insurance companies, over-the-counter broker-dealers, private colleges (references are provided in Foster, 1978, pp.494-6) and savings and loan associations (Altman, 1977a).

The studies reviewed below (considered in the following order) are: (1) Altman (1968); (2) Altman et al (1977); (3) Daniel (1968); (4) Deakin (1972); (5) Deakin (1977); (6) Edmister (1972); (7) Blum (1974); (8) Taffler (1977a); (9) Taffler (1977b); (10) Marais (1979); (11) Tamari (1966) and (12) Parosh and Tamari (Tamari, 1978, pp.130-5). The latter two studies are ranked the last because Tamari's (1966) has been a subjective study.

(1) Altman's (1968) Study

The objective of Altman was to assess the quality of ratio analysis as an analytical technique in the context of failure prediction using Mutliple Discriminant Analysis (MDA). Failure was operationally defined to include companies which filed a bankruptcy petition under the US Bankruptcy Act. The initial sample included 33 manufacturing firms which failed during the 1946-1965 period and 33 continuing firms paried by industry, asset size and accounting year (see the comment on Beaver's sample). However, Altman stated (fn.17) that "matching exact asset size of the two groups seemed unnecessary" (though size was not one of his variables). The first of two secondary samples included 25 bankrupt firms whose asset-size range is the same as that of the initial bankrupt group. The second contained 66 manufacturing firms which suffered losses in the year 1958 or 1961, i.e. a sample from non-bankrupt firms (33 in 1958 and 33 in 1961) which experienced losses. The two samples relate to the time period covered by the initial sample.

Twenty-two ratios were computed for each company in the initial sample and were classified on an a priori basis into five groups including liquidity, profitability, leverage, solvency and activity ratios. Five ratios constituted the final model and were selected by the stepwise procedure guided by the intercorrelation between ratios and judgement of the analyst. Although the selected ratios appear to measure five distinct financial attributes, their persistence in measuring these attributes for the different periods of time and for the two groups of companies was not established.

MDA is a multivariate statistical technique which (in the case of corporate failure) simultaneously considers several financial characteristics of failed and non-failed companies and represents each company by one (z) score which is then used to classify a company as failed, if its financial characteristics resemble those of the failed group, or non-failed, if otherwise. The statistical application of MDA assumes that the variables are multivariate normally distributed and that the two groups' dispersion matrices are equal. Accounting ratios are known to violate these two assumptions, but it is a convenient procedure to try to improve the normality of the marginal (univariate) distrfibutions (see: Chapter 3). However, Altman did not even test the marginal normality of his variables.

The finally selected model using MDA is:

$$Z = .012\, X_1 + .014\, X_2 + .033\, X_3 + .006\, X_4 + .999\, X_5$$

where X_1 = Working capital / Total assets

X_2 = Retained earnings / Total assets

X_3 = Earnings before interest and taxes / Total assets

X_4 = Market value equity / Book value of total debt (i.e. a market component)

X_5 = Sales / Total assets.

The variables were ranked by thier relative contribution (measured by the standardized discriminant coefficients) as X_3, X_5, X_4, X_2, and X_1, respectively.

The model classified correctly 95, 94, and 97% of all, failed and non-failed firms for the first year before failure (the model's year). The corresponding results were 83, 72, and 94% for the second year and unreliable for the years prior to the second before failure (for which the model was only applied to the failed firms).

To test the model excluding the bias due to searching for the best discriminating variables, Altman split his initial sample in five different ways into two subsamples, re-estimated the model's coefficients using a subsample and used the latter to classify the firms in the other subsamples. Apparently, this is not an application of the split sample procedure (see: Chapter 3) and the restimated coefficients of a previously developed model are not expected to reflect the searching bias. The latter exists only when a sample is used to develop a model, i.e.to search for its best predictors and estimate their coefficients. Therefore, the above procedure used by Altman cannot, in any way, be considered an application of the split sample procedure or a hold-out test of his model.

To test the predictive power, the model was used to classify the firms in the two secondary samples (mentioned above). The correct classifications were 96% of the 25 bankrupt firms and 79% of the 66 non-bankrupt firms reporting losses. In fact, this is the only hold-out test that was undertaken by Altman. It is not a test of the predictive power because (as mentioned above) the data of the two secondary samples relate to the time period covered by the initial (analysis) sample (see the above comment on Beaver's study). Also, the classification of the firms in the initial sample upon the basis of their ratios for some years prior to the first before failure is not a hold-out test.

However, the value of the proportion classified correctly of the secondary sample of non-bankrupt firms is doubtful because their existence in 1966 was not a sampling criterion. Both the method of selecting these firms (see: Altman, 1968, p.602) and the unreliability of the model for the years prior to the second before failure could indicate that those firms were approaching an early stage of failure and, thus, they might have been correctly classified as failed.

Finally, Altman traced the univariate annual change in the average values of the failed firms' five ratios (and some others) for five years prior to failure and found that the most serious deterioration in the majority of ratios occurred between the third and the second years prior to failure, a result supporting the deteriorating results of his model for the years prior to the first before failure.

However, the mere change in a ratio's average values might not represent the trend of its distribution because it might have been caused by an extreme change in very few values of the ratio. Therefore, the trend displayed by the ratio averages should be supported by inspecting their distribution. Beaver's profile analysis supported by the depicted histograms is a good example of univariate analysis which is also relevant and necessary for any multivariate study of failure prediction.

As mentioned before, any claimed predictive power for the first year before failure is almost practically useless (see the comment on Beaver's study).

However, the evaluation of Altman's model by Joy and Tollefson (1975) and Altman's (1977) reply to them are considered below because of their relevance for any failure prediction study.

Joy and Tollefson (1975) argued that the population's prior probabilities should be allowed for if the developed linear discriminant function (LDF) is to be used in classifying other samples which are drawn at random from the population and, in addition, costs of misclassification should also be considered if the LDF is to be used as an applied decision-making tool. Accordingly, they used the results of Altman's secondary samples (i.e. 24 and 52 correct classifications of the 25 and 66 bankrupt and non-bankrupt firms, presented above) to investigate the two aspects of using his LDF:

1. The expected performance of LDF on a random sample from a population with priors q_1 and q_2 (estimated at .01 and .99 for bankrupts and non-bankrupts) is estimated as:

$$q_1 \, (n_{11}/n_{1.}) + q_2 \, (n_{22}/n_{2.})$$

where n_{ii} is the correct classification of group i and $n_{i.}$ is the total number of companies in group i

$$= .01 \, (24/25) + .99 \, (52/66) = 79\%$$

while the proportional chance criterion is

$$(q_1)^2 + (q_2)^2 = (.01)^2 + (.99)^2 = 98\%.$$

Thus, they concluded that Altman's LDF, using his cut-off point, would not be expected to perform significantly better than cahnce if the assumed prior probability of 1% bankruptcy is properly included in the analysis.

2. Using a Bayesian approach, the expected cost (EC) of using LDF, proportional and maximum chance criteria, respectively, per entity of decision making are: $EC_{LDF} = q_1 (n_{12}/n_{1.})\ C_{12} + q_2\ (n_{21}/n_{2.})\ C_{21}$

$$EC_{Prop} = q_1\ q_2\ C_{12} + q_1\ q_2\ C_{21} = q_1\ q_2\ (C_{12} + C_{21})$$

$$EC_{max} = q_1\ C_{12}$$

Where $(n_{12}/n_{1.})$ and $(n_{21}/n_{2.})$ are type I and type II errors, $q_1\ (n_{12}/n_{1.})$ and $q_2\ (n_{21}/n_{2.})$ are the estimated probabilities that a randomly selected entity will be misclassified by LDF, and C_{12} and C_{21} are the costs of misclassifying a bankrupt and a non-bankrupt firm, respectively.

Solving the above equations using 4% type I error and 21% type II error, without quantifying costs of misclassifications, Joy and Tollefson concluded that Altman's LDF would be superior to the proportional chance criterion (i.e. EC_{LDF} will be less than EC prop.) if - and only if - the costs of misclassifying a bankrupt firm are more than about 21 times as great as the costs of misclassifying a non-bankrupt firm (and 28 times to outperform the maximum chance criterion).

Altman in 1977 reviewed his original study, referred to the subsequent tests of the model, evaluated the arguments of Joy and Tollefson (1975), and referred to a plan for a subsequent study (Altman, et al., 1977).

Altman's (1968) model was subsequently tested in two studies. First, Altman and McGaugh (1974) used Altman's (1968) model to classify 34 bankrupt firms, during the period 1970-73. The model classified correctly

28 (82%) firms for the first year before failure, but the model still deteriorates for the years prior to the first before failure (only 58% were correctly classified for the second year before failure).

Second, Altman and Brenner (1976) computed the z-scores for about 1800 companies and found that 92 companies had scores below the cut-off point for the years ending 1960-63 (none of these companies was bankrupt). Thus, Altman (1977, p.93) made a crude approximation of type II error as being 5% (92/1800) and, despite the problems of this biased approximation, stated that "still, the 5 percent error rate is probably much closer to the true type II error than the 21 percent error rate assumed by Joy and Tollefson (1975) in their discussion on model efficiency".

Accordingly, Atlman (1977) objected to using 21% as an estimate of Type II error and showed that if it was estimated as 5% (which he believes is more realistic) or 10% his LDF would be superior to the proportional chance model - for $C_{12} > 4.2\ C_{21}$ - and superior to the maximum chance model - for $C_{12} > 5.2\ C_{21}$ - (these values were $C_{12} > 9.37\ C_{21}$ and $C_{12} > 10.31\ C_{21}$ for 10% type II error).

Moreover, Altman estimated that C_{12}/C_{21} might be in the range of 16.5 to 30 times (upon the basis of investigating the reports of the US 25 largest banks) and stated that from the commercial bankers' viewpoint the estimate might be closer to 30 times. Thus, he concluded the superiority of his LDF.

However, this exchange of ideas is interesting and has implications for the present study, as indicated in Chapter 3.

(2) <u>Altman', Haldeman' and Narayanan's (AHN) (1977) Study</u>

AHN's objective was to develop a failure prediction model which considers recent developments with respect to business failure. Specific-ally, size was included as a dependent variable (the average asset size of sampled firms reflected the fact that large firms have also become prone to failure), a quadratic discriminant function was fitted because of the inequality of the group dispersion matrices, retailing and manufacturing companies were about equally reprsented in the selected sample (although the industry factor was not explicitly considered), prior probabilities and costs of mislcassifications were considered for the evaluation of the developed LDF relative to the alternative chance models in terms of the expected costs of misclassification (in a way similar to that presented above), Lachenbruch's hold-out test was used for validation, and accounting data were adjusted to reflect the most recent and expected changes in financial reporting standards (e.g. capitalization and amortization of lease costs and deferred charges) so that the model might be relevant to data that will appear in the future.

The selected sample consisted of 58 firms (5 firms were subsequently excluded because of lack of data) which went bankrupt during the period 1962-1975 paired with 58 non-bankrupt firms by industry and year of data (see the comment above on Beaver's paired sample). The bankrupt group included 5 nonbankruptcy petition companies either because of substantial government support (1), a forced merger (1), or banks took over the business (3). One could expect that these 5 firms might have been otherwise bankrupt but in a later period of time. This latter situation might affect the homogeneity of the bankrupt group.

Seven financial ratios were finally selected, through the stepwise procedure, from a set of 27 ratios classified a priori into six groups - profitability, leverage, liquidity, capitalization, earnings variability, and miscellaneous measures. The seven variables, as ranked according to their importance by four out of six methods of ranking, were: 1. retained earnings to total assets, 2. the standard error of the estimate around a ten-year trend in variable no.7 (see: below), 3. capitalization, measured by common equity to total capital (common equity was measured by a five-year average of the total market value rather than book value and preferred stock was included at redemption value), 4. size, measured by total assets including the capitalization of leasehold rights, 5. current ratio, 6. earnings before interest and taxes to total interest payments (including that amount imputed from the capitalized lease liability), 7. earnings before interest and taxes to total assets. The ranking of this last variable conflicts with almost all the other studies, but ANH stated that it was still an important contributor to the model's success.

Logarithmic transformation was applied to some variables, e.g. variables 4 and 6 above. It was decided that this transformation might improve those variables' normality, but neither the original nor the transformed distributions were subjected to any test of normality.

The relationship between the above variables, the financial attributes they are supposed to measure and their stability in measuring them are not clear, especially as they are not measured in the usual way. A principal components analysis may have been helpful, especially as Altman, Margaine, Schlosser, and Vernimmen (1974) used it successfully in 'a study of French commerical loan evaluation'.

A quadratic and a linear discriminant function (QDF and LDF) were fitted to the model (the coefficients are not published). The classification results confirmed the statistical literature in that LDF outperforms QDF in the case of small samples even where the dispersion matrices are not equal (see: Chapter 3). Thus, the rest of the analysis was restricted to the LDF.

This latter function, classified correctly 93, 96 and 90% of all, failed and no-failed firms for the first year before failure. The correct classification decreased for the years which were more remote from failure but they still correctly classified 77,70 and 82% of the three categories of firms for the fifth year before failure. However, Lachenbruch's hold-out test is the only one of the performed classification tests that can be regarded as a true hold-out test (see: Chapter 3 for elaboration on this test). The results of using this test were 91, 93, and 90% correct classifications for all, failed and non-failed firms, (for the first year before failure). Other tests used included classification for the four years prior to the first before failure, recomputing the coefficients on a random half of the original sample and using them to classify the other half (see the above comment on these tests relating to Altman's 1968 study).

AHN estimated prior probability of failure to be 2% and the cost of type I error to be 35 times the cost of type II error (the latter is based upon both empirical and questionnaire investigations). These estimates were then used to compute a new cut-off point which is defined as:

$$Z_c = L_n \quad \frac{q_1 \, C_I}{q_2 \, C_{II}}$$

Where q_1 and q_2 are the prior probabilities of failure and non-failure and C_I and C_{II} are the costs of type I and type II errors. The original cut-off point, which was used in the above classifications, was zero because it assumed that $q_1 = q_2$ and $C_I = C_{II}$. The new cut-off point was (-0.337). Thus it affected the previous classifications so that the chances of type I and type II errors became 8 and 7% instead of 4 and 10%. The new estimates of errors were used to compare the expected cost of using the LDF in decision-making with those of both the proportional and maximum chance criteria (see the argument of Joy and Tollefson referred to above). The comparison suggested the superiority of the LDF (ZETA model). However, the error estimates which resulted from Lachenbruch's test should have been used rather than those of the original sample (though apparently this would not have changed the results). Also, AHN did not evaluate the expected performance of their LDF on a randomly selected sample given the prior probabilities which, as previously defined, could be computed as:

$$.02(.93) + .98(.90) = 90\%$$

A comparison of this performance with that of the proportional chance model ($.02^2 + .98^2 = 96\%$) indicates that the ZETA model would not be expected to perform better than the proportional chance model. However, as Morrison has stated, the impressive result is the proportion correctly classified of all the firms classified in group 1 (failed), which is 89%, compared with a chance of 50% in the case of AHN's study. The latter Proportion is computed as:

$(q_1$ x number of failed firms)/(q_1 x total number of failed and non-failed firms) = .02x53/.02 (53 + 58) = 1.06/2.22 ≈ 50%.

AHN preferred not to consider both prior probabilities and error costs in the development of the LDF. This treatment is supported and adopted in the present study as discussed in Chapter 3.

(3) Daniel's (1968) Study

Daniel (1968) was only concerned with predicting corporate failure. His study was the first to use factor analysis for the reduction of the number of variables and to emphasize the importance of sampling from the extreme cases to minimize the overlap between the groups of firms.

(4) Deakin's (1972) Study

Deakin's study (1972) was concerned with the development of a model for predicting failure as an alternative to those of Beaver (1966 and 1968b) and Altman (1968). His sample included 32 firms failed between 1964-1970, 32 non-failed firms matched with the failed firms by size, industry and years of data and other 32 non-failed firms selected at random to match the failed firms only by the year of data. The latter non-failed firms were used only for the purpose of computing the discriminant functions.

The fourteen accounting ratios used by Beaver (1968b) were also used by Deakin to replicate Beaver's study and to fit discriminant functions to the fourteen ratios of each of the five years before failure. Thus, Deakin defined his model by those fourteen ratios. This defintion appears to lack both a priori and empirical reasoning because the fourteen ratios are, a priori and empirically, more than what are needed to measure a firm's financial attributes (see: Deakin's next reviewed study).

All the fourteen ratios were claimed to be necessary for the five fitted functions, but the variables' relative importance was not the same for all functions.

The five functions classified correctly 97, 95, 95, 79 and 83% of all firms in the analysis sample, for the first to the fifth year's functions. The corresponding classifications of a hold-out sample of 11 failed and 23 non-failed firms were 78, 94, 88, 77 and 85%. Deakin, thus, argued that it is not surprising that the second year (the middle of the first three) provides the greatest classification ability. This last statement implies that symptoms of failure are severer in the second than in the first year before failure, which is not consistent with the univariate finding that ratios of failed firms deteriorate as failure approaches.

However, the unexpected performance of the model's five functions (compare the correct classifications of both the analysis and hold-out samples) is explicable by the fact that the model (defined by the fourteen ratios) lacks both a priori and empirical reasoning. Prior probabilities and costs of misclassifications were ignored altogether and no attempt was made to test the normality of ratios nor to test the relationship between them. Deakin, however, was the first to fit a function for each of the years before failure and he was followed by Blum (1974) (see also Altman et al., 1977, fn. 14).

(5) Deankin's (1977) Study

In this study, Deakin was concerned with the modification of his (1972) study. The original fourteen ratios were subjected to principal components analysis by Libby (1975) using the data of Deakin's first study (1972). Libby selected five ratios each of them loaded highly on one of the components and found that the discriminant model based upon the five ratios performed about the same as the fourteen ratios' model, both models being developed for Libby's combination of Deakin's data (each company was randomly represented by one of the three years of data before failure). Based on these findings, Deakin defined his model on Libby's five ratios and fitted both quadratic and linear discriminant functions to that model using the data of the second year before failure.

His sample - included 63 firms which went bankrupt during the period 1966-71 (most of which were used (as he said) in his first study - Deakin, 1972) and 80 non-failing firms matched with the failed group by the year of data (however, Deakin claimed that the two groups were not matched by any criteria). He rejected industry matching "on the grounds that industry factors could confound the results. In fact, the industry mix of failing companies in 1964 was found to be somewhat different from that in 1970-1971, and both of these were different from the mix of failing companies in 1973-1975".

These changes in the industry mix of failing companies should have at least initiated a further investigation. The latter might indicate that the industries' prone to failure was differently affected by the different phases of the economic cycle. Thus, not only the industry indicators should be considered but also the economy-wide indicator (see:

Chapter 1).

The linear discriminant function classified correctly 94, 89, and 99% of all, failed and non-failed comapnies, respectively, in Lachenbruch's hold-out test. The corresponding classifications by the quadratic function were 84, 98 and 73%. Although the linear function outperformed the quadratic function, Deakin adopted a decision rule which uses both function. According to this decision rule, a company is classified failing or non-failing only if it is so classified by the two functions, otherwise the rule is investigate further. This decision rule correctly classified 83% of a sample of 47 companies which went bankrupt in the yeasrs 1972-1974. This prediction, which was based upon the ratios of the second year before failure, was better tahn those of the first and the third years before failure. However, the following table presents the linear discriminant function which was fitted to the model.

Variables	Coeffic-ients	Scaled vector	Group Means		
			(1) non-failing	(2) failing	1-2
X1 = Net income/Total assets	0.0400	.0523	.0500	-.0666	.1166
X2 = Current assets/Total "	0.0028	.0094	.5844	.5711	.0133
X3 = Cash/Total assets	0.9992	1.0000	.0701	.0604	.0097
X4 = Current assets/current liabilities	-.0088	-.2171	2.8188	1.5806	1.2382
X5 = Sales/Current assets	-.0003	-.0101	3.1964	3.1635	.0329

The relative contribution of each independent variable (see the method of Mosteller and Wallace in Chapter 3) to the Mahalanabis distance, D^2, should be positive and the sum of these contributions should be unity. The above table shows that the coefficients of variables X4 and X5 are negative while the differences between the two group means of these variables are positive. Accordingly, they are negatively contributing to the model's D^2. Because the mere removal of these variables may result in a total contribution which is less than unity, the search for other variables is necessary for the development of a consistent model. Once again Deakin's (1977) model lacks both the a priori and empirical reasoning. It is not consistent with the findings of all the previous univariate studies that the model developed for the second year before failure can be less efficient for the first year before failure (see: hypothesis 4 of Chapter 1). On the other hand, defining a model by those ratios which (for a previous study) loaded highly on some components and were judged to be the most common ratios (see: Libby, 1975), is not a proper definition. Principal components analysis should be performed using the ratios of the specific study for each available period of data (see: Pinches et al., 1973 and 1975 for the instability of some ratios over time) and its results should be used to guide the statistical selection of the best ratios by the stepwise discriminant (or regression) technique. Thus, the a priori formulation of a model should be made in terms of financial attributes rather than the ratios and the finally selected model should be consistent in the terms of the contribution of each variable and all the variables (as indicated above) and the results of testing it must confirm the a priori argument or the a posteriori explanation must be given.

(6) Edmister's (1972) Study

This study was concerned with testing the usefulness of financial ratio analysis for predicting small business failure. A sample of 42 small firms to which loans were granted by the Small Business Administration (SBA) were selected, loss and non-loss borrowers were equally represented and the non-loss cases were selected randomly. Three consecutive annual statements were available, within the years 1958-1965, prior to the date of granting the loan, so this sample was called the 'tri-annual sample'.

A similar sample of 280 firms which had submitted only one financial statement before the loan was granted were selected for further tests.

Nineteen accounting ratios were considered in five different ways, namely: level of ratios, relative level of ratio to the industry average ratio, three-year trend of ratios, three-years average of ratios, and a combination of relative trend-relative level. All the variables were then given the two binary values (0 and 1), according to whether the value of a ratio is less than a specified level, showing an up or down trend.

The model's ratios were selected by the stepwise discriminant analysis with the condition that the simple correlation coefficient between a variable and any other variable already in the function was not greater than 0.31. The ultimate model included seven variables and correctly classified 93% of the analysis sample. The model developed for the single-year sample included 25 variables and failed to discriminate between loss and no-loss borrowers. Therefore, Edmister concluded that while one financial statement is sufficient for the development of a discriminant model for large companies, at least three consecutive financial statements are necessary for the analysis of small firms. However, this conclusion would not appear to be well founded where the 25-ratio model is not acceptable because of the known multicollinearity among the 25 accounting ratios.

Although Edmister (1972) frequently stated that he employed discriminant analysis and his study is viewed in the literature as one of discriminant analysis, it appears that he employed regression analysis because he provided the R^2, the coefficient of determination, which is a statistic known in regression but not in discriminant analysis. However, Dake (1972) pointed out the conflict between using the dummy values 0 and 1 and the discriminant assumption of multivariate normality, the importance of testing the model on a new set of outside data and that the model was developed for firms which were granted loans and thus it cannot be used in the accept or reject decision. (See also: Joy and Tollefson, 1975 on this latter point). Finally, prior probabilities of laon loss and non-loss and costs of misclassifications were not considered.

(7) Blum's (1974) Study

Blum constructed a discriminant model to aid in assessing the probability of business failure by American courts. Failure was defined to include bankruptcy (90% of the cases) and explicit agreement with creditors to reduce debts (the remaining 10%). The sample included 115 firms which failed during the years 1954-1968 and 115 non-failed firms paired by industry, sales, number of employees, and fiscal year.

Twelve variables were chosen to represent liquidity (5 ratios), profitability (1 ratio), and variability of net income and liquidity indicators (6 ratios). Another set of 12 non-ratio variables were used to test a non-ratio version of the model. The data (for at least 3 years and up to eight years where available) were divided into 21 ranges of at least 3 years (i.e. from year i to year n, n = i + 2 for each i, and i = 1 to 6), and a discriminant function was fitted to half the data of each range.

The function fitted to the middle ranges (which include 4, 5, or 6 years) correctly classified 93 to 95% of companies in the held-out sample at the first year before failure, 80% at the second year before failure and 70% at the third, fourth, and fifth years before failure. These classifications of hold-out samples were considered indicators of the predictive accuracy of the computed functions.

Because of variables' multicollinearity, it was not possible to rank them by their standardized discriminant coefficients - and none of the other methods were considered. Blum's model appears to have been mis-specified because it included 12 variables which were subjectively classified into three groups, with profitability represented by one ratio, and no attempt was made to reduce the variables or to study the nature of their distributions. Also, prior probabilities were not considered and it was only argued that the costs of type II error may be greater than those of type I from the legal and social points of view.

(8) Taffler's (1977a) Study

This study was concerned with the development of a model for the identification of UK listed industrial firms at risk of failure. Failure was defined to include the cases of liquidation, winding-up by court order, entry into receivership and reconstruction with government financial assistance.

The sample included 23 companies which failed during the years 1968-1973 and 45 sound firms rather than non-failed or continuing firms. Thus, the sound group was not of the same size as the failed group, was not matched by any criteria with the failed group and the sound firms were so identified by the analysts of a broking firm. As mentioned above, Daniel (1968) was the first to emphasize the importance of sampling from the extreme cases to minimize the overlap between the groups of firms. Marais (1979, p.14) argued that restricting the sample to sound companies would result in a higher efficiency in classifying the analysis sample which "cannot be extrapolated with certainty to the total population of continuing firms to which the discriminant function will typically be applied". This criticism appears to be not only valid for the case of sampling from sound firms, but also for all the other cases of failure prediction. It is the purpose of the secondary samples (cross and inter-temporal validation samples) and the methods of allowing for the population's prior probabilities and costs of misclassifications, to reveal the expected efficiency of a model for the population of companies. Marais also pointed out the difficulty of defining the population of healthy or sound firms. This would be a researcher's problem. However, size, industry and economy-wide indicators were neither explicitly considered nor controlled for.

From a large number of accounting ratios and trend measures, Taffler finally selected 50 ratios for further analysis. The distributions of each ratio for each group of firms were carefully examined and appropriately transformed (logartihmic or reciprocal) to improve normality. The 50 ratios of failed and non-failed firms were subjected to principal components analysis - both together and separately for the first year before failure. Six readily interpretable components were identified for the two groups of firms taken together; however, the analysis of the groups separately provided similar dimensions and as a result were not reported. The high loading of some ratios on a component other than their expected a priori component (e.g. the ratios of quick assets to current liabilities and fixed assets to net capital employed loaded highly on the components of leverage and working capital position, respectively) was explained by the ratios' common elements or by the relationship between their elements. This explanation does not appear to be very convincing because it is the purpose of principal components analysis to handle the correlation between ratios which is the result of their common elements and the correlation between their different elements. The potentially convincining explanation is that some ratios are not stable measures of specific financial attributes for the different periods of time (see: Pinches, et al., 1973 and 1975 and Johnson, 1979) or, expectedly, for the different groups of firms. Because Taffler's principal components analysis was concerned with only the first year before failure it could not reveal which were the volatile ratios.

Stepwise discriminant analysis was used and resulted in a final model constructed from five ratios which were ranked according to their relative importance as (by two of the three methods employed): total liabilities to net capital employed, earnings before interest and tax to total assets, sales to average inventory, quick assets to total assets and working capital to equity. Each of these ratios loaded highly on one of the principal components.

The population's prior probabilities of classifying a firm as failed or as health were subjectively estimated by a group of financial analysts at an odds ratio of 1:10. Similarly, the odds ratio of costs of type I error to the costs of type II error was estimated at 40:1. Using these estimates resulted in a cut-off point of 1.39 ($Ln \frac{1}{10} \times \frac{40}{1}$). This cut-off point was not used and another cut-off point was arrived at by assuming that the decision maker is indifferent to the costs of misclassifications. Thus, the employed cut-off point was -2.303 ($Ln \frac{1}{10} \times \frac{1}{1}$). The model classified correctly 98.5, 96, 100% of all, failed and non-failed companies for both the analysis sample and Lachenbruch's hold-out test. The model also classified 61, 48, and 35% of the 23 failed companies for the second, third and fourth years before failure. As argued above, the high efficiency of a model for the first year before failure (the last published accounts) is probably of little practical value to a decision maker. Given the high costs of misclassifying a failed firm, the proportions classified correctly for the years prior to the first before failure are very low. The model was also used to classify a new sample including 33 companies which failed between 1973-1976 and 10 companies similar to those healthy companies of the original sample. The correct classifications were 91, 88, 100% of all, failed and non-failed companies for the first year before failure. The two samples were combined (excluding 4 failed and 1 non-failed firms) to recompute the model's coefficients. The new function proved disappointing in classifying the data from which it was computed. One possible explanation of this result is that the inclusion of the more recent failures changed the financial attributes that were measured by some of the model's ratios and thus caused the disappointing results. This explanation seems to have not been recognized by Taffler since he paid no attention to the instability of accounting ratios.

(9) Taffler's (1977b) Study

In this study, Taffler developed another model using a more satisfactory sample of solvent companies. He represented his model to illustrate the correct way to use existing accounting data. His sample included 46 failed firms which are those of the above combined sample excluding the 6 firms that failed before 1969, and 46 healthy firms matched by size and industry with the failed firms.

Using the same methodlogy as in the previous study, the final model included four ratios which were ranked by the method of Mosteller and Wallace (see: Chapter 3) as: profit before tax to average current liabilities, current liabilities to total assets, no-creidt interval and current assets to total liabilities. The prior probabilities odds ratio was reestimated at 1:7, thus resulting in a cut-off point of -1.95 ($Ln \frac{1}{7} \times \frac{1}{1}$). The model correctly classified 98, 96, 100% of all, failed and non-failed companies of the original sample. The corresponding classifications for Lachenruch's hold-out test were 95, 89, and 100%. The nine companies which failed in the six months to the end of June 1977 were correctly classified as "failed' in the first year before failure while only seven of them were correctly classified (78%) in the second and third years and only four (50%) in the fourth year before failure. Thus, on the basis of this small sample, the model's efficiency deteriorates significantly as failure becomes more remote.

(10) Marais's (1979) Study

Marais adopted the objective of evaluating the susceptibility to failure of all UK-quoted industrial companies. Other purposes included testing the possibility of improving upon the results of earlier work and comparing the usefulness of the flow of funds variables with the more conventional balance sheet and profit and loss ratios - in the context of failure prediction. Failure was defined to include the cases of entry into receivership, liquidation, takeover by the National Enterprise Board as an alternative to failure, and the need for extensive bank support to avoid failure. The sample included 39 companies which failed during the period 1974-1977 and 53 continuing (rather than healthy) companies. These were not matched with the failed companies and their data were stratified over the period 1973-1977 "to average out any short-term cyclical effects".

This study considered 59 ratios classified into 6 a priori groups (liquidity, gearing, profitability, turnover, cash flow and funds flow). Regression rather than discriminant analysis was applied in this study (see: Chapter 3). Marais stated that the regression model performed as well as the discriminant models. However, a comparison between a discriminant function and a regression function fitted to the same model was not made.

Two models were developed. The ratios of the first model are (in order): cash flow to current liabilities, 1/gross total assets, current assets to gross total assets, interest payments to operating profits plus non-trading income. This latter ratio was replaced by funds generated from operations minus net increase in working capital to total debt for the second model.

The proportions classified correctly of all, failed and non-failed companies by the first model were 95, 97, and 92% for the first year, 86, 87 and 84% for the second year and 77, 67, and 88% for the third years before failure. The corresponding classifications for the second model were 93, 97 and 91% for the first year, 87, 92 and 82% for the second year and 84, 74 and 94% for the third year before failure.

Neither of the two models were subjected to a specific hold-out test. However, the second model was employed to classify a sample of 10 companies which more recently failed (in 1978) and 19 non-failed but known to have financial problems. The total efficiency of the model was very low because of the expected high type II error. To show that his models perform better than the models of Taffler (1977b) and Deakin (1977), Marais computed the coefficients of the latter two models using his data. Not surprisingly, the two functions performed badly.

(11) Tamari's (1966) Study

Tamari constructed an index of risk by giving each of six ratios a weight, according to its importance in the eyes of financial analysts, economists and credit men. The values of each ratio were then divided into intervals and each interval was assigned a number of points within the total weight given to the ratio. Apart from the subjectivity of this index, it leaves a very wide range of the index values (30 to 60 points of the index) within which a company is not classifiable. Also, it cannot account for the interaction between the six ratios.

However, Tamari (1978, pp.108-113) argued that the usefulness of his index, relative to the other multivariate statistical models, lay in its simplicity and applicability.

The claimed relative simplicity does not appear to exist because the users of his index and of a discriminant or a regression model will have to perform exactly the same calculations. The claimed relative applicability seems to be overstated. It may appear true that the ratios and weights of Tamari's index are independent of actual data, but they are related to these data through the eyes of the experts consulted. Moreover, the selected ratios and their weights may not represent the only or the optimal possible combination, even for a given economy within a particular period of time. This non-optimality of the index is perhaps suggested by its low predictive power. As Tamari's reported results indicate, of 16 failed firms (in 1960) 69% were correctly classified and 19% were not classifiable upon the basis of their data in 1958; and of 114 non-failed firms 50% were correctly classified and 41% were not classifiable.

Moreover, there is some doubt about the lower costs of constructing and revising the index claimed by Tamari and its supposed applicability to other economies. The costs of consulting and interviewing financial analysts, economists and credit men may well exceed those of the computer time required to develop a discriminant or a regression model. Equally, substantial costs will be incurred in modifying the index so as to make it suitable for use in other economies. For instance, Tamari himself has suggested that if the index is to be used for UK companies its weights should be adjusted according to the observed distributions of UK accounting ratios. This suggests, perhaps that he is overlooking the point that one of the mark virtues of his index is that it reflects the way in which credit managers make their decisions; yet he seems to ignore the fact that credit managers in different economies may have different criteria for these decisions. For example, bank overdrafts may indicate financial problems for US companies but not for UK companies (see the comment on Beaver's sample).

(12) Parosh' and Tamari's Study

Parosh and Tamari (see: Tamari, 1978, pp.130-35) developed a regression model which included five ratios to predict business failure. The proportion classified correctly of the analysis sample appears to be very low (56%). The results of classifying an inter-remporal validation sample of 8 failed and 8 non-failed companies appear to indicate that the model's predictive power, upon the basis of this small sample, is 75%. Nevertheless, Tamari claimed the model would be applicable for all types of company under any economic conditions. This claim, however, is inconsistant with his argument in favour of his subjective index.

2.2.2 Other Appraoches

Three studies representing three different methods of analysis are reviewed in this subsection. The three methods of analysis are: Informational Decomposition Measures (IDM), Simulation, and the Gambler's Ruin Model.

2.2.2.1 Informational Decomposition Measures

Lev (1971) used Beaver's (1966) sample to test the predictive power of theIDM's. The latter measures are based on concepts of information theory where the fractions of a group of assets or claims to total assets or total claims at time t-1 and at time t are regarded as prior and posterior probabilities, respectively, relative to time t. Thus, the balance sheet at time t is considered a message which transforms the assets and claims fractions of time t-1 (as prior probabilities) to those of time t (as posterior probabilities) (Theil, 1969). The informational value of this message, conveyed by the balance sheet of time t, can be defined as:

$$I(q:p) = \sum_{i=1}^{n} q_i \text{ Log } \frac{q_i}{p_i} \qquad (2.1)$$

Where, I(q:p) is the expected information of the message which transforms the prior probabilities $p_1,\ldots\ldots\ldots,p_n$(the fraction of time t-1) to the posterior probabilities $q_1,\ldots\ldots,q_n$ (the fractions at time t) (see: Theil, 1969). Therefore, assets', liabilities' and balance sheet's decomposition measures can be defined in terms of equation (2.1). In the case of balance sheet's measures, each group of assets or claims must be divided by twice the balance sheet's total. Computationally, an information measure can be produced for any number of the sub-classifications (decompositions) of an item (assets, liabilities or balance sheet). Since the resulting measure of assets (for example) "is a measure for the degree of change of the relative position of the individual assets in total assets as a whole" (Theil, 1969, p.463), the sub-classifications of assets will only produce a meaningful measure if they have economic significance. The classification scheme is therefore subjective - a point not specifically acknowledged by Lev. However, IDMs are measures of financial stability because they take the proportional change of the individual (subjectively determined) items as a norm and indicate the degree to which the actual change of these items deviates from a proprotional one.

Lev (1971) computed these measures for each firm in the sample for consecutive and nonconsecutive years. Assets were grouped into current and fixed. Claims were grouped into current liabilities and long-term liabilities and equity. He found that the average IDMs were substantially larger for failed firms than for the non-failed firms. This finding suggests that IDMs can be used to discriminate between failed and non-failed companies. It can be explained by noting that IDMs indicate the stability of the relative contribution of financial statement items over time. Failing firms are expected to undergo larger and more disproportionate changes in their current/non-current assets and claims than non-failing firms and, thus, their IDMs are expected to be larger (see: Lev, 1971).

Accordingly, for each pair of firms (see the above discussion of Beaver's sample) the one with the larger measure is classified a failed firm. The balance sheet's decomposition measure (the best of the three measures) was found to perform slightly less well than Beaver's cash flow to total debt ratio, but better than some other ratios. However, since

IDMs are constructed from balance sheet data they may be compared only with balance sheet ratios (as argued by Lev, 1971).

Perhaps the major shortcoming of the IDMs is that they are only 'distance measures' and hence are directionless (Theil, 1969, and Lev, 1969a, p.27). Therefore, they cannot discriminate between an increase and a decrease in a specific item - or between very successful and failing firms - without additional indicators. Moreover, these measures cannot be computed when the value of a fraction is zero or less, which is not uncommon for failed firms (see: Theil, 1969).

2.2.2.2 Simulation

Bazley (1976) employed a simulation model to examine the relative predictive ability of alternative income measurement models when the object of prediction is business failure. Three income measurement models were examined: historical costs (HC), historical costs adjusted for general price level changes (CPP), and current costs (CC).

The initial state of the model was represented by the average values of the actual financial statements of 119 companies within a certain industry and asset size class (between $1 and 10 million) for the year 1969. The assumptions and relationships of the simulation model were made according to those observed for the empirical data. These assumptions and relationships covered dividend policy, symptoms (causes) of failure (according to which the six variables used in the model were sales, costs, receivables, inventory, fixed assets and liabilities), three trends for each variable, period of simulation (20 years), rising, failing and fluctuating specific price index, increasing general price index, CPP income (including monetary gains and losses) and CC income (including realized and unrealized holding gains and losses).

A firm is defined as being a failure when it has a negative cash balance and either has had a negative income for four years or has a ratio of total debt to total equity greater than 70% (all measurements are historical costs). Simulated failed and non-failed firms were matched by the year of data. Six accounting ratios were used in an analysis similar to that of Beaver's (1966), comparison of means and dichotomous classification test.

The results of the analysis indicated that the use of financial statements adjusted for changes in the general price level or the specific price level does not significantly alter the ability to predict failure. The small and insignificant differences that did occur indicated that the HC model is slightly superior to the CPP model, which in turn is slightly superior to the CC model. The results of the three income models were generally similar to those of Beaver's study.

However, the findings of a simulation study are not generalizable beyond the conditions assumed in the simulation model. Moreover, the reliability of a simulation finding regarding the usefulness of alternative accounting models is questionable (see: Chapter 4). Nevertheless, the simulation technique appears to be promising for the purpose of formulating a model which simulates both the business environmental factors (e.g., business cycle, market shares, pricing restrictions, technological changes) and the firm's financial and operating policies and decisions. Such a model can foretell the effects of both the external factors and the management decisions on a firm's financial state as to failure or success and it can also evaluate the alternative procedures that may alter a failure trend (e.g. cash infusion).

2.2.2.3 Gambler's Ruin Model

Wilcox (1971) used the classic model of gambler's ruin to develop a model which can discriminate between high-risk and low-risk firms. The model indicates that at any given time, a firm is regarded as existing in one (n) of an infinite number of financial well-being states, with 0 as the state of zero liquid wealth. At the end of the next time-period the firm is expected to move either to state n+1 with probability p or n-1 with probability q, and p+q=1. Thus, there is no probability of remaining in the same state unless the firm is in the state of zero liquid wealth - the absorbing state. Reaching that state constitutes failure, or "gambler's ruin". The parameters q and p are called "transition probabilities", towards or away from failure. Thus, the probability that a firm will utlimately end up in the abosrbing state 0 (failure) is:

$$p(\text{ultimate failure}) = \begin{matrix} 1, \text{ if } p \lesssim q \\ (q/p)^N, \text{ otherwise} \end{matrix} \qquad (2.2)$$

This probability, given the stability of the model's parameters p and q, "is typically a good indicator of the probability of failure over the next five years".

To estimate the parameters N and q/p using accounting data, a firm's average gain or loss of liquidity during an accounting period is assumed to be σ , thus σ is a measure of the distance between neighbouring states. The firm's existing liquidity at the end of a period, C, is estimated by the Adjusted Cash Position, thus $W = C/\sigma$ is roughly the number of times the firm can lose its periodic business gambles before it experiences gambler's ruin. The ratio q/p is related to average profitability, or the firm's mean "drift rate" towards states of greater and greater liquid wealth, thus, the dirft-rate per period along the sequence of states in cash terms is $(p-q)\sigma$ and is estimated by the Mean Adjusted Cash Flow. If "x" is used to represent the Mean Adjusted Cash Flow divided by σ, then q/p = (1-x/1+x). The following definitions were used: Adjusted Cash Flow = Net Income - Dividends - (0.3) (Increase in other current assets)

- (0.5) (Increase in long-term assets)

Adjusted Cash Position = Cash + (0.7) (Other current assets)+(0.5)

(Long-term assets) - (liabilities)

$$\sqrt{(\text{Mean adj. Cash Flow})^2 + \text{Statistical Variance of Adj. Cash Flow}}$$

(The weighting factors are used to deflate asset values according to their degree of illiquidity and they are subjective).

Wilcox (1973) empirically tested the model using a sample of 52 bankrupt and 52 non-bankrupt firms paired by asset size, industry and year of data. The above measures (N and x) were computed for each firm for each of the five years prior to failure. The prediction was based on equation 2.2 and some tie-breaking rules (e.g. $x < 0$ and $N < 0$. The firm has become "theoretically" insolvent. The chances of practical realization of bankruptcy are greater the more negative is N). This model was found to improve the results of Beaver's study.

However, Benishay (1973) argued that Wilcox's mathematical model is not sufficiently realistic (because it assumed that a firm may move from state n to either n+1 or n-1 and exclude the possibility of staying in state n which is the most probable) and it does not seem to be necessary for the execution or interpretation of Wilcox's empirical work (because the N and x variables only represent the financial strength of a firm while Wilcox attributed to them sophisticated and specific mathematical meaning). Kinney (1973) questioned the statistical validity of estimating the model's parameters using only five observations (for a firm) and argued that Beaver's best ratio method was a simple one-year (deterministic) model and yet in its simplicity predicted failure rather well.

Thus, the above section (2.2) reviewed all the studies which are concerned with using accounting data in models (univariate, multivariate and others) to predict corporate failure. Despite the shortcomings of the developed models, all studies have claimed success. The following section (2.3) is concerned with the ability of the stock market to anticipate failure.

2.3 Anticipating Failure in an Efficient Capital Market

The informational content which published accounts may have for investors regarding corporate failureas a forthcoming event has rarely been.tested. However, given the efficiency of the capital market, the market model (see: Chapter 3) provides the best available tool for that test.

Only two of the previous studies have used the market model. The first and the most relevant to the present study was concerned with the ability of the stock market to anticipate corporate failure (Westerfield, 1970). The second was concerned with testing the reaction of the stock market to the information conveyed by published financial statements of some continuing companies which were only predicted to fail (Altman and Brenner, 1976). Three other studies were concerned with the ability of the market to anticipate failure but they employed three different approaches - other than the market model. All these studies are reviewed below after a brief presentation of the concept and forms of stock market efficiency.

2.3.1 The Concepts and Forms of Capital Market Efficiency

West (1975) identified three different types of market efficiency: external efficiency, interal efficiency and allocational efficiency.

External efficiency means "a market in which prices always fully reflect available information" (Fama, 1970, p.383 as quoted by West, 1975). This type of efficiency is also known as "fair game" efficiency. West (1975) argued that substituting the word "external" or "outside" for the modifying phrase "fair game" would be a clearer description of this type of efficiency. The market conditions sufficient to ensure that prices fully reflect available information are: (1) free availability of information, (2) homogenous investor expectations and (3) zero transaction costs. These conditions are unattainable in the real world, but it is generally accepted that information should necessarily be readily available to a "sufficient number" of investors and that heterogenous expectations can be tolerated so long as they do not enable some investors to outperform others systematically (see: West, 1975). Fama (1970, p.388) argued that all these three conditions exist to some extent in real world markets and that the departure from them is not necessarily a source of market inefficiency but a potential one.

Internal efficiency means that the market "should provide the types of transaction services buyers and sellers desire at prices as low as possible given the costs of providing these servies" (West, 1975). This type of efficiency (known also as operating or transactional) is closely related to the organization and the structural characteristics of the markets and is, thus, of no concern to the present study.

Allocational efficiency "implies in macroeconomic sense that share prices are established at "economically" correct levels which optimise capital allocation within the economy as a whole rather than simply with the quoted sector" (Henfry, et al., 1977). West (1975) argued that an allocationally efficient securities' market must be both externally and internally efficient, but an externally efficient market is not, necessarily, allocationally or internally efficient. However, the three types of efficiency should always be distinguished.

The present study is only concerned with external or fair game efficiency to the extent that it provides a relevant basis for examining the content of published accounts and for investigating how the UK market reacts to the early signals of a firm's financial problems. Thus, our concern lies in the ability of the stock market to fully reflect the available information, which is the semi-strong form of the market's external efficiency. The two other forms of external efficiency are the weak form and the strong form. The weak form implies that historical share price data contain no information that can be used to earn above average profits and that the behaviour of share prices follows the random walk model (see: Firth, 1976, p.4 and Henfry, et al., 1977). The strong form implies that no investor or group of investors have monopolistic access to any information relevant for the formation of prices. (see: Fama, 1970). "Whilst there is bound to be some use of inside information, this is so small that it does not disturb market efficiency, protagonists of the strong-form model would claim" (Firth, 1976, p.4). Thus, "this incidentally is much the most controversial form of the model" (Henfry, et al., 1977).

In the test of the semi-strong form of the market's external efficiency (which concerns this study), the goal is to determine whether prices adjust fully and instantaneously to the public information about the event of interest (see: Fama, 1976, p.136). The information which is presumed to be used for pricing the securities is of two types: the information that affects the prices of all securities and is reflected by a market index, and the information that is specific to a security and is reflected in a residual term which is the result of abstracting from general market conditions. This abstraction has been made by the market model (see: Chapter 3 for detailed description) which regresses a security's return on the market return. The market model has been "used extensively {since February 1969}in more advanced tests of efficiency" (Fama, 1976, p.151). Therefore, the market model is regarded as the relevant methodology of testing both the content of accounting information and the ability of the stock market to anticipate corporate failure.

2.3.2 The Market-Model Studies

(1) Westerfield's Study

Westerfield (1970, as reviewed by Altman, 1971, pp.80-81, Lev, 1974, p.148, and Firth, 1977, p.78) used the market model to investigate the monthly share price movement of twenty bankrupt firms for ten years prior to bankruptcy declaration. He found that the market began bidding down the prices of the future bankrupt securities as much as five years prior to bankruptcy. "The fact that the market performance continued downward, especially in the year immediately prior to bankruptcy, means that although investors were aware of the firm's deteriorating condition for a long time prior to failure, the situation's seriousness was consistently underestimated" (Altman, 1971, p.81). However, the seriousness of the situation to the investors appears to be dependent on what they expect to get in liquidation.

(2) Altman' Brenner's Study

Altman and Brenner (1976) used Altman's (1968) model to classify about 1800 continuing firms, listed on compustat data tapes, for the years ending 1960, 1961, 1962 and 1963 and found that 92 firms were misclassified as failed (i.e. type II error). Then they investigated the share price movement of the 92 misclassified firms for the 20 months following the date of publishing their accounts (assumed to be the end of March) to assess the ability of the market to fully reflect the information contained in the published accounts which were found (according to Altman's 1968 model) to show signs of future deterioration. Altman and Brenner found that their companies' relative share prices were not significantly marked down until several months after the data were available and accordingly concluded that the market was not efficient in pricing the considered securities. They qualified this conclusion by stating that either the market was inefficient or their model was mis-specified. The latter in fact seems more likely because their companies were only mis-classified rather than bankrupt and they were still continuing in the subsequent years. Also, the actual date of publishing the accounts may have been significantly after the end of March.

2.3.3 Other Approaches

(1) Beaver's Study

Beaver (1968) investigated the extent to which share price changes can be used to predict failure and the reliance that investors place on accounting ratios in assessing the solvency position of firms, in an attempt to "explore the degree of association "between share price changes and accounting ratios. The same sample of Beaver (1966) was used in this study. The annual rate of return and the adjusted annual rate of return were computed for each firm. The latter was defined as the residual rate of return and computed by subtracting the market average rate of return (Fisher's Link Relative) from the individual rates of return (i.e. assuming $\hat{\alpha} = 0$ and $\hat{\beta} = 1$, see Chapter 3 for the definition of the market model). The comparison between the median values of the unadjusted and adjusted rates of return for the two groups of firms showed that the median rates of failed firms were poorer than those of the non-failed firms for five years prior to failure and that the difference between the median values increased as failure approached.

Based on this finding, Beaver (1968, p.182) argued that "investors appear to adjust to the new solvency position of the failed firms continuously over the five-year period, but the largest unexpected deterioration still occurs in the final year before failure. The implication is that investors are still surprised at the occurrence of failure, even in the final years before failure". Beaver performed his 1966 dichotomous classification test using both rates of return and compared the results with those of the cash flow to total debt ratio. He found that the latter outperformed the former in terms of correct classification. To determine how soon investors (as compared with financial ratios) can forecast failure, Beaver defined the point in time at which failure is clearly predicted by the two rates of return and four accounting ratios (cash flow/total debt, net income/total assets, total debt/total assets and working capital/total assets). Thus, a cut-off point was selected for each rate of return and two cut-off points were selected for each ratio. The results indicated that investors forecast failure sooner than any of the ratios did, with average length of time from the year of failure's forecast to the date of failure being 2.45 and 2.31 years for the rate of return and the ratio of net income to total assets, respectively. Finally, contingency tables were constructed for the return forecasts versus those of the four ratios. These tables indicated imperfect association between the ratio and rate of return forecasts. Thus, Beaver concluded that his finding that investors forecast failure sooner than ratios is consistent with the contention that investors use the ratios in assessing the solvency positions of the failed firms. The lack of perfect association between ratio and return forecasts indicates that "investors either respond to non-ratio sources of information, they did not use the ratios as they are used here (by Beaver), or both".

However, in view of the development (subsequent to Beaver's study) of the market model for testing the capital market's external efficiency, Beaver's methodology is not acceptable. For example, Beaver's selection of one cut-off point for each of the two returns was based on his belief that improvement of ratios implies an improvement in solvency position which is not necessarily reflected in the rate of return. This belief is not consistent with the efficient market hypothesis.

(2) Blum's Study

Blum (1974), in the study reviewed above, concluded that the stock market was unable to anticipate the timing of failure and that the market prefers to invest in failing rather than non-failing firms, where his 'going to market' measure was higher for failing companies. This finding, however, is not reliable because it is not consistent with the efficient market hypothesis, supported by evidence elsewhere, and because it was based on a new unfounded measure called "Going to the market". This measure was defined as "the fair market value of the shares offered to the public or issued in mergers during a range of years, divided by the sum of the fair market value of net worth of the company at then end of each of the years in the range" (Blum, 1974, p.11). However, the numerical example given by Blum is not even consistent with the definition of his new measure. Moreover, he noted that "the market rate of return and fair market value of net worth were consistently higher for non-failed than failed companies".

(3) Gooi's Study

Gooi (1974) studied the share price behaviour of 26 UK-failed copmanies. He collected quarterly share price data for the fifteen quarters ending one week before the date of failure. The same data were collected for 26 non-failed firms. Each of the fifteen share prices was considered as an independent variables. The mean values of some of these variables were significantly different for the two groups. The variable x_{jt}, which is the residual for security j at quarter t was computed (assuming $\hat{\alpha} = 0$ and $\hat{\beta} = 1$) as:

$$X_{jt} = \text{Ln}\ (\text{price}_{jt}/\text{price}_{j(t-1)}) - \text{Ln}\ (\text{index}_t/\text{index}_{z-1})$$

The cumulative sum technique, borrowed essentially from the quality control field, was used to detect any significant change in mean share price - a change that forewarns of possible impending bankruptcy. The technique implies subtracting a selected constant (c) from the value of each observation (x_{jt}) and accumulating the resulting values (x_{jt}-c). These accumulated sums are then plotted and a V-mask is used to determine the onset of cumulated price changes. The value of the subtracted constant (which was set to zero) and the parameters of the V-mask are all subjectively determined. Thus, the technique (apart from the plotting and masking) appears to be a mere accumulation of the individual residuals (as defined by x_{jt} above). However, it was concluded that although share price changes for bankrupt companies tended to show a down-turn three or four years before bankruptcy, they could be used to identify bankrupt firms only 12 to 15 months before bankruptcy.

A discriminant model was developed for the two groups of firms using the residuals, X_{jt}, as independent variables (15 in number). The resulting function incorporated 7 residuals. It was concluded that despite the unreliability of the discriminant function it confirmed that share price changes might be used to identify bankrupt firms as far back as 12 to 15 months before bankruptcy. Thus, it was argued that accounting ratios might perform better than share prices, in the context of failure prediction.

In short, the discussion of this section (2.3) indicates that the market model, which has been extensively used to test the semi-strong form of the stock market's external efficiency (i.e. that share prices fully reflect all publicly available information), offers the best methodology for examining the content of accounting information and the ability of the capital market to anticipate corporate failure. Only one of the previous studies appears to have, properly, used the market model to investigate the pre-bankruptcy behaviour of share prices. However, also the results of Beaver and Gooi appear to be interesting despite their inconsistency with the efficient market hypothesis.

2.4 Concluding Remarks

This chapter reviewed the previous studies which are closely related to the problem of the present study. These studies were classified into two broad groups. The first group reviewed the studies which are concerned with predicting corporate failure using accounting data and included the univariate, multivariate and other studies. The second group reviewed the studies which are concerned with the ability of the stock market to anticipate corporate failure. However, the following remarks can be safely made about the above reviewed studies.

1. All the previous studies adopted the objective of developing models to predict corporate failure either for the usefulness of these models, to reveal the usefulness of accounting information when used in a multi-variate models, or to test the usefulness of a particular model or technique. Thus, none of the previous studies was concerned with the previously determined two aspects of the usefulness of accounting information.

2. Industry and economy-wide indicators were not explicitly considered in any of the previous studies while there are reasonable a priori grounds for believing they may be good predictors of corporate failure.

3. Accounting ratios considered in the above reviewd studies were frequently not properly examined before being included in the prediction models. Specifically, none of the previous studies has investigated the stability of accounting ratios as measures of a firm's financial attributes. The available empirical evidence indicates that some ratios may measure different financial attributes for different periods of time and (as may be expected) for different groups of companies. Consequently, failure prediction models ought to be improved by avoiding unstable ratios.

4. All the models of the previous studies were single-year models except those of Blum (1974) and Edmister (1972) were multi-year models. All the single-year models, except Deakin's (1977), were based on the data of the first year before failure. Deakin (1977) fitted a discriminant function to a predefined model using the data of the second year before failure.

5. Regarding the a priori definition of a failure prediction model, some studies (e.g. those of Deakin and Blum) defined their models by a number of specific ratios. This procedure may result in an inconsistent function (see: the comment on Deakin's (1977) study). Therefore, models can be better defined in terms of financial attributes rather than particular accounting ratios.

6. Most of the previous studies did not allow for prior probabilities and costs of misclassification.

7. All the previous studies have claimed success in predicting corporate failure. The deteriorating efficiencies of those models for the years prior to the first before failure (the year of the models) were not explained (see: Chapter 1 for our explanation).

8. The pre-bankruptcy behaviour of share prices has been examined in some studies. The finding of only one of these studies was consistent with the efficient market hypothesis. However, none of them was concerned with the evaluation of the usefulness of accounting information.

Finally, the above remarks and review of this chapter have their implications for the design of the present study's methodlogy which is the subject of the next chapter.

CHAPTER III

RESEARCH METHODOLOGY

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

This chapter reports on the methodology which is necessary to develop and verify failure prediction models and to test the content of accounting information regarding business failure, as an information generating event.

The essence of failure prediction is the establishment of a combination of selected characteristics which can discriminate between failing and non-failing companies. For a specific company, failure is predicted if its combination of characteristics resembles the combination of the failed firms, otherwise success may be predicted. Therefore, accounting ratios (the measures of a firm's financial attributes) are used to define the characteristics of the two groups of companies and to predict failure or non-failure afterwards. Since industry and economy-wide indicators are believed to affect the firms' financial characteristics, they are also considered. Statistically, the problem of failure prediction is one of classifying companies according to their individual attributes into one of two a priori groups. Multiple Discriminant Analysis (MDA) and Multiple Regression Analysis (MRA) can equally handle this problem. However, their successful application requires a statistical preparation of the independent variables and a particular sample design.

The essence of testing the content of accounting information is to isolate from the security's returns those proportions which reflect the specific infromation which was used by the market in pricing that security. Those proportions are measured as the residuals of the market model. The analysis of the residuals reveals the investors' attitude towards the failing securities. The parameters of the market model are estimated by simple regression analysis and are then used to calculate the residuals. The successful application of the market model requires the proper computation of both security and market price relatives and adopting a validation procedure to avoid biasing the estimates of the model's parameters.

Although the above presentation appears to suggest that the argument of this chapter is divided into two parts, it seems better to present this argument by separating out the models' definition, the methods of processing, the independent variables and the samples design. Thus, each of these elements is the subject of one of the following sections.

3.2 Models Definition

Each of the following two models is concerned with one aspect of the usefulness of accounting information and tests of one or more of the hypotheses of Chapter 1.

3.2.1 Failure Prediction Model

A failure prediction model (3.1) is defined as a formal expression of the functional relationship between a firm's financial state as to failure or success and, on the other hand, its financial attributes, as measured by accounting ratios and industry and economy-wide indicators, the latter two factors are exogenous variables.

$$y_i = f\ (x_{1i},\ x_{2i},\ldots\ldots\ldots\ldots,x_{ki},\ I_{ji},\ E) \qquad (3.1)$$

Where y_i = a nominal dependent variable representing failure or non-failure for the ith firm

$x_{1i}\ldots\ldots x_{ki}$ = 1.......k independent variables representing the ith firm's financial attributes.

I_{ji} = represents the jth industry of which the ith firm is a member.

E = represents the economy-wide indicator.

The following points should be noted regarding the above model:

(1) It is not defined in terms of particular financial attributes nor in terms of accounting ratios which measure those attributes. Instead, it includes all the measurable financial attributes and industry and economy-wide indicators. As previously argued, the final selection from all of these variables is made in this study through the stepwise procedure guided by the results of the principle component analysis for the different periods of time and for the two groups of companies (see: section 3.4). The latter procedure tests hypothesis 5 and the development of the above model tests hypotheses 1, 2, 3 and 4 of Chapter 1.

(2) Operational versions of the above model are developed using the data of each year before failure (as defined in section 3.5) separately and collectively. The purpose of this procedure is to test hypothesis 4 of Chapter 1 and to select the most powerful model(s).

(3) Two statistical techniques, MDA and MRA, can be used to develop this model.

Although the two techniques are mathematically identical, their distributional assumptions and derivations are in fact quite different (Ladd, 1966 and Meyer and Pifer, 1970). Empirical data always violate the assumptions of the two techniques (see: Eisenheis, 1977 and Kendal, 1975, p.150 regarding discriminant analysis; and Frank, 1971, p.273, and Nguyen, 1975 regarding regression analysis). Therefore, the selection between MDA and MRA has to be empirical and distributional, i.e. select the method with the assumptions that can be more approximately satisfied by the empirical data (see: Ladd, 1966). In this study, both techniques are used and their empirical results are compared.

3.2.2 The Market Model

The well known market model is used to test the ability of the London Stock Exchange (LSE) to anticipate corporate failure (or the investors' attitude towards the securities of failing companies). Thus, it tests hypothesis 6 of Chapter 1 and provides evidence regarding the content of accounting information and the efficiency of LSE.

The market model was first used by Fama, Fisher, Jensen and Roll (FFJR) (1969) "to examine the process by which common stock prices adjust to the information (if any) that is implicit in a stock split." The "methodology used in this work has been a model for subsequent research on both sides of the Atlantic." (Henfrey, et al., 1977).

The market model specifies a linear relationship between returns on security i and returns on the market portfolio in month t. The logarithmic form of this model is:

$$\log_e R_{it} = \alpha_i + \beta_i \log_e R_{mt} + u_{it} \qquad (3.2)$$

Where:

$R_{it} = (P_{it}+D_{it})/P'_{i,t-1}$ = price relative of the ith security for month t.

P_{it} = price of the ith security at the end of month t.

$P'_{it} = P_{it}$ adjusted for capital changes in month t + 1.

D_{it} = cash dividends for the ith security traded ex-dividend in month t.

R_{mt} = price relative based on an appropriate market index (e.g. Financial Times Actuaries Index, FTA).

u_{it} = residual term, which is assumed to satisfy the usual assumptions of the linear regression model (see subsection 3.3.3).

As indicated in subsection 2.3.1, the market model is used to test the semi-strong form of the stock market's external efficiency. The information which is presumed to be used for pricing the securities is of two types: the information that affects the prices of all securities and is reflected by a market index and the information that is specific to a security and is reflected in the residual term u_{it} (the abnormal return) of the above model (3.2). Thus, the relationship presented by the market model (3.2) is used to isolate the residual term. The analysis of the latter might be expected to reveal the effect of any information that has been available to the market about a particular event.

Therefore, the application of the market model implies two related sets of analyses - the estimation of the model's parameters which are then used to compute the residuals and the analysis of these residuals. The two sets are considered below, as well as some comments on the market model.

3.2.2.1 Estimating the Paramters

The unbiased estimate of the model's paramters requires eliminating the effect of non-trading and the satisfaction of the usual assumptions of the linear regression model.

First, the non-trading effect or Fisher effect refers to the lack of actual transaction prices at the regular intervals of share price data (which is a month in the data of this study). Thus, a monthly price may reflect a transaction which has taken place some time ago. In the latter case, the security's price relatives R_{it} will represent gains and losses over varying lengths of elapsed time while, on the other hand, the price relatives for the market index can hardly be affected by the non-trading. "The resulting lack of correspondence between the two sets of price relatives can seriously affect the covariance between them. The result would be a bias in estimates of Beta" (Franks, et al, 1977).

Fortunately, the details of the data bank used in this study (see: Chapter 4) are sufficient as to allow for the effect of non-trading. The method used by Franks, Broyles, and Hecht (FBH) (1977) is adopted in this study. According to that method, each period is assumed to have ended on the day of the last transaction rather than the end of the particular month.

Then both the security price relatives and the market price relatives are computed as at the former date. Accordingly, the dates and elapsed time for both price-relative series are made to correspond exactly. Each variable (R_{it} and R_{mt}) is divided by the age of the security price in order to restore all measurements to an equivalent monthly basis. The age of each price in days was computed as the difference between the "end of month date" and the "transaction date", excluding non-working days.

The daily market index which is used in this study is one composed of the Financial Times Actuaries Index (FTA)-consisting of over 500 companies - and the Financial Times 30 Index (FT30). The FTA was introduced in 1.3.1962. Before that date FT30 was available. The two indices have been linked together using the actual level of the FTA (i.e., 1.3.62 = 100, see: London Business School, 1977, p.12.1). The FTA is based on an arithmetic mean of price relatives and is weighted by the market capitalisation of each company, whereas the FT30 is based on a geometric mean and is equally weighted. Despite these differences in the two indices, their movements were found to be highly correlated subsequent to 1962 when the FTA was introduced (see: Franks, et al, 1977).

Second, the parameters of the model α_i and β_i are estimated by the linear regression program which is described in subsection 3.3.3. Because the market uses the available information to anticipate the event, there is likely to be abnormal behaviour of the residual ($E(u_{it} \neq 0)$) in the months close to the event's announcement date. Those months should be excluded from the estimating samples to avoid the possible biased estimate of α and β , because of violating the regression assumption of $E(u_{it}) = 0$ (FFJR, 1969).

The exclusion procedure used by FFJR, 1969, consisted of two steps. In the first step, the parameters of (3.2) were estimated using all available data; and then the residuals were computed for each security for some months preceding and following their studied event. In the second step, all months with a number of positive residuals substantially different from the number of negative residuals were excluded. Then the remaining months were used to estimate the parameters α_i and β_i.

FBH (1977) stated that the initial choice of the number of months to be excluded is arbitrary but it may be adjusted according to the resulting estimate of abnormal residuals. However, they "devised an alternative simple test for validation purposes."

FBH's, 1977, validation test is used in this study as the exclusion procedure. This test includes three steps. In the first step, the parameters of (3.2) are estimated using all the available data and then the residuals are computed for each security for a number of months before failure announcement. In the second step, both the mean and standard deviation of the residuals of each security are computed and the months with residuals more than two standard deviations from the mean are excluded from the sample. This procedure excludes the abnormal residuals within the whole series but it does not exclude the abnormal returns which are not outliers. In the third step, the parameters of (3.2) are reestimated using the reduced sample of data and the residulas of each security are computed and subjected to the type of analysis described in the next subsection. The latter analysis provides an estimate of the number of months, before failure announcement, that should be excluded from the data for the purpose of the final estimate of the market model's parameters. Using these estimated paramters, the residuals can be computed as:

$$\hat{u}_{it} = \log_e R_{it} - (\hat{\alpha}_i + \hat{\beta}_i \log_e R_{mt}) \qquad (3.3)$$

3.2.2.2 Residual Analysis

The above residuals (3.3) are computed for each company in the sample for the number of months before failure announcement. These residuals are then analysed as follows:

(1) The behaviour of cross-sectional averages of the computed residuals may indicate the ability of the stock market to anticipate corporate failure. The average residual for month m can be measured as:

$$u_m = \frac{1}{N_m} = \sum_{i=1}^{N_m} u_{im} \qquad (3.4)$$

where m is measured relative to the failure announcement date (month zero) and N_m is the number of securities in the sample at time m. The average residual u_m can be interpreted as the average deviation (in month m relative to the failure month) of the returns of failed stocks from their relationship with the market (see: FFJR, 1969).

(2) The cumulative impact of the residuals can be measured in one of two ways:

a. The cumulative average residual (CAR), which is used by FFJR (1969) and is defined as:

$$U_m = \sum_{t=-k}^{m} u_t \qquad (3.5)$$

where k is the number of months, which is selected for analysis prior to the failure announcement date. U_m can be interpreted as the cumulative deviations of the return on the securities from their relationships to market movements (see: FFJR, 1969). Firth (1977, pp.129-130) pointed out that the CAR approach assumes a portfolio in which the investment in each security is adjusted so that there is an equal dollar investment in each security at the start of each period.

b. The Abnormal Performance Index (API), which is first used by Ball and Brown (1968) and is defined as:

$$API_m = \frac{1}{N_t} \sum_{i=1}^{N_t} \prod_{t=-k}^{m} (1 + u_{it}) \tag{3.6}$$

where N_t is the number of all securities at time t = -k).
The API traces out the value of £1.0 invested in equal amounts in all securities (i = 1, 2,.....N) at the end of month t = -k and held to the end of month m, after abstracting from market effects (Ball and Brown, 1968). Firth (1977) noted that "unlike the cumulative average residuals the API does not rebalance the portfolio for each day or period so as to obtain equal dollar investments at the start of thatperiod." However, both CAR and API are used in this study.

3.2.2.3 Remarks on the Market Model

The validity of using the market model for empirical research purposes has recently been questioned. Brenner (1977) has referred to the false results of a mis-specified model and argued that "the possibility that the efficient market hypothesis has not been rejected because the wrong market model was used, was never adequately considered" (p.57).

Schwartz and Whitcomb (1977) provided further evidence on the observed positive market index autocorrelation, negative autocorrelation of the market model's residuals and a deterioration in the market model's R^2 as the returns measurement period is shortened. However, they found that the fall of R^2 was caused by the two autocorrelations and that the major cause of the latter was the "Fisher effect" encompassing, according to them, both the market thinness and the delayed portfolio rebalancing.

Roll (1977 and 1978) was not concerned with the market model but his argument about the true market portfolio and its possible proxies are relevant to the applications of the market model. Mayers and Rice (1979) criticized some of Roll's conclusions because they appear to falsify the tests of both the market model and the capital asset pricing model, unless the exact composition of the true market portfolio is known and is used in the tests. Roll's reply (1979) included that the methodology of the market model should give an unbiased estimate of the value of the information associated with the event under study, even if the market index proxy is not ex ante efficient.

However, Roll (1978) referred also to the possible specification errors in the market model as a result of omitting an independent variable or because the market index is imperfectly diversified.

The industry price relative appears to be an omitted variable in the above market model (3.2). The industry effect which is common to all securities in a particular industry is believed to account for about 10% of share price movements (King, 1966). Meyers (1973) estimated the industry effect to be less than 10% while Livingston (1977) estimated it to be 18%. FBH (1977) found that the introduction of an industry component in the market model removes the bias which resulted from their sampling bias in favour of only those firms in the Breweries and Distilleries sector.

In this study the industry effect is not introduced in the market model because of the lack of daily indices for each of the industries covered by the sampled failed companies. However, there is no evidence to invalidate the findings of the above market model (3.2) which omits the industry effect.

Finally, the above discussion indicates that the adopted methodology gives consideration to the possible specification errors. It allows for the effect of non-trading, uses the best available market index and adopts a more objective procedure for determining the number of months to be excluded from the estimating sample.

So far, the failure prediction model and the market model have been defined and the latter's methodological points have been specified. All that follows is concerned with the former model.

3.3. Methods of Processing

The above discussion has referred to the fact that Multiple Discriminant Analysis (MDA) and Multiple Regression Analysis (MRA) are used in the development of the failure prediction models and that simple regression analysis is the method of developing the market model. Thus, MDA, the applicability of a discriminant function and MRA are briefly discussed in the following subsections. The discussion of the second point is also relevant to a regression function.

3.3.1 Multiple Discriminant Analysis (MDA)

The nature and assumptions of MDA and the SPSS's discriminant sub-program (The Statistical Package for the Social Sciences, Nie, et al., 1975) are each discussed in one of the following subsections.

3.3.1.1 The Nature and Assumptions of MDA

The objective of MDA is to classify objects, e.g. companies, by a set of independent variables into one of two or more predetermined, mutually exclusive and exhaustive categories (two or multi-point nominal dependent variable) (Morrison, 1969). MDA can be used as both a descriptive and predictive technique. Descriptive uses include the investigation of mean group differences and the overlaps among groups; while predictive uses require the formation of classification schemes to assign objects on the basis of their discriminant score to appropriate groups (Pinches and Mingo, 1973).

In the two group case, G = 2 as in this study, the MDA has the advantage of reducing the space dimensions from n - independent variables to one dimension, or generally to the smaller of n and G-1. In other words, the MDA simultaneously considers the independent variables as well as the interaction between them and represents each object, e.g. company, by one discriminant score.

The geometric interpretation of MDA can be seen for the case of two groups and two variables in Figure 3.1, as explained by Cooley and Lohnes (1971, pp. 244-5). The two variables, X and Y, are moderately positively correlated. The two sets of concentric ellipses represent the bivariate swarms for the two groups, A and B (e.g. failed and sound firms) in idealized form. Each ellipse is the locus of points of equal density (or frequency) for a group and might define the region within which 90 percent of the group lies. The two points at which the ellipses intersect define a straight line, II. If a second line, I, is constructed perpendicular to line II, and if the points in the two-dimensional space are projected onto I, the overlap between the two groups, A and B, will be smaller than for any other possible line.

The discriminant function, therefore, transforms the indiviudal attributes to a single discriminant score, and that score is the objects' location along line I. The point b where II intersects I would divided the one-dimensional discriminant space into two regions, one indicating probable membership in group A and the other region for membership of group B.

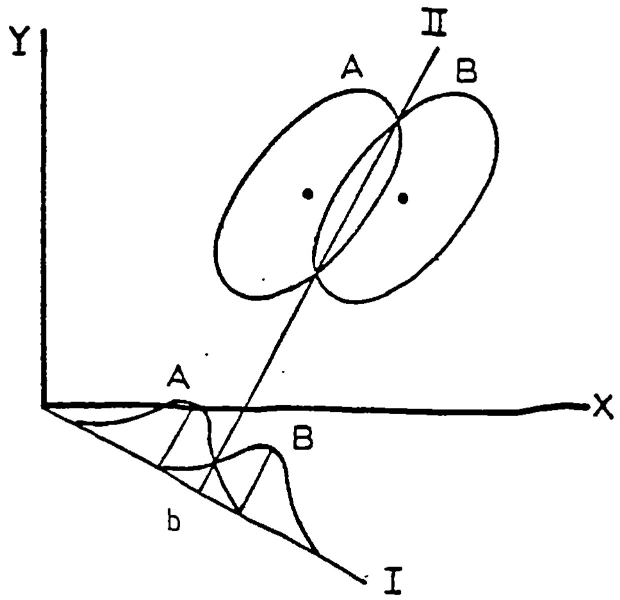


Figure 3.1 Geometric Interpretation of MDA

The basic assumption of MDA are that: (1) the independent variables of each group are multivariate normally distributed and (2) the group dispersion (variance - covariance) matrices are equal across all groups.

In practice, the technique is very robust and these assumptions need not be strongly adhered to (Nie, et al., 1975, p.435). As regarding multivariate normality, Lachenbruch (1975, p.45) concluded that the linear function performs fairly well on discrete data of various types (e.g. dummy variable). It is also suggested that continuous non-normally distributed data should be transformed and bounded from above and below because the linear discriminant function performed better on bounded data (see: Lachenburch, et al., 1973). "When continuous and discrete variables are mixed, procedures are proposed to split the samples based on the values of the discrete variables. Then standard discriminant analyses were employed on the subdivided samples" (Eisenbeis, 1977). This procedure seems plausible in either the case of a very large sample of data or the case of one dichotomous variable. In this study, for example, if the industry factor is represented by a set of n-dummy variables (n = number of industries - 1), this procedure would mean that a separate function should be fitted for the data of each industry, which is impossible because of the lack of data. However, Pinches and Mingo L973) used a dichotomous variable together with five continuous variables. Their predictive model was successful and their dichotomous variable was the most important variable for predicting bond ratings. Therefore, it seems plausible to represent the industry factor by dummy variables.

As regards the equal covariance matrices, statistical studies have indicated that the linear function is quite satisfactory, if the covariance matrices are not too different, and that the quadratic function is very poor for small sample sizes - which is the typical situation for this and similar studies (see: Lachenburch, 1975, pp.46-7). These findings are also confirmed by a failure prediction study (see: Altman, et al., 1977, which is reviewed in Chapter 2).

Since the function obtained under these conditions is not optimal, its usefulness has to be established by applying it to replication samples (see for example: Cooley and Lohnes, 1971, p.38 and p.262 and Kendall, 1975, pp.159-60).

Accordingly, the linear discriminant function is used to develop the operational versions of the failure prediction model above (3.1). Thus, the linear function fitted to the latter model can be expressed as:

$$Z_i = b_o + b_1X_{1i} + b_2X_{2i} + \dots + b_kX_{ki} + b_{n-1}X_{n-1,i} + b_nX_n \qquad (3.7)$$

Where: Z_i = the discriminant score of the ith company.

b_n = the discriminant coefficients, n = 0, 1, 2....K + 2

$X_{n-1,i}$ and X_n replace I_{ji} and E, respectively, in model (3.1).

Although the mathematical derivation of this discriminant function (DF) is beyond the scope of this study, defining the approaches of that derivation may aid tackling some of the problems of utilizing a discriminant function.

The problem of deriving a discriminant function is one of defining a rule to assign a vector of independent variables $\underline{X}$ (which represents an individual) to one of two groups G_1 or G_2. Since we use samples of size n_1 from G_1 and n_2 from G_2, we need a criterion of goodness of classification. Different criteria have been advocated and, accordingly, different rules of assignment have been adopted and resulted in the variation in the mathematical derivation of the discriminant functions. (see: Lachenbruch, 1975, pp.8-16).

In general terms, the Fisherian approach advocates the maximization of the ratio of the among-groups sum of squares on the function to the pooled within - groups sum of squares on the function (see: Cooley and Lohnes, 1971, p.246). This ratio can be defined as:

$$(\bar{Z}_1 - \bar{Z}_2)^2 \Big/ \sum_{i=1}^{2} \sum_{j=1}^{n_i} (Z_{ij} - \bar{Z}_i)^2$$

Where: $\bar{Z}_i$ is the mean discriminant score for group i, n_i equals the number of individuals in group i and Z_{ij} is the discriminant score of the jth individual of group i(see: Johnston, 1972 , pp.337-8).

Johnston (1972, pp.337-8) argued that this criterion provides an intuitive justification for the discriminant function for we would like to have discriminant coefficients which would differentiate the two populations as much as possible by maximizing the above ratio. The resulting assignment rule is to classify an individual according to its discriminant score (Z_j) as follows:

G_1: if Z_j is closer to $\bar{Z}_1$

G_2: if Z_j is closer to $\bar{Z}_2$.

The second (Welch's) approach advocates minimizing the total probability of misclassification. The derivation of a DF according to this approach requires that the population's prior probabilities and the form of the density functions ($f_1(\underline{X})$ of the vector $\underline{x}$ if it comes from G_1 and $f_2(\underline{X})$ if it comes from G_2) are known. The resulting assignment rule is to classify an individual as follows:

G_1: if $Z_j > \log_e \frac{P_2}{P_1}$

G_2: if $Z_j < \log_e \frac{P_2}{P_1}$ where p_1 and p_2 are the prior probabilities.

The discriminant coefficients of the independent variables are seen to be identical with those of the Fisherian approach (see: Lachenbruch, 1975, pp.10-11). This latter observation is consistent with Morrison's (1969) argument that the unequal prior probabilities only affect the constant term b_o, of the discriminant function (3.7).

The third approach minimizes the maximum probability of misclassification. It protects the users from a rule that does very badly on one population and is known as a minimax procedure. The requirements of this approach are similar to those of the previous one, but the resulting assignment rule is:

G_1: if $Z_j > \beta$

G_2: if $Z_j > \beta$

Where: β is determined by the distributions involved and equal 1 for the normal case with equal covariances (Lachenbruch, 1975, pp.15-16).

The last approach minimizes the total cost of misclassification. In addition to the requirements of the previous two approaches, the costs of misclassification are assumed to be known. The resulting assignment rule is:

$$G_1\text{: if } Z_j > \log_e \frac{c_2P_2}{c_1P_1}$$

$$G_2\text{: if } Z_j < \log_e \frac{c_2P_2}{c_1P_1}$$

where: C_1 and C_2 are the costs of misclassifying a member of G1 and G2, respectively.

Thus, although a degree of similarity can be noted among the above approaches, they do not result in the same assignment rule (cutt-off point) and at least the constant term of the DF is not identical under the different approaches. Consequently, the determination of a cut-off point should refer to the approach applied in the computer program to compute the DF.

3.3.1.2 <u>The SPSS's Discriminant Subprogram</u>

The stepwise discriminant subprogram of the SPSS is used to develop operational models of the above form (3.7) using the analysis sample (see: Nie, et al., 1975, pp.434-67). As previously mentioned, this stepwise procedure must be guided by the results of principal components analysis which is considered in section 3.4 below. However, according to any of five stepwise criteria, the independent variables are selected for entry into the analysis on the basis of their discriminating contribution. The five criteria are termed Wilks, Mahal, Maxminf, Minresid and Rao. Each of these criteria emphasizes a different aspect of "group separation", e.g., maximizing the overall multivariate F ratio for the test of differences among the group centroids and maximizing the Mahalonabis distance between the two closest groups (see: Nie, et al., 1975, pp.447-8). Thus, each of them is tried for the purpose of selecting one of them. In addition, this program allows the user to specify his own prior probabilities, so it is one of the best available discriminant programs (see: Lachenbruch, 1975, pp.19-20). Since the SPSS's discriminant subprogram is based on the Fisherian approach of deriving the DF, it uses the specified (if any) unequal prior probabilities at the stage of classifying the cases which is subsequent to the stage of computing the DF (see: Nie, et al, 1975, p.435 and p.445). Thus, this latter classification is not the same as classifying the cases according to their discriminant scores unless prior probabilities are set equal (which is the default value in the program). For this reason, for the purpose of comparing discriminant and regression functions and because of the problems of estimating prior probabilities and costs of misclassification (mentioned below), the latter two estimates are only considered in performing the last test of the functions (described below).

However, the output of this discriminant program includes standardized and unstandardized coefficients, group means, centroids of groups in reduced space (i.e., mean discriminant score of each group) a classification matrix and a classification of the cases other than those of the analysis sample. This output is then used to test the developed model and to make predictions.

3.3.2 The Applicability of A Discriminant Function

The fitted discriminant function should be statistically significant and each of its independent variables must contribute significantly to its overall discriminating power. Then the function's unstandardized coefficients together with a cut-off point can be used to classify companies for the purposes of testing the function's classifying and predictive powers.

Also, the performance of the function given estimates of the population's prior probabilities and the costs of misclassification must be evaluated before concluding the function's applicability. Each of these points is considered in the following.

3.3.2.1 The Function's Overall Significance

The statistical significance of a discriminant function indicates whether the observed between-groups differences are greater than would be expected by chance. "This determines if there is any hope of classifying future observations using the given variables" (Lachenbruch, 1975, p.25). This significance can be measured by F-statistics:

$$F = \frac{n_1 n_2}{n_1+n_2} \; \frac{(n_1+n_2-k-1)}{(n_1+n_2-2)k} D^2 \qquad (3.8)$$

Where: n_i is the number of observations from group i, k is the number of independent variables, and D^2 is the Mahalanobis's distance which is the difference between the group means of the discriminant function:

$$D^2 = \sum_{i=1}^{k} b_i \, (\bar{X}_{i1} - \bar{X}_{i2}) = (\bar{Z}_1 - \bar{Z}_2) \qquad (3.9)$$

where: b_i is the discriminant coefficient of the ith variable, $\bar{X}_{iG}$ is the mean of the ith variable of the Gth group, and $\bar{Z}_G$ is the mean discriminant score of the Gth group.

The resulting F-statistic has K and $n_1 + n_2 - K - 1$ degrees of freedom.

However, the statistical significance is a first necessary step but it is not a good indicator of the efficiency of a discriminant function (Morrison, 1969), so the latter can be evaluated by classifying the companies of other samples.

3.3.2.2 The Relative Importance of Independent Variables

The relative importance of each independent variable can be measured by one of the following methods:

(1) The standardized discriminant coefficients which are readily computed by the SPSS discriminant subprogram can be used to rank the variable according to their importance. Lachenbruch (1975, p.29) argues that this method is not generally useful, because the coefficients are determined only up to a constant multiple.

(2) The measure suggested by Mosteller and Wallace (1963), recommended by Joy and Tollefson (1975), and used in some previous studies (e.g., Altman, et al., 1977, and Taffler, 1977a). It measures the importance of a variable in terms of the proportion of the Mahalanobis's distance, D^2, accounted for by that variable which is defined as:

$$r_k = \frac{b_i(\bar{X}_{i1} - \bar{X}_{i2})}{\sum_{i=1}^{k} b_i\ (\bar{X}_{i1}-\bar{X}_{i2})} \qquad (3.10)$$

Where: r_k is the relative contribution of kth variable and b_i and $\bar{X}_{iG}$ are as defined above in (3.9).

The relative contribution of a variable r_k should have the same sign of the other variables' contributions. In failure prediction studies, this sign must be positive if we assume that group 1 (G = 1) is the non-failed group. Thus, the relative contribution of each variable must be positive and all the contributions must sum up to unity. If any of the latter two conditions does not hold, the model is not consistent and is unacceptable (see: Taffler, 1977a, and the comment on Deakin's, 1977, model in Chapter 2). Taffler (1977a) argues that a variable's negative contribution may be due to multicollinearity or very unequal dispension matrices and suggests the removal of such a variable. This latter procedure may not result in the satisfaction of the above two conditions.

(3) The conditional deletion method which removes each variable in turn from the k variable set, with replacement, and orders variables according to the resulting reduction in overall discriminating power - as

measured by the (k - 1) variables' F-statistic (see: Eisenbeis, 1977). This method was also used in previous studies (e.g. Altman, et al., 1977 and Taffler, 1977a).

However, it appears that none of the above methods is generally accepted as a measure of the relative contribution of each independent variable. Although method '2' appears to be measuring that contribution it cannot reveal how the contribution of the interaction between the variables affects that of each variables. Therefore, all the above methods can be regarded as methods of ranking the variables according to their importance.

3.3.2.3 Classification Tests

The classification of companies other than those of the analysis sample is the most important and acceptable test of a discriminant function's classifying and predicting powers. It, also, protects against capitalization on chance, where hazards of overfitting in multivariate analysis are great (Cooley and Lohnes, 1971, p.38). These tests of a function's classifying and predicting powers require determining a cut-off point, computing the discriminant scores of the companies of the corss validation and inter-temporal validation samples and, accordingly, classifying the companies to compute the efficiency measures.

(1) Determining a cut-off point: As indicated above, the determination of a cut-off point (a rule of assignment) depends on the approach to computing the DF. Since the discriminant program used in this study is based on Fisher's approach its cut-off point can be defined as follows:

$$Z_c = \frac{1}{2} (\bar{Z}_1 + \bar{Z}_2) \qquad (3.11)$$

Where Z_c is the cut-off point and $\bar{Z}_i$ is the mean discriminant score of group i. Thus, this cut-off point is the midpoint of the interval between

$\bar{Z}_1$ and $\bar{Z}_2$. If the independent variables are multivariate normally distributed, Lachenbruch (1975, pp.11-12) shows that $\bar{Z}_1 = \frac{1}{2} D^2$, the Mahalanobis's distance, and $\bar{Z}_2 = -\frac{1}{2} D^2$ and , thus Z_c is zero.

However, it is argued that if the prior probabilities are assumed equal and the costs of misclassification are also assumed equal while they are actually different, the results of the discriminant analysis may be misleading. Thus, the unequal probabilities and costs should enter the analysis in the computation of the DF and in both the determination of both the outcome of the chance models (as presented below) and the cut-off point (Lachenbruch, 1975, pp.8-16, Morrison, 1969, and Eisenbeis, 1977). In this latter case the cut-off point can be determined as follows: (Joy and Tollefson, 1975 and Morrison, 1969):

$$Z_c = \log_e \frac{q_2 C_2}{q_1 C_1} \qquad (3.12)$$

Where q_i stands for the prior probability of membership in group i and C_i stand for the cost of misclassifying a member of group i.

It should be emphasized that the above cut-off point cannot be used in this study for two reasons. First, the DF is computed to maximize the separation between the two groups while this cut-off point minimizes the total or expected costs of misclassification. Second, the development of a discriminant model includes the search for the best discriminating variables and it appears likely that this search is affected if a different approach is used to compute the DF or if different estimates are made about the prior probabilities or costs of misclassification.

These latter two points do not appear to have been properly considered by some authors. Joy and Tollefson (1975) defined a DF that maximizes the separation between the two groups and selected a cut-off point (3.12 above) which minimizes the expected total cost of misclassification. Another example is the restatement of the results of a study in terms of a different cut-off point (see: Eisenbeis, 1977).

However, Joy and Tollefson (1975) preferred (as indicated in Chapter 2) to use prior probabilities and costs of misclassification to test the performance of a DF (Altman's, 1968) regardless of the method of its computation and its cut-off point, i.e. as a classification strategy. This approach is used below.

(2) Testing the classifying power: The analysis sample is that which is used to develop a discriminant model or to fit a DF. The cross validation sample is similar to the analysis sample but is saved to test the classifying power of a DF. In terms of the split sample procedure the sample of companies covering a particular period of time is divided into two subsamples; one of which is the analysis sample and the other is the corss validation sample which is also referred to as the calibrating or hold-out sample (see: Frank, et al., 1965).

As previously indicated, the output of the SPSS's discriminant sub-program includes a classification matrix of the analysis sample. The proportion correctly classified of this sample may be due to true differences between the groups or an upward bias caused by sampling errors (as a result of using the sample means and variance as a proxy of the population's parameters) and intensive search for the variables that work best for the sample (see: Frank, et al., 1965). To eliminate the upward classification bias the DF should be used to classify the companies in the hold-out sample. Thus, the discriminant coefficients are used to compute the discriminant score of each company in the hold-out sample, then the cut-off point is used to classify the companies into one of the two groups and the results are presented in a classification matrix of the form of table 3.1 below.

The efficient classification of the cross validation sample proves the ex post discriminating power of the computed function, but it does not provide sufficient evidence on the function's predictive power. Assuming successful ex post discrimination, Joy and Tollefson (1975) recommend the reestimation of the coefficients of the same variables using the combined data (combined sample) of both the analysis and hold-out samples. Although this latter procedure is a part of the hold-out (split sample) method of estimating the error rates (see: Lachenbruch and Mickey, 1968) it has always been overlooked in the financial studies using the MDA technique. The major drawbacks to this method are that the coefficients which will be used for prediction are not the evaluated ones and it does not make the optimum use of the available data.

Alternatively, Lachenbruch proposed the "leaving-one-out (or U) method" (see: Lachenbruch and Mickey, 1968 for the method's performance). This method holds-out one observation at a time, estimates the descriminant functions based upon $n_1 + n_2 - 1$ observations and then classifies the held-out observation. This process is repeated until all observations are classified and then m_i/n_i is the proportion of misclassified observations out of n_i of group G_i. The disadvantage of this method is that it requires the computation of $N_1 + N_2$ discriminant functions for each function to be tested.

However, both the split sample and Lachenbruch's leaving-one-out methods are used to develop and test the classifying power of failure prediction models. In this way the drawbacks of the split sample procedure are avoided while making benefit of the advantages of the two methods.

(3) Testing the predictive power: Given that the above tests do not provide evidence on a model's predictive power, Joy and Tollefson (1975) suggest that this power can be tested by classifying the companies of an inter-temporal validation sample. The latter sample comprises some companies' data which are concerned with a time period subsequent to that covered by both the analysis and hold-out samples. Therefore, the efficient

classification of this sample provides sufficient evidence on the predictive power of a discriminant function.

However, the results of this and the previous classification tests are represented in classification matrices of the following form (Table 3.1).

Classification Matrix - Table 3.1

Actual Group	Classified as		
	Failed	Non-Failed	Total
Failed	n_{11}	n_{12}	$n_{1\cdot}$
Non-Failed	n_{21}	n_{22}	$n_{2\cdot}$
Total	$n_{\cdot 1}$	$n_{\cdot 2}$	$n_{\cdot\cdot}$

Where: the first subscript in n_{ij} refers to actual group while the second refers to the classification group.

The purpose of these matrices is to prepare for computing the following measures of the discriminant function's efficiency (see: Joy and Tollefson, 1975):

a. Total efficiency is measured by the ratio of total correct classifications to the total number of observations. It shows the overall efficiency of a model and is computed as:

$$\text{Total Efficiency} = n_{11} + n_{22} \,/\, n_{\cdot\cdot} \tag{3.13}$$

b. Conditional efficiency: These measures are ancillary to the total efficiency measure and can be divided into two groups:

1. Measures concerned with the probability of correctly classifying a company given its group membership, i.e., the two probabilities of correctly classifying a failed firm and a non-failed firm:

$$P(n_{.1} / n_{1.}) = n_{11} / n_{1.} \quad (3.14)$$

$$P(n_{.2} / n_{2.}) = n_{22} / n_{2.} \quad (3.15)$$

2. Measures concerned with the probabilities of actual group membership similar to the given classified group membership, i.e., the two probabilities of correctly classifying a classified failed firm and a classified non-failed firm:

$$P(n_{1.} / n_{.1}) = n_{11} / n_{.1} \quad (3.16)$$

$$P(n_{2.} / n_{.2}) = n_{22} / n_{.2} \quad (3.17)$$

The measures 3.14 and 3.16 are concerned with the population's smaller group and are the most important measures (see: Morrison, 1969). However, these measures should be compared with the results of other classification strategies. Given estimates of prior probabilities and costs of misclassification the expected performance of a discriminant function can be evaluated as described below.

3.3.2.4 Prior Probabilities and Costs of Misclassification

According to the argument made by Joy and Tollefson (1975) the population's prior probabilities are used to evaluate the expected performance of a DF on a random sample from that population. In addition, the costs of misclassification are used to evaluate the expected cost (EC) of using a DF per entity of decision making (see: Chapter 2 for an application of this evaluation to Altman's (1968) DF).

(1) Evaluating the Expected Performance: This evaluation is made by comparing the expected performance of a DF on a random sample (EP_{DF}) with that of the proportional chance criterion ($EP_{prop.}$) which are defined as follows:

$$EP_{DF} = q_1 \ (n_{11} \ / \ n_{1.}) + q_2 \ (n_{22} \ / \ n_{2.}) \qquad (3.18)$$

Where: q_1 and q_2 are the population's prior probabilities of failure and non-failure. n_{ii} is the correct classifications of group i and $n_{i.}$ is the total companies in group i.

$$EP_{prop} = (q_1)^2 + (q_2)^2 \qquad (3.19)$$

It should be noted that the population's priors rather than the sample frequencies are used above. Neter (1966) advocated the application of the former because the decision makers are not expected to be faced with the latter (usually 1:1).

Also, the proportional rather than the maximum chance criterion is used above. Morrison (1969) argued that, since the discriminant function defies the odds by classifying an individual in the smaller group, the chance criterion should take this into account and therefore the proportional chance criterion should be used.

(2) Evaluating the Expected Cost: the expected cost of making a decision using the DF (EC_{DF}) can be evaluated by comparing it with that of using the proportional chance model (EC_{prop}). The two costs are defined as follows:

$$EC_{DF} = q_1 \ (n_{12}/n_{1.})C_1 + q_2 \ (n_{21}/n_{2.})C_2 \qquad (3.20)$$

Where: n_{ij} is the number of companies of group i misclassified in group j, $(n_{12}/n_{1.})$ and $(n_{21}/n_{2.})$ are type I and type II errors, $q_1 \ (n_{12}/n_{1.})$ and $q_2 \ (n_{21}/n_{2.})$ are the estimated probabilities that a randomly selected entity will be misclassified by the DF and C_1 and C_2 are the costs of misclassifying a bankrupt and a non-bankrupt firm, respectively.

$$EC_{prop} = q_1 \ q_2 \ C_1 + q_1 \ q_2 \ C_2 = q_1 \ q_2 \ (C_1 + C_2) \qquad (3.21)$$

The DF would be superior to the proportional chance criterion if and only if $EC_{DF} < EC_{prop}$. For the purpose of the above evaluation the population's prior probabilities and the ratio of C_1/C_2 must be known. The latter needs not to be known exactly. It is sufficient to know that the ratio C_1/C_2 is greater or less than some critical number (see: Joy and Tollefson, 1975).

However, estimating the prior probability of corporate failure is not an easy task for four reasons: (1) the population priors are not stable over time; (2) the computed function is to be used to make predictions about the future; (3) the data on the failed group is usually obtained by pooling observations from different time periods (see: Eisenbeis, 1977) and failure rates are expected to vary for the different classes of firm's size and for the different industries. Therefore, the prior probability of corporate failure may only be subjectively estimated.

On the other hand, the estimation of costs of misclassification is, admittedly, subjective and can only be made by the decision makers (see: Lachenbruch, 1975, p.15).

However, the above approach allows for the consideration of alternative estimates of prior probabilities and costs of misclassifications. The subjective estimates used by Taffler (1977a) are used in this study. These estimates were made by a group of financial analysts who estimated prior probability of failure at 10% and C_1/C_2 at 40:1.

Finally, a DF which satisfies all the above tests (of section 3.3.2) can be used in practice to predict corporate failure. As shown below, these tests are also applicable to the regression function which is fitted to a failure prediction model.

3.3.3 Multiple Regression Analysis (MRA)

Regression analysis is the most popular technique in econometrics (Farrar and Glauber, 1967), the most important technique in statistics

(Kshirsagar, 1972, p.4) and the equivalent to discriminant analysis in the case of a dichotomous dependent variable (for mathematical derivation, see for example: Ladd, 1966, Kshirsagar, 1972, pp.206-14, and Kendall, 1975, p.157). Although, most of the previous financial studies have referred to the equal capabilities of both discriminant and regression analysis, the selection between them has not been made upon the basis of their empirical results (see for example: Altman, 1968 and Meyer and Pifer, 1970).

The geometric interpretation of the regression line for a dichotomous dependent variable and one independent variable can be seen in Figure 3.2. Since Y is only 0 or 1, all the observation points must lie on either the horizontal line Y = 0, for failed firms, or at Y = 1, for sound firms.

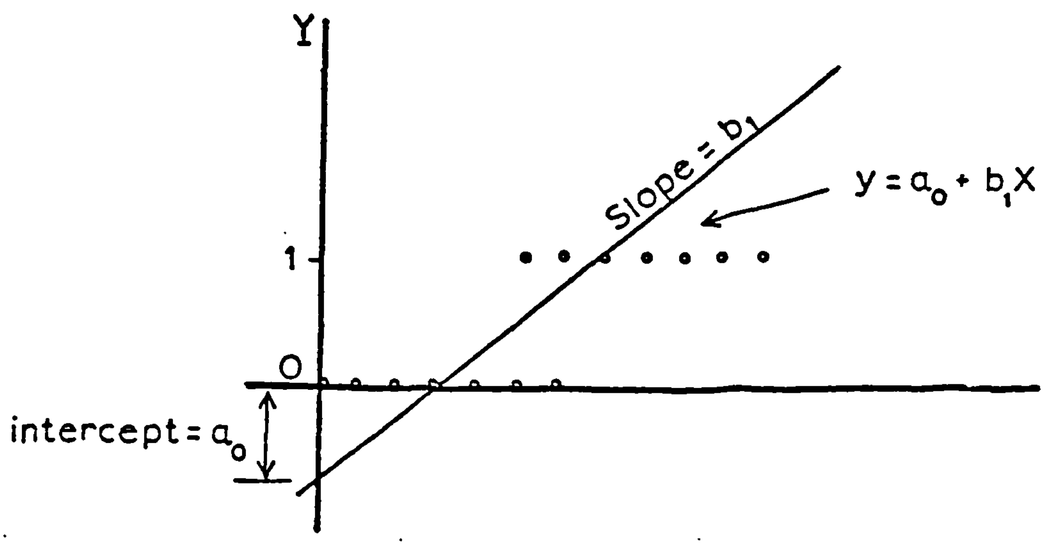


Figure 3.2 Regression Line for a Dichotomous Dependent Variable

The predicted value of Y has been interpreted as an estimate of the conditional probability that the event will occur given the X value (Goldberger, 1964, p.249 and Meyer and Pifer, 1970). Since the predicted value of Y may be outside the interval between 0 and 1, this interpretation is inconsistent. Alternatively, the predicted values of Y will be interpreted in this study as an index of scores assigned to the firms given the Xs (see: Frank, 1971, p.346 for the idea of regressing a dichotomous variable Y on the Xs to compute an index of values or scores). As Fig.3.2 indicates, the intercept a_0 is the constant term and represents the value of Y when X = 0. The slope of the regression line b_1 is the regression coefficient and indicates the expected difference on Y between two groups that happen to be different on X by one unit. Therefore, the computed functions are used to assign firms to either group 0 or group 1. They are used in the same way as the computed discriminant functions(see: section 3.3.2). However, the basic assumptions of the least squares linear regression model are (see for example: Chiswick and Chiswick, 1975, p.139):

(1) The residual is normally distributed with a zero mean.

(2) The residual is uncorrelated with the explanatory variable.

(3) The residual variance is consistant for all values of X.

(4) The values of the residual are not correlated with each other.

Frank (1971, p.344) stated that very few of the usual assumptions are satisfied if a linear regression model is used when the dependent variable is limited to 0 or 1. The violation of the above assumptions results in biased estimates of both the regression coefficients and their standard errors and makes the application of the standard tests of significance unjustifiable.

Despite the consequences of violating the above assumptions, Kshirsagar (1972, p.209) indicated that "The discriminant function and the regression function are thus the same, apart from a constant of proportionality, and this regression approach will also lead to the same classification procedure....." Moreover, he stated (p.211) that the F-test can be used to test for the null hypothesis that the true regression coefficents are all null, which is equivalent to $\underline{U}(1) = \underline{U}(2)$, and that "The justification of the test does not come from the usual regression theory, but from the distribution of D^2 (Mahalanobis D^2)."

Therefore, a linear regression function will be fitted to our model (3.1) which will have the following form:

$$\hat{y}_i = b_0 + b_1X_{1i} + b_2X_{2i} + \ldots\ldots + b_kX_{ki} + b_{n-1}\, X_{n-1,i} + b_nX_n + u_i \quad (3.22)$$

Where:

y_i = the score assigned to the ith company.

b_n = the regression coefficients, $n = 0, 1, 2, \ldots, K + 2$

X_{n-1} and X_n, respectively, replace I_{ji} and E in model (3.1).

The stpewise regression subprogram of the SPSS (Nie, et al., 1975) can be used to develop a regression model of the above form using the analysis sample. Alternatively, a regression function can be fitted directly to the variables of the models which were developed using discriminant analysis. Therefore, some experimental runs using the stepwise regression may indicate the extent to which the results of the stepwise discriminant and the stepwise regression (both guided by the results of principal components analysis) are different. Accordingly, a selection can be made between the above two alternatives. However, a comparison between discriminant and regression functions can be better made when the two functions are fitted to the same model.

The output of the SPSS's regression subprogram include the standardized and unstandardized regression coefficients, R^2 - the coefficient of determination, the estimated values of the dependent variable (which are the discriminating scores) and the residuals of the model.

The coefficient of determination R^2 can be used to comput D^2, the Mahalanobis's distance between the two groups. The relationship between R^2 and D^2 is expressed as follows (see: Lachenbruch, 1975, p.19):

$$D^2 = \frac{R^2}{1 - R^2} \; \frac{(n_1 + n_2)\,(n_1 + n_2 - 2)}{n_1 \, n_2} \qquad (3.23)$$

Thus, the statistical significance of the regression function can be tested by the F-statistic which can be computed by equation (3.8) above. Also, all the tests presented in section 3.3.2 above can be applied to the regression function. Finally, a comparison is held between the discriminant and regression functions upon the basis of the results of those tests.

So far, the models of this study, their methods of processing and the methodological points associated with their application have been specified. It is thus relevant to identify the independent variables of the failure prediction model, their measurement, their statistical nature and problems and the methods of dealing with these problems.

3.4 The Independent Variables

The independent variables of the failure prediction model (3.1) can be classified into two groups: (1) the firm's financial attributes, e.g. profitability, liquidity, capital gearing, growth, risk and size - and (2) the environmental or uncontrollable variables, i.e. the industry and the economy-wide factors.

The firm's size is classified in this study as one of the firm's financial attributes for two reasons: (1) it can be measured by accounting numbers as the firm's other financial attributes and (2) it is relatively more controllable than the above mentioned environmental variables.

However, the firm's financial attributes are related to each other (as shown below) and are affected by the environmental variables.

Size was found to have only marginal (Barna, 1962) or no effect on both growth and profitability but the variation of profitability and growth was found to decline as asset size increases (Singh and Whittington, 1968, pp.191-2, Whittington, 1971, p.146 and Jacquemin and Cardon, 1973). However, Gupta (1969) found that there is a dependence between accounting ratios (except those of profitability) and firms size. He argued that smaller-sized firms face a strong constraint on the availability of investment funds and, thus, they have to economize on the use of available resources. This partly explains their high inventory turnover, high cash velocity, low average collection period, higher fixed assets turnover, higher gearing and lower liquidity.

As regards growth and profitability, the findings of the above mentioned studies indicate a high correlation between them (see also: Marris, 1967). Profitability (the rate of return) was found to be the best discriminating variable in almost all the previously discussed models of failure prediction. However, growth was not one of the variables of any failure prediction model. This may be explained by its high correlation with profitability, but more importantly growth may be one of the symptoms of failure (see section 1.5 of Chapter 1). Deakin (1972) noted that the failed firms (in his sample) tended to expand rapidly in the third and fourth years prior to failure and that the expansion was financed by increased debt and preferred stock rather than common stock or retained earnings. These firms were unable later to generate the sales and net income to support their heavier debt and, so they lost their assets rather rapidly after the third year prior to failure. There is also the danger of financing growth through current liabilities. Thus, the effect of growth should be considered in the context of both capital gearing and liquidity.

Capital gearing and liquidity are both concerned with a firm's ability to pay its debts when they come due. The former is concerned with the long-term debt while the latter is concerned with those of the short-term. Capital gearing is also associated with a firm's risk (see: Beaver, et al., 1970). The latter is measured by earning variability (five of these measures are considered in this study, see appendix B) or by the accounting beta - derived from the accounting analogue of the market model (see: Ball and Brown, 1969, Beaver, et al., 1970, Gonedes, 1973 and Derstine and Huefner, 1974). Thus, higher gearing and higher earnings' variability imply higher risk and higher-risk firms are more prone to failure.

In addition to the above mentioned attributes of a firm, there is another attribute that deserves consideration - that is a firm's "prestige" or the "importance of a firm" as termed by Prais (1976, pp.2-3). This attribute may be supported by the belief that a company's interested parties usually give their support to the company during its hard times if it enjoys a high prestige or assumes a high importance. However, not all the aspects of a firm's importance are amenable to quantitative measurement, e.g. its importance to the employees, consumers, public and society. Although a firm's importance may adequately be measured by the ratio of the firm's value added to the national product, the lack of data and the conceptual problems of the value added at the firm's level make this measurement almost impossible (see:Rutherford, 1977). Therefore, a measure similar to, but less inclusive than, the value added is used in this study in addition to the ratio of exports to sales.

As concerns the industry and economy-wide indicators, Brown and Ball (1967), using accounting measures of earnings, found that the market earnings (also measured by accounting earnings) may explain 35 to 40 percent of the variability of a firm's earnings and that a further 10 to 15 percent can be explained by the industry earnings (see section 3.2.2 for similar effects on the share prices).

The studies by Lev (1969), Gupta (1969) and Bird and McHugh (1977) indicate that the industry factor affects a firm's accounting ratios. Altman (1970) suggested that ratio models dealing with firms in a particular industry will yield more representative parameters which can be useful for future predictions of other firms in the same industry. Taffler (1977b) though controlled for the industry effects and omitted some accounting ratios as being potentially industry dependent, he questioned the impact of industries on accounting ratios if the analysis is undertaken at the company level. However, the analysis at the company level also indicated the impact of industries on accounting ratios (Brown and Ball, Lev, Bird nad McHugh, as above). In addition, as argued in Chapter 1, there is a strong belief that industry and economy-wide indicators are good predictors of failure.

The above two groups of independent variables are each considered below, as to their measurement and statistical nature and problems.

3.4.1 The Firm's Financial Attributes

Financial attributes can be measured through the use of accounting ratios - where each ratio expresses a relationship between two accounting items or an aggreate of itmes (e.g. capital employed) that are contained in published financial statements. It is usually argued that a ratio conveys information about a particular financial attribute of the firm. Usually, a large number of similar accounting ratios can be computed to measure the same attribute or to convey a similar information about it. Thus, there appears the need to select "logically independent ratios" and to avoid, as far as possible, redundant ratios (see: Benishay, 1971).

In many of the previous studies, accounting ratios were selected on the basis of one or more of the following criteria: (1) frequent appearance in the literature; (2) effectiveness in previous studies; (3) dependence upon a "cash-flow" concept and (4) consultation with experts (see: Beaver 1966, Horrigan 1967, Fadel 1977, p.19 and Taffler 1977a).

In this study, a large number of accounting ratios are included, providing that each ratio satisfies two conditions:

1. The ratio has been, or is being, perceived as a measure of one of the firm's financial attributes.
2. The ratio can be calculated within the limits of published accounting information which is available for this study.

A large number of logically justifiable ratios should meet these conditions (for some examples of illogical ratios, see: Myer, 1969, pp.195-7). However, as mentioned above, most of these ratios are redundant and only few of them can convey the information contained in most of the considered ratios. This fact is explicable by the statistical characteristics of accounting ratios, which are discussed in subsection 3.4.1.1. Also, as mentioned in the previous chapters, some ratios may measure different attributes for the different periods of time and for the different groups of companies. Therefore, a method of Factor Analysis is used in this study to select those few accounting ratios which appear to convey most of the information contained in the considered ratios and which appear to measure the same attributes. Factor Analysis is a multivariate statistical technique which has been successfully used in some previous studies and is briefly discussed in subsection 3.4.1.3.

However, a list of the considered accounting ratios is presented in Table B1 of appendix B. These ratios are classified on an a priori basis into eight groups according to the firm's financial attributes. Each group comprises some possible measures of a particular financial attribure. The eight groups are profitability, liquidity, capital gearing, growth, prestige or importance of a company, size, risk, and other ratios. The comparison between this and the empirical grouping of accounting ratios (by the selected method of factor analysis) may validate the proposed procedure of selecting one ratio from each a priori group of ratios to construct a set of "logically independent ratios".

As indicated in the previous chapters, accounting ratios reflect the firm's financial state as to failure or success. The previous univariate studies found that there are persistent differences in the ratios of failed and non-failed firms for some years before failure and that the ratios of failed firms deteriorate as the year of failure approaches (see: Chapter 2). This finding appears to be the main premise behind all the failure prediction models. Therefore, a univariate analysis is needed to test whether that finding holds for the present study and to support hypotheses 1, 2 and 4 of Chapter 1. The method of this univariate test is described in subsection 3.4.1.2 which is mainly concerned with tests of univariate normality.

3.4.1.1 <u>The Statistical Nature of Accounting Ratios</u>

The statistical nature of accounting ratios can be described in terms of the type of their distributions and the correlation among them.

Generally, the validity of the statistical inference is dependent on satisfying the assumptions of the statistical methods. The normality of distributions is a common assumption in parametric statistics and variables' independence is a required feature for almost all the methods of multivariate statistical analysis (except for factor analysis as shown below). Therefore, these two statistical characteristics are considered below. The statistical methods of tackling the problems of the distribution and correlation are each considered in a following subsection.

(1) <u>The Type of Distribution</u>

In both univariate and multivariate statistical analyses, the type of variable's distribution (either a single variable or a vector variable) defines whether it can be subjected to parametric statistical techniques. Non-parametric statistics are advisable for non-normal distributions, while the usual parametric statistical techniques assume normal or approximately normal distribution.

Most of the previous studies, where parametric statistical tools were employed, have assumed that each of their accounting ratios exhibited approximate (univariate) normal distribution. The validity of this assumption is questionable (Horrigan, 1965, Mecimore, 1968, Deakin, 1976 and Bird and McHugh, 1977).

Horrigan (1965) stated that in some early studies "financial ratios tended to be approximately normally distributed but were often positively skewed" and that his samples exhibited the same pattern. This skewness is to be expected because most accounting ratios have an effective lower limit of zero but an indefinite upper limit. Horrigan (1965) also stated that "logarithmic transformations of the ratios might be in order where the positive skew is extreme."

Mecimore (1968) confirmed the positive skewness of accounting ratio distributions, but he questioned Horrigan's conclusion that accounting ratios tend to be approximately normally distributed. However, some of Mecimore's ratios exhibited a symmetrical bell shaped distribution, of which the normal distribution is an important case.

Deakin's study (1976) indicated that some accounting ratios, e.g., total debt to total assets in his study, are normally distributed and "it does appear that normality can be achieved in certain cases by transforming the data {using the square roots or natural logs of the data}." This study also indicated that financial ratios might be more normally distributed within a specific industry group.

Bird and McHugh (1977), in an Australian study, concluded that the distribution of ratios within an industry can be approximated by a normal distribution in most cases. Some of the considered ratios were often substantially non-normally distributed and their skewnesses were either positive (if there is an effective lower limit) or negative (if there is an effective upper limit).

In conclusion, the above studies indicate that the distribution of accounting ratios can be made approximately normal if the ratios are stratified by industry classification and if the non-normal ratios are appropriately transformed. Thus, the distribution of each ratio and its possible transformations should be tested for normality to select the distribution which approximates normality more than others.

However, in multivariate analysis we are interested in the normality of the distribution of a vector variable, which is a column of single accounting ratios for a company in the sample. "If the vector variable is multivariate normal in distribution, then everyone of its marginal distributions (the single ratios) is normal. But, even if all the marginals are normal, it is not necessarily true that the vector variable is multivariate normal" (Cooley and Lohnes, 1971, p.36). However, we are interested in univariate normality because it is generally useful in a multivariate context (as mentioned in subsection 3.3.1.1 the LDF performs better for the bounded univariate normal distributions) and because the F-statistic may be used to test the significance of each independent variable.

Tests for multivariate normality are not well developed. Cooley and Lohnes (1971, p.38), after they presented the properties of a multivariate normal distribution (m.n.d.) and the three distributions which can be derived from it, stated that they did "not know of any useful test for multivariate normality." Malkovich and Afifi (1973) generalized the univariate skewness, Kurtosis and the W-statistic (defined below) to test the hypothesis of multivariate normality. They called for a "more extensive empirical studies to obtain precise tables of significance points and to point out subtle differences in the powers of these tests." Yet these tests have not been used in discriminant analysis problems (Eisenbeis, 1977).

Taffler (1977a) has used a test based on a specific feature of the multivariate normal distribution which is pointed out by Cooley and Lohnes (1971, pp.35-6). This test turned out to be a procedure for detecting outlier cases. However, tests of multivariate normality and methods of detecting outliers appear to be applicable to a particular vector variable which includes, most probably, the variables of a developed model. If a failure prediction model satisfies all the tests of section 3.3.2 above, a test of multivariate normality will be less valuable. Thus, it appears that as long as a model's variables have to be empirically selected, the tests of the model's applicability (section 3.3.2) are far more important than that of the multivariate normality.

Therefore, it is only necessary to bound the distribution of each accounting ratio, to test the normality of its distribution and the latter's possible tranformation and to represent it by the most normal distribution. The methods of bounding, transforming and testing univariate normality are described in subsection 3.4.1.2.

(2) Correlation Among Accounting Ratios

It has been established that many accounting ratios are significantly correlated with each other because they are formed from common components and "even when unique components are involved, collinearity may still be present because some items in accounting statements tend to move in the same direction as other items and more or less proportionately" (Horrigan, 1965). Furthermore, many accounting ratios, especially those involving long-term components, are significantly correlated over time. Both the collinearity and inter-temporal correlations of accounting ratios are empirically supported by the findings of Horrigan (1965 and 1966) and Bird and McHugh (1977).

However, the favourable implication of the collinearity of accounting ratios is that, as mentioned before, a very small number of the suggested ratios will convey almost all the information contained in all other ratios. Naturally, this advantage calls for careful selection of the needed ratios. As mentioned before, the objective selection of the most appropriate ratios, from a large number of ratios, can be made by using the factor analysis technique. Such a statistical selection of ratios has been successfully made in some previous studies (e.g., Pinches and Mingo, 1973, Pinches, et al., 1973 and 1975, Taffler, 1977a and 1977b, and Johnson, 1979).

The unfavourable implication of the ratios' collinearity is that the inclusion of collinear ratios, as independent variables, which are related to a dependent variable in the same fashion, would obscure and possibly worsen the results of a multivariate analysis (see: Horrigan, 1965, Johnston, 1972, p.160, and Lev, 1974, p.65). Therefore, the typical procedure, in almost all the multivariate studies, has been to exclude the highly correlated ratios.

As regards Multiple Discriminant Analysis, it was found that this procedure is not valid and that any negative correlation and only high positive correlation among the independent variables increase the discriminatory power of the set of independent variables (see: Lachenbruch, 1975, pp.75-6 and Eisenbeis, 1977, pp.883). Furthermore, Kuh and Meyer (1955) found that the correlation between ratios, which have a common deflator, are not always higher than the correlation between their numerators. They also found that in some cases ratios may result in a better estimate of the regression coefficients.

The implication of the ratios' inter-temporal correlations is that the past relationships can be used to predict future values of ratios for a given firm. However, Horrigan (1965) warned against the possibility of disappointing results in making such a prediction.. "That is, correlations of independent variables which are correlated over time with dependent variables which are not will yield significant relationships only occasionally, at least."

However, the approach adopted in this study, basically the application of factor analysis and then the stepwise MDA and MRA, selects the best discriminating set of variables. Factor analysis is presented below following the tests of normality.

3.4.1.2 Tests of Normality and Univariate Analysis

According to the above discussion, the distribution of each ratio is bounded from above and below and transformed into different linear forms. The bounded distribution and its transformations are then tested for normality. Also, profile analysis and t-test for each ratio are described below.

First, the distribution of each ratio for each group of companies is bounded from above and below by replacing the outlier values with the values of the group mean plus or minus 2 standard deviations. These boundaries appear to be reasonable because they cover 95.45% of the area under the normal curve (i.e., the probability that the values of a ratio lie between plus or minus 2 standard deviations from the mean). However, bounding a distribution is expected to improve its normality.

Second, the distribution of each ratio is transformed to test whether transformation improves their normality. Since there are no guidlines as to which transformation would be appropriate in a given situation, the reciprocals, natural logs and square roots of the ratios are used as they are the most promising forms. However, since these transformations cannot be performed if some values of a ratio are zero or less (for the latter two forms), a constant is added to the values of each ratio. The values of 1, 0.5 and 0.375 have been proposed as the constant values which may improve normality (see: Zar, 1974, pp.184-8). In addition some other values are tried. The resulting large number of distributions are tested for normality to select one of them.

Third, two powerful statistical tests of normality are used in this study (see: Gnanadesikan, 1977, pp.164-5):

(1) The Shaprio and Wilk's (1965) W-test: This test is defined as:

$$W = b^2/s^2 = \frac{\left[\sum_{i=1}^{k} a_j(y_j - y_i)\right]^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}, \quad j = n-i+1 \qquad (3.24)$$

Where: the values of each ratio are ordered to obtain an ordered sample $y_1 \leq y_2 \leq \ldots \leq y_n$. The values of a_j are tabulated in Shapiro and

Wilk (1965). y_j and y_i are the values of a ratio of the order j and i (respectively) and order of y_i is not significant in the denominator of W. The computed values can be evaluated relative to the distribution of W which is tabulated in Shapiro and Wilk (1965). K = n/2 or (n -1)/2, if n is odd.

(2) The D'Agostino's (1971) D-test: This test is defined as:

$$D = T/\sqrt{n^3 s^2} \qquad (3.25) \text{ and,}$$

$$T = \sum_{i=1}^{n} \left(i - \frac{n+1}{2}\right) X_i$$

Where: n and s^2 are defined as above and x_i is the arranged value of X.

The computed D is to be compared with the tabulated upper and lower critical values of D.

However, the two tests have to be programmed by the researcher. In addition to these tests, some descriptive statistics - e.g. mean, variance, skewness and kurtosis are also computed for each ratio and the latter two can be used to test for the departure from normality (see: Pearson and Hartly, 1976, pp.207-8).

Fourth, a univariate comparison between the mean values of each ratio for the groups of companies is made through the application of both profile analysis and t-test. Profile Analysis is a graphic comparison between the two groups' means of each ratio for some years. It indicates the trends of a ratio which are exhibited by failed and non-failed companies. Since the mean value is only one point of a distribution and it may be affected by few extreme values, profile analysis should be supported by a test for the differences between the distributions of the two groups. Therefore, t-test is used to examine the significance of the difference between the group means of each ratio. The t-test assumes that the observarions of the two groups are normally distributed with a common variance. If the two groups are not subject to a common variance an approximate to t may be computed (see: Nie, et al., 1975, pp.267-70).

Thus, the above four points indicate the methods of dealing with univariate non-normality and the comparison between the behaviour of accounting ratios for the failed and non-failed companies.

3.4.1.3 Factor Analysis

Principal components analysis as a method of factor analysis is used to group accounting ratios according to the financial attribures which they are empirically measuring. The comparisons between the results of that analysis for each of the years before failure and for each group of companies indicate the stability of ratios, as measures of financial attributes, for the different years and the different groups of companies. As mentioned before, using the results of this analysis together with the stepwise procedure helps to select the best discriminating variables.

The term "Factor Analysis" subsumes a large variety of procedures for analysing the intercorrelations within a set of variables (Rozeboom, 1966, p.210 and Cooley and Lohnes, 1971, p.129). The classification of these procedures may conveniently be organized around three major dichotomies associated with the three major steps (mentioned below) of factor analysis (Nie, et al., 1975, p.469, see also, Rozeboom, 1966, p.211). However, the widely known uses of factor analysis are: (1) to reduce the dimensionality of a set of independent variables; (2) to test hypotheses about the communality within a set of variables; (3) to produce a composite score measuring what some variables have in common (see: Cooley and Lohnes, 1971, pp.130-2 and Nie et al., 1975, pp.487-9). All these uses of factor analysis are ultimately based on its capability of data-summarizing.

Generally, the purpose of factor analysis is to extract a set of m-factors out of a correlated set of p-variables, $m < p$. Each factor is a linear combination of the p-variables and accounts for a part of the common effects which are shared by the set of variables. The effect which is not shared by any other variable is treated as a residual specific to an individual variable. The general model of factor analysis can be defined as:

$$X_i = \sum_{k=1}^{m} a_{ik} f_k + e_i \text{ , } i=1,\ldots\ldots, p \text{ and } m < p \qquad (3.26)$$

Where a_{ik} is the loading of the ith variable on the kth factor or the loading of the kth factor in the ith variable, f_k is a factor common to all the x's and e_i is a residual or a factor specific to x_i. The a's measure, regardless of the individual member, the extent to which a variable x is compounded of the underlying factors f's. The score of any particular individual j is regarded as the selection of a value of each f_k peculiar to it and a value of the e also specific to it (Kendall, 1975, pp.48-9):

$$X_{ij} = \sum_{k=1}^{m} a_{ik} f_{kj} + e_{ij} \qquad (3.27)$$

The basic assumptions of the above model (3.26) are that: (1) the factors are independent normal variables with zero mean and unit variance; (2) each e is independent of all other e's and of the factors (Kendall, 1975, p.48).

Since the purpose of factor analysis is to extract the smallest possible number of factors m, the a's matrix, being m x p, is not invertible. Therefore, the factor solution is indeterminate, i.e., there is an infinity of possible solutions, and we cannot express the f's in terms of X's (Kendall, 1975, p.49).

If m, the number of factors, were equal to p, the number of variables, then: (1) the e's would be unnecessary and we should revert to the case of a transformation to a set of independent variables; (2) the a's matrix would be invertible and thus the f's would be transformable into X's and vice versa and there would be only a finite set of solutions (Kendall, 1975, p.13). This special case, m = p, of factor analysis leads to the following model of principal component analysis wich "in fact, can hardly be described as a model - it is merely a convenient variate - transformation" (Kendall, 1975, p.48).

$$P_i = \sum_{k=1}^{p} a_{ik} X_k \qquad , i = 1....,p \qquad (3.28)$$

or

$$X_i = \sum_{k=1}^{p} a_{ik} P_i \qquad , i = 1,...,p.$$

The following conditions are imposed to ensure that the components are uncorrelated with each other (orthogonal) and to limit the variance that can be captured by the first and each subsequent component.

$$\sum_{i=1}^{p} a_{ik} a_{ij} = 0 \qquad j = k+1$$
$$= 1 \qquad j = k$$

These conditions will produce principal components which are normalized by setting $\sum_{i=1}^{p} a_{ik} a_{ik} = 1$ and, orthogonal, by setting $\sum_{i=1}^{p} a_{ik} a_{i,k+1} = 0$ (see: Johnston, 1972, p.323 and Peasnell and Skerratt, 1977a).

However, the following are the three steps of factor analysis as well as our selection from the procedures which are available for each step in the SPSS's (Nie, et al., 1975, pp.468-513) factor analysis program:

(1) Preparation of Correlation Matrix

The first step in factor analysis involves the calculation of appropriate measure of association between variables (R-factor analysis) or between individuals (Q-factor analysis). These two types, R and Q, are the most important types, the first is the most common, of the two-mode (two-dimension) factor analysis. Further modes can be added, e.g., technique of measurement, in which case there will be an infinite number of possible types (see: Gorsuch, 1974, pp.276-91).

Since we are concerned with the association between variables, the variables' covariance matrix should be used as a measure of their association. If there is a prior or empirical indication that the variables are not measured on the same scale, the variables should be standardized, i.e., we should use the correlation matrix instead of the covariance matrix.

Although our variables, apart from size, are ratios which are measured in units of money, they are not expected to be measured on the same scale. Only each group of accounting ratios, most of which may have a common denominator, is expected to be measured on a similar scale. However, a comparison between, on the one hand, the relationship between the selected ratios' standard deviations and, on the other, the relationship between their coefficients of variation indicates whether the ratios are measured on the same scale. This test confirmed that the ratios are not measured on the same scale (it was also used by Peasnell and Skerratt, 1977a). The correlation matrix can be computed from raw data by the SPSS factor analysis program which will be used in this study.

(2) Extraction of Initial Factors

The classification of the methods of extracting the factors is based upon whether the specific factor, or the residual e_i in 3.26, is assumed to exist or not. The two groups are (see: Rozeboom, 1966, p.211 and Nie, et al., 1975, pp.470-82):

(1) Defined Factors: there is only one method in this group which is the principal components method, where the factors are defined as an exact mathematical transformation of the original data.

(2) Inferred Factors: the methods in this group are based on what is called classical factor analysis model, i.e., they assume the existence of the residual. All these methods replace the main diagonals of the correlation matrix with communality estimates before factoring. The differences between the methods of this group are mainly due to the methods of estimating the communality. However, satisfying the assumptions of factor analysis, random errors of measurement and indeterminacy in selecting communalities are the main problems of this group relative to the former.

Accordingly, principal components method will be used in this study as the method of extracting the factors for the following reasons:

(1) It is a relatively straightforward method and requires no particular assumptions about the general structure of the variables (see: Nie, et al., 1975, p.479).

(2) It is "a generally useful procedure whenever the task is to determine the minimum number of independent dimensions needed to account for most of the variance in the original set of variables" (Cooley and Lohnes, 1971, p.129).

(3) It has performed well in some previous studies, e.g., Taffler (1977a) and Peasnell and Skerratt (1977 and 1977a).

(4) It "requires less computer time than do other factor extraction methods" (Nie, et al., 1975, p.479) and it is recommended for the conventional econometric regression problems (Johnston, 1972, p.329).

In principal components analysis, the number of components that may be computed is equal to the number of variables, unless one or some of the variables are perfectly determined by the rest of the variables in the data. However, the first few components usually explain most of the variance in the data and they only should be retained for further rotation. In this concern Kendall (1975, p.27) stated that:

> "If the significance of components is to be judged on a subjective basis it is better to look at the pattern of them all (which, inter alia, implies that one should not use programs which print out only the eigenvectors with $\lambda > 1$ {the average λ is 1 in the case of using the correlation matrix} and supress the rest."

The SPSS factor analysis program outputs any required number of components. Thus, many components are printed out and few of them are selected.

(3) Methods of Rotation

Rotation is a process of linear transformation, the purpose of which is to simplify the structure of the factors, or components, so that the rotated factors may be more readily named and understood by the researcher (Cooley and Lohnes, 1971, p.144). Since the very high and very low factor loadings are easily interpretable, while middle-sized loadings give trouble, the rotation methods transform the factors such that all the loadings approach either zero or unity (see: Cooley and Lohnes, 1971, p.144 and Kendall, 1975, pp.53-4).

The methods of rotation are classified into two groups:

(1) Orthogonal Rotation: the methods of this group - varimax, quartimax and equimax - are all directed more or less to the same end (Kendall, 1975, p.54). Varimax is the most widely accepted and employed method for orthogonal rotation. "The factors are rotated in such a way as to maximize the sum of the variances of the squared loading within each column of the rotated loading matrix" (Kendall, 1975, p.54).

(2) Oblique Rotation: in the methods of this group the requirement of orthagonality among the factor axes is relaxed. Thus, the oblique rotation indicates the actual correlation between the factors. "Such rotation, however, can be adequately achieved only with some visual or graphical aid

and the discerning eye of the researcher" (Nie, et al., 1975, p.486).

Therefore, the Varimax orthogonal rotation method is used in this study to rotate the extracted principal componens.

However, for our selected factor solution which is termed "Varimaxed principal components" (see: Cooley and Lohnes, 1971, p.137), the output of the SPSS's FACTOR program includes:

(1) The Matrix of Rotated Factors' Loadings - these loadings represent: (I) the regression weights of the common factors which may be used to describe a variable in terms of the factors (each row of the maxtrix - see model 3.28); (II) the correlation coefficient between each variable and each factor which can be used to group the variables according to their loadings on the factors. This grouping is usually the reported output of factor analysis in the studies concerned with the dimensionality of accounting ratios (see: Pinches, et al., 1975 and Taffler, 1977a).

(2) The variance accounted for by factor k = the corresponding eigenvalue λ_k =

$$\sum_{i=1}^{p} a_{ki}^2 \qquad (3.29)$$

(3) the proportion of total variance accounted for by factor k = $\frac{\lambda k}{p}$ where the total variance of the standardized variables= p the number of variables.

(4) The cumulative proportion, the sum of the proportions of (3) above, indicates the proportions of the total variance accounted for by the first m factors.

The above are the important outputs of principal component analysis which are reported in Chapter 5 of this study.

3.4.2 The Environmental Variables

Both the a priori and the empirical importance of industry and economy-wide indicators were discussed in this and Chapter 1. The following two subsections are concerned with the question of "How to measure these two factors for the purpose of including them in a multi-ratio multivariate model?"

3.4.2.1 The Industry Factor

Almost all the previous studies which are concerned with business failure have controlled for the industry effect by stratifying the samples according to an industry classification. Horrigan (1966) and Edmister (1972) removed this effect. The former divided the difference between a firm's ratio and its industry ratio by the industry ratio. The latter divided the firm's ratio by its industry ratio. Gonedes (1969), Martin (1971) and Bilderse (1975) used dummy variables to handle the industry effect.

Falk and Heintz (1975 and 1977) criticized the above methods of accounting for the industry effect because they did not make the most efficient use of the available accounting data. However, their explicit measure of the industry factor is based on the Guttman scalogram technique, which is a subjective technique.

In this study, as indicated before, the industry effect is represented by a set of dummy variables. The latter are easy to use, but they may result in severe statistical problems. However, it was indicated before that the linear discriminant function is robust and dummy variables have been successfully used before. But, however, it may not be feasible to use a set of 19 dummy variables for the 19 industries which are represented in the selected sample of companies. Therefore, a broader classification which groups the 19 into a fewer number of broader industries is needed.

One such a priori classification is to group the 19 industries acording to the functions they perform into manufacturing, construction and distribution. This classification as the Standard Industrial Classification (SIC) emphasizes the techniqal terms of a firm's activities, e.g. the industrial processes, rather than its financial or trading activities. It may not be the best perceived classification, but it appears to be the best possible one in the context of the available data. For example, demand elasticities may appear to be better criteria for an industrial classification, but the relevant data are not available. Also, similarity may exist between the industries of the above three groups, e.g. food manufacturing and food retailing and these two may exhibit a lower degree of similarity with a third industry.

However, the above three-groups classification is used in this study and is empirically tested by cluster analysis and three-groups discriminant analysis.

(1) Cluster Analysis

Cluster analysis classifies units (industries) upon the basis of their data (aggregate accounting ratios) without making any assumptions about their a priori grouping. Because of this letter feature and because the above selected grouping is not based on the industries' accounting ratios, clusteranalysis cannot be used to test the validity of that grouping. Instead, it is used to indicate how different are the industries, or that they are similar at different levels. The similarity between some industries at the higher levels supports the need to reclassify them into fewer number of groups while the similarity at the lower levels indicates the difference between industries and, thus, the need to account for the industry effect.

However, hierarchical cluster analysis, which is used in this study, starts from the weak clustering, i.e. cluster for each unit, and ends up with the strong clustering, i.e. one cluster for all units (at the lowest level). The strength of clustering increases as one goes from one level to another (see: Granadesikan, 1977, p.104). The output of cluster analysis can be presented in a similarity matrix or in a graph (dendrogram). The latter is reported in this study.

(2) Three-groups Discriminant Analysis

The 19 industries represented in this study are assigned to the above three groups and then two discriminant functions are fitted to their accounting ratios (see: section 3.3.1). The two functions are then used to reclassify the industries into the three groups. The higher the classifying power the more valid is the above three-groups classification. It should be noted that discriminant analysis is the proper statistical technique to classify individuals according to an a priori grouping.

The 19 industries represented in this study are those of the SIC excluding industries number 24, 43, 70 and 88 (see: table A2 in Appendix A).

Depending on the results of the above analysis a set of three dummy variables is used to represent the industry factor (see: Chapter 5).

3.4.2.2 The Economy-wide Factor

As indicated in the previous chapters, the economy-wide effect was not considered explicitly in any of the previous failure prediction studies.

Altman (1971, Chapter 2) used the quarterly changes in gross national product (GNP), the market index of share prices (SP) and money supply (MS) to predict the quarterly changes in the overall rate of failure, but he did not use any of these indicators in his models (e.g. Altman, 1968 and Altman et al., 1977) to predict corporate failure. Equally, Brown and Ball (1967, in their study of communality in earnings measurements, noted that "all firms in the economy are affected to some degree by monetary policy or changes in interest rates"; however, they did not include any such indicator in their study.

Nevertheless, it seems clear that different types of firms are vulnerable at different stages in the economic cycle, and intuitively one might expect economy-wide indicators to have considerable explanatory power, particularly if one were studying failure over (say) a period of twenty or thirty years.

The economy-wide effect can be represented by a large number of indicators which purport to reflect the general state of the economy. GNP, SP, MS, interest rates and the prices of raw materials or energy (which affect costs for certain types of business) could be used in different forms to measure different aspects of the state of the economy. For example, changes in interest rates or in the growth rate of money supply might be used to signal the onset of a credit squeeze and first difference in SP could be used to measure the trend in the stock market and thus identify turning points in the economy; while the standard deviation of this index could signal the general level of uncertainty. (These three indicators are considered in more detail below).

Some of the information contained in these indicators is almost certainly not independent of the industry factor and consequently much of the economy-wide effect may be picked up in the industry variable. Nevertheless, it might be interesting to examine the communalities in economy-wide and industry indicators, but such a task is beyond the scope of this particular piece of research.

However, in this study the Financial Times Actuaries (all share) Index (FTA - the published daily index for the London Stock Exchange) is used to develop an economy-wide indicator. The FTA is selected for its availability on a daily basis so that the economy-wide indicator can be computed for each company over the working days of its financial year, where the ends of these years differ markedly among companies (see: table A3 in Appendix A).

Three indicators may be derived from the FTA. First, the trend in the stock market during a company's financial year. This trend can be measured by regressing the market returns (see: section 3.2.2) on the serial numbers of the considered intervals of time (e.g. days or months), by plotting the former against the latter, or by observing the returns' first differences over the intervals. However, any measure of trend (except the slope of the regression line if significantly different from zero) results in a nominal variable, e.g. up, down and stable. Accordingly, the economy-wide variable can be represented either by a set of dummy variables or by assigning arbitrary scores to the defined trends.

Second, turning points in the economy can be revealed by comparing the returns' first difference over successive (arbitrary) periods (months, 3 months or six months) prior to failure or by comparing the ratio of the first difference at the beginning of a period to the first difference at the end of that period over the successive periods. These comparisons may indicate whether a particlar year was 'boom' or 'slump'. Accordingly, this measure (as the previous one) results in a nominal variable, i.e. a year was 'boom', 'slump' or neither.

Third, the level of uncertainty in the economy can be measured by the standard deviation of the market returns over the working days of a company's financial year. This measure (as compared with the previous two) results in a numerical variable which indicates the variability of the market return over a particular year, i.e. the state of securities' trading within that period.

Only this measure is used in this study since it was regarded as highly likely that the general economic trend and changes in that trend would be adequately reflected in the industry indicator any way, making the introduction of two new sets of dummy variables of very doubtful value. Although the standard deviation of market returns is a directionless measure, it should nevertheless reflect the market's uncertainty about the state of the economy in general.

Finally, as mentioned before, all the above variables (presented in this section 3.4) will be selected for inclusion in the models through a stepwise process. Of the large number of the resulting models, only two are selected and reported in this study. They are the most consistent and powerful models, and each of them includes a very limited number of variables which together provide the best discriminating combination. Therefore, those variables which are not included in the models are not necessarily unimportant. There is the possibility that if another set of variables was considered some of our unselected variables might be included in a selected model.

3.5 Sample Design

As indicated above, the adopted methods of prediction are based upon the establishment of a combination of selected characteristics which can dsicriminate between two groups of companies, failed and sound, using a sample of the two groups (the analysis sample). For a specific company, failure is predicted if its combination of characteristics resembles the combination of the failed firms, otherwise success may be predicted. Thus, our samples(or subsamples) are constructed of two groups:
(1) the experimental group, the group representing the phenomenon of the study, i.e. the failed or 'at riks' group; (2) the control group, i.e. sound or 'not at risk' group. The greater the communality (the overlap) between the characteristics of the two groups, in the analysis sample, the more difficult is the prediction of only failure or success, i.e. the less is the predictability of the models.

To maximize the predictive power of the models, the two groups should be independent of each other. Since companies' attributes are inter-correlated, only relative independence can be achieved by sampling from the extreme cases of each group (see: Daniel, 1968 and Taffler, 1977a) and, as discussed in section 3.4 above, by selecting the best discriminating variables.

In the previous studies, as discussed before, the experimental group included companies which satisfied some defined conditions of failure or bankruptcy and, in the majority of these studies, the control group was selected to control for the effects of firm's size, industry and the economy-wide factors.

In this study, these latter three factors are explicitly considered as independent variables. The advantages, for sampling, of this procedure are that: (1) the control group of companies can be selected at random - but this is not true if the top sound companies are selected; (2) the inter-temporal validation test will not be necessary, but it produces additional evidence, to prove the predictability of the models, containing the industry and the economy-wide factors.

The companies' age will not be considered in this study because of the lack of adequate information about the companies' dates of birth. In the two data-banks, the Share Prices (LSPD) and Company Accounts (W/DT1) data-banks which are discussed in the next chapter, the date of birth is defined as the date in which the companies were first quoted. Thus, companies may have been in business for different periods before their data-banks' date of birth.

However, the sample which is used for the purposes of the market model includes only failed companies. The criteria for selecting each sample group of companies are discussed below.

3.5.1 The Failed Firms

The sample of failed firms includes all those which failed during the period 1960-1971 and satisfy the following conditions:

1. The company was engaged in manufacturing, construction or distribution activities and was listed on the London Stock Exchange for five years before failure.

2. The company was liquidated, wound up by court order, or a receiver was appointed.

3. The company's share price or accounting data are available in the data-banks (LSPD and W/DT1) and, if necessary, can be completed from other sources.

The total number of companies which meet these conditions was 53. The share price data were available for only 20 of these companies. Some other failed companies have only share price data, but they were discarded after examining their Ex-Tel cards because they were found to be overseas companies. Therefore, the sample of the market model (3.2) included only those 20 companies. The accounting data of 2 of the 53 companies were completed from their Ex-Tel cards (Pickles (Robert), No.41499 and Devas Routledge & Co., No.81058). These two companies were withdrawn from the W/DT1 data-bank in 1964 and 1961, respectively, because they did not meet (at these periods of time) the size criterion of the data-bank, while they failed in 1970 and 1964 respectively.

Only two companies were exempted from the above conditions. The first (Howarth of Burnley Ltd, No.50130) has data for only four years before failure, thus, the total number of failed companies for the fifth year before failure is 52. The second (Dennis Motor Holdings, No.38108) was sold by the directors, however it is included in the inter-temporal validation subsample (see: table A3 of Appendix A).

The dates of failure announcement were collected from other sources because the W/DT1 data-banks includes the approximate date of the last financial statements before failure announcement and LSPD includes the date ofcancelling a security's quotation, which may be well after failure announcement dates. These latter dates are particularly needed for the purpose of the market model and to ensure that the last published financial statements are available in the data bank. However, the Ex-Tel cards and 'The Investor's Chronicle' were used for that purpose. The former were available for most of the companies and the latter was only used for a few.

The period 1960-1971, 11 years, is selected because of the small number of companies which failed in any of the considered years (see: subsection 3.3.2.4) and because accounting data are available up to and including the fiscal year 1973/74, but there were no failed companies in the data of the years 1972 and 1973. This 11-years period is long enough to reflect the changes in the general economic condidtions, but the number of companies which failed within each of these years is not large enough to allow for a study of failure at different points of the economic cycle. A major problem with that period, however, is that turnover figures are not available prior to 1967.

However, the first year before failure is defined by the year of the last published financial statements and each of the four years prior to the first before failure aredefined as the second, third, fourth and fifth before failure.

3.5.2 The Sound Firms

The selection of the sound companies is made in two stages.

In the first stage, a large number of continuing companies which are engaged in manufacturing, construction or distribution are selected according to the following criteria:

1. The company is recorded as a continuing company for the last year of data in the W/DTI data-bank, which is the fiscal year 1973/1974.

2. The company is not a subsidiary of another company and has not undergone any significant changes, e.g. acquisition or merger activities, during the period 1969-1973, which is a period of 5 years (1973 is considered the first year before failure for the sound group)

3. The company has been listed for at least five years, for which the company's accounting data are available in the W/DTI data bank.

In the second stage, the selected continuing companies are ranked (in a descending order) for each of the five years by their accounting rate of return (operating profit/net capital employed). The top n companies in each of the five years of data are separated and, then, those which are present in the top n companies of the first year of data (the fifth before failure) and in those of each subsequent year of data are isolated for visual inspection. The latter m companies are those which maintained their rank in the top n companies over each of the five years ($m < n$). A number of companies equal to that of the failed group, 53, is selected from the m companies by visually inspecting their ranks over the five years.

The number of companies which satisfied the first stage's criteria was 252 companies and 60 companies were found to maintain their rank in the top 120.

The above selection of failed and non-failed companies was made by computer programs written by the researcher.

3.5.3 Dividing the Sample

The 53 failed and 53 sound (non-failed) companies are divided into the following subsamples.

1. The analysis and the cross validation (calibrating or hold-out) samples, for which 44 failed and 44 sound companies are assigned. The failed companies are those which failed during the period 1960-1968. The 88 companies are equally divided (according to the previously mentioned, split sample procedure) into:

a) The analysis sample.

b) The cross validation sample.

Thus, 22 failed and 22 sound companies were assigned to each of these samples. In assigning the companies to these samples, a balance was maintained between them regarding the distributions of the companies' year of failure and industrial classification (see: table A3 in Appendix A).

2. The inter-temporal validation sample, for which 9 failed and 9 sound companies are assigned. The failed companies are those which failed during the period 1969-1971, i.e., the most recently failed companies.

Thus, the two groups of the above samples are of equal size to facilitate the interpretation of the results. "But there are actually no compelling reasons for any a priori proportions" (Joy and Tollefson, 1975 and see also Morrison, 1969). Also, the above samples are available for each of the five years before failure, except that the analysis sample of the fifth year before failure includes data for 21 failed companies (because a company of the failed group has data for only four years before failure) and, thus, the data of non-failed companies are limited to 21 companies. Accordingly, different models are developed for the different years of data and for combinations of them (see: Chapter 6). However, it should be noted that each of the years before failure is not the same financial year for each sampled company but it has the same distance from the event of failure for each company. The time effect of using the data of different financial years for the different companies may be accounted for by the economy-wide indicator.

6 Concluding Remarks

In this chapter, the two models which are used in this study are efined. The market model is extensively used in the stock market research. he methodological points of its, hopefully, successful application are also presented. The failure prediction model is defined in its general form and its empirical development requires: (1) the selection of samples of failed and sound companies; (2) improving the normality of each ratio's distribution and allowing for the effect of ratios' multicollinearity; (3) testing the behaviour of each ratio for the two groups of companies; (4) the proper specification of the industries' dummy variables and the proper measurement of the economy-wide indicator; (5) the application of the stepwise discriminant analysis or regression analysis (both of them are used in this study) and (6) testing the applicability of the developed models and their different functions. All these points are detailed above. However, the comparison between the results of the two models concludes this study. It is hoped that the above selected methodology extracts the best feasible results of the two models so that the comparison between these results fulfils the main obejctive of this study.

CHAPTER IV

CONVENTIONAL ACCOUNTING AND DATA LIMITATIONS

CHAPTER 4

Conventional Accounting and Data Limitations

4.1 Introduction

The previous chapters indicate that this study is concerned with evaluating UK conventional accounting information relative to share price information and that both types of information are used in the measurement of the identified variables. The purposes of this chapter are therefore to highlight the present state of conventional accounting; its effects on accounting ratios; and the characteristics and limitations of the company accounts and share price data-banks. Each of these elements is presented in one of the following sections.

Generally, this chapter argues that accounting measures are incomplete and outdated surrogate repersentations of real world events or situations. They are incomplete because they do not fully reflect a firm's future stream of expected earnings. For instance, the balance sheet net asset value is not the same as a firm's value as it might be perceived by its owners or by the capital market; nor, where relevant, do the accounts normally fully allow for changes in the value of a firm's human assets and the effects of price changes. By contrast, these factors are substantially reflected in economic concepts of income and value, because they are concerned with expectations rather than past transactions. On the other hand, investors, in setting security prices, rely on information from various sources including a firm's published accounts. Therefore, share price data will, presumably, represent the investors' evaluation of all (accounting and non-accounting) data available to them - in comparison accounting data by themselves are incomplete. Moreover, accounting measures are outdated because they are expressed in terms of values which are peculiar to different periods in the past. The application of various proposed methods of accounting for price changes may only update the accounting measures but they will nevertheless remain incomplete. In addition, conventional accounting information is subject to the flexibility of accounting practice and the statutory rules of disclosure.

However, despite the shortcomings of conventional accounting, previous empirical studies (in different areas, e.g. failure prediction, bond rating and risk measurement) have suggested it is useful to many types of potential reader - although the use of data from other sources may improve the performance of some models.

As for the effects of conventional accounting on accounting ratios, they are shown to be tolerable - by adjusting for the known affects, by including data from other sources and by the statistical methods selected for the analysis.

Finally, the chapter indicates that the company accounts and share price data-banks used in this study are the best available data-banks for the purposes of academic research. They are produced on IBM magnetic tapes which must be translated when they are to be used on a different computer installation (as was the case in this study).

4.2 The Nature of Conventional Accounting

Conventional accounting is basically concerned with the measurement and communication of a firm's past economic operations which are expressed in money terms (see: Study Group at the University of Illinois, 1964).

Such measurement is governed by the conventions of realization, objectivity and conservatism. The first two conventions apply to revenues and capital gains while (scaling differently) the latter applies to expenses and losses. Accordingly, no revenue or asset-value increase is usually recognized until realized in terms of an objective event. The objectivity convention defines that objective event in terms of verifiable evidence which is associated with a transaction, thus invoicing goods to a customer is the point of selling transaction at which a revenue or a capital gain can be recognized. Perhaps the most obvious exceptions to the conventions of realization and objectivity occur in the evaluation of work-in-progress, where (in the construction industry, for instance) revenue is often treated as realized in proportion to production. According to accounting conservatism, the realization convention is relaxed in the case of losses where any expected loss should be estimated and charged. Also, the rule for valuing inventory (at historic cost or market-price whichever is the less) and the conservative estimates of fixed assets' productive lives are applications of the conservatism convention and they result in conservative (over-stated) estimate of expenses in one period; understatements later. Finally, conventional accounting, unrealistically, assumes the indefinite continuity of a business entity, the stability of the monetary unit (which is the unit of measurement) and, apparently, 'certainty' - e.g. the use of depreciation charges determined ex ante when the asset was purchased.

From the professional point of view, to ensure a degree of "objectivity" for published accounting information, the preparation, verification and publication of financial statements are controlled by various legal, institutional and professional requirements. These requirements emphasize the above mentioned conventions and a large number of alternative (generally accepted) methods of measurements.

Accordingly, accounting measures exclude explicitly the effect of even firm specific economic events (operations) which are not "objectively" expressable in money terms. Also, they are biased measures by the virtue of their conventions and alternative methods of measurement and because they do not allow for the price changes.

However, some or all the excluded economic events, the aspects biased by the application of accounting conventions and the effect of price changes appear to be of significant importance to investors and other users in making their decisions. Accounting information is therefore a subset from specific data set available to its users. The following two subsections consider the incompleteness of accounting measures. The second of them is devoted to the effect of price changes because of the importance accorded to this aspect in the accounting literature. The flexibility of accounting practice and accounting disclosure policies are considered in the last two subsections (4.2.3 and 4.2.4).

4.2.1 Incompleteness of Accounting Measures

All users need information in an uncertain world to help reduce uncertainty. The value of information is therefore related to the extent to which it reduces the users' uncertainty. Accounting data do not appear to provide the whole set of information which reduces the users' uncertainty.

All available data are used as signals, which investors and other users use in their expectation models. Presumably a user interprets these signals by comparing outcomes against expected outcomes; and then on the basis of the difference between outcomes and the expected level of performance, makes his estimate of future likely outcomes and values the security accordingly.

The expectation model the investor will use will incorporate all information available which he perceives as relevant. That model is perhaps best regarded as a black-box. However, if investors act rationally, the mean expected outcome should be the same; and additional information will mainly tend to reduce the dispersion around that mean.

Accordingly, the problem in using an accounting ratio model is that one is using a mechanical expectation model which only takes into account part of the information set. For instance, if conventional accounting profit is used as a variable it will not reflect all aspects which may be relevant to an investor trying to assess performance against some bench mark (be it time series, cross sectional, or budgeted). Thus it ignores price changes (considered in the next subsection) and also non-quantitative aspects. The following are some of the latter aspects, which are not reflected by accounting measures:-

(1) A firm's human assets (HA)are not reported in conventional financial statements while it is believed that human resource accounting (HRA) could benefit the external users of accounting information (see: Likert and Pyle, 1971, Lev and Schwartz, 1971, Flamholtz, 1972 and Hendricks, 1976). The main problems of HRA appear to be defining the conditions that justify reporting the HA and their relevant measurement. In this respect, Dittman, Juris and Revsine (1976 and 1980) argue that many studies have failed to distinguish between an employee's own human capital and the unrecorded human assets accruing to the employer. The latter does not exist if the employees appear to be equally productive to many firms in the market, in this case wages will represent the market replacement price of labour. If the employees' productivity to a particular firm is greater than their market-wide productivity, recording HA may be justified. But the methods of determining their value are, however, disputable.

Apart from the above problems, the changes in a firm's working groups appear to be more important than HRA, although one of the latter's objectives is, perhaps, rationalizing such changes (see: Likert and Pyle, 1971 and Flamholtz, 1972). Likert and Pyle (1971) have warned against the drastic reduction in the working force by a program of cost reduction. They argue that "the increase in cash flow from such cost reduction efforts is not necessarily earnings, however, since the cost reduction program usually has liquidated assets with value to the firm substantially in excess of the reported increase in "earnings"." More importantly such a cost reduction may be followed by reduced productivity, a situation which was faced by the National Coal Board. One striking example of the importance of the changes in top management is concerned with the resignation of the eight top executives from the US Motorola and their appointment in the US Fairchild Companies. The market value of the former's share's dropped suddenly by more than \$49 million and rose simultaneously for the latter by more than \$34 million during the 24 hours following these changes (as stated by Fadel, 1977, p.40).

Thus, the above two examples indicate that conventional accounting measures are not entirely representative of real world situations. In the first case, the cost reduction may improve the firm's conventional profit in the year when the labour force was reduced (and perhaps also in the subsequent year or two) but there presumably would be some indication for impaired productivity of the working labour only in subsequent years. In the second case, conventional accounts of the two companies would not reflect anything about the event which was perceived by the capital market to be very important.

(2) Conventional accounts can be misleading in the following cases because none of the relevant events will be reflected in conventional accounting measures.

(a) The increase of selling price due to market or international forces (e.g. oil companies) which will take place from the beginning of the next financial year.

(b) The effect of the above increase on oil consuming companies (e.g. British Airways).

(c) A change in the market share for the next year(s), e.g., if the main product of a drugs company was found, by the end of its financial year, to have dangerous side effects;

and this will result in a substantial reduction of the company's sales over the next four years.

(d) The increase in the proven reserves of an oil company.

(3) The dispute concerning, for oil companies, the costs of drilling unsuccessful and successful wells indicates the inadequacy of accounting measures for the value of an oil company. Neither the full costing nor the successful efforts costing approaches has any relevance in determining the value of an oil well. Instead, only the discovery value seems to be relevant (see for example: Ijiri, 1979).

(4) Conventional accounts can also be misleading in the case of a company that has undertaken a long-term research program and ended up with a discovery which will considerably increase its future earning power. Although the capital market may appreciate the importance of the new discovery and, consequently, marks up the company's share prices, the conventional accounts may indicate that the company is financially exhausted and performing badly - until the sales revenues of the new product eventually reflect the changed situation.

The above and similar aspects which are ignored by accounting measures are presumably used by investors and are thus reflected in share prices. According to the efficient market hypothesis (see: Chapter 2), the latter are supposed to fully and quickly reflect all publicly available (accounting and non-accounting) information. This explains why share prices reflect the importance of changes in top management (in the previously given example) while this would never be reflected in the current accounts of the two companies. Accounting data are thus incomplete because they represent only part of the information set used by investors and impounded into share prices.

Although the investors' evaluation of all available information and their perception of the firm's future are the essence of the economic concepts of income and value (see: Hicks, 1946) they are subjective matters and, therefore, cannot be considered for the purposes of conventional accounting measurement.

Finally, despite the incompleteness of accounting information, previous empirical studies(failure prediction, bond rating and risk measurement) have suggested it is nevertheless potentially helpful to users. However, users may have to supplement it with other information (see: Section 4.3 below).

4.2.2 Accounting and Price Changes

The accounting assumption of the stability of the monetary unit has been falsified by the fact that inflation is dominating the economic life in most countries for at least forty years (see: Kirkman, 1974, Chapter 1). Under inflationary conditions there are mainly specific and general price changes (the difference between them is termed relative price changes, see Lee, 1974, p.107). The former reflects both the relative price change (which is not peculiar to inflationary conditions) and an increase in the general price level. The latter reflects only an increase in the general price level which is a decrease in the purchasing power of the monetary unit. The implications of these inflationary price changes for conventional accounting are that:

1. The firm's income is over-estimated because costs of goods sold and other periodical expenses are expressed in terms of historical cost while revenue is expressed in current values. The under-estimation of costs of goods sold and other expenses are caused by the time-lag between the date of acquiring the assets and services and both the date of selling the goods and the end of the financial year.

2. The firm's non-monetary assets are under-evaluated and the purchasing power of its monetary assets and of its liàbilities are decreased. The decrease of the purcahsing power of monetary assets (cash and debtors) is considered a loss because it reduces the general command of a particular level of monetary assets over the other goods and services. Therefore, a firm would have to increase its cash - for instance - to maintain the services that used to be performed through having a particular level of cash. The decrease of liabilities' purchasing power is considered a gain

because, in real terms, the firm would have to pay less than it borrowed, providing that lenders premium charges, if any, are less than the rate of inflation (see: Egginton and Morris, 1973 and Sandilands report, 1975, para. 539). However, these effects on a firm's assets mean that its capital is no longer maintained.

3. Historical costs of the assets which were acquired at different points in the past can represent the values of these assets only at the dates of their acquisition. Therefore, conventional accounting measures are outdated.

4. The inflated income may induce increased tax (unless tax allowances are offered), dividends and wages, while otherwise these increases should not have been made and even tax and dividends may have not been due. However, since these items are not justified by real income and they always have to be paid immediately in cash (except tax) they may impair the firm's level of cash - and perhaps its capital.

However, for the accountant, both phenomena of general and specific price changes are given events (Edwards and Bell, 1961, p.16). Conventional accounting measures do not reflect these events, although in some cases they can be measured objectively and even they may have some realized effects. For example, the published (inflated) general price index can be considered as objective evidence to record its effect which may also be considered realized either by the publication of the index or by any subsequent event. However, some proposals have been made to account for price changes but they have remained proposals because they violate the generally accepted conventions of accounting. Although some of these proposals may appear to be attempting to narrow the gap between accounting and economic concepts, accounting measures remain incomplete but they may be updated.

Three approaches have been advocated as complete methods of accounting for the effect of price changes (a part from the partial procedures of allowing for the effect of inflation - i.e. LIFO and accelerated depreciation).

The first is the current purchasing power approach (CPP) which considers that general price increases are the only inflationary changes that affect conventional accounting measures. It involves a restatement of historic cost in units of the same purchasing power. Therefore, the historical cost conventions are not affected by this adjustment, but only the units of measurement are changed (see: Edwards and Bell, 1961, p.18). This approach emphasizes the ownership or equity concept of an accounting unit, where it maintains the investors' investment in terms of the general purchasing power(see: Baxter, 1975, pp.68-73). The concepts of purchasing power gains and losses (monetary holding gains and losses) are associated with this approach. The main objection to CPP is concerned with the relevance of a general price index, where it is argued that each individual (person or entity) might have his own general price index according to his spending pattern (Gynther, 1974 and Lee, 1976, p.99). However, Peasnell and Skerratt (1977) found a high degree of communality amongst the inflation rates experienced by different income-groups, an evidence suggesting the relevance of a general price index for adjusting financial statements.

The second approach is current cost accounting (CCA) which considers only the specific price changes in accounting for inflation. It involves the evaluation of a firm's assets at their current costs and adjusting the costs of goods sold according to that evaluation. The major problem of this approach is defining and estimating the assets' current costs. Current replacement cost is usually considered a reasonable practical approximation of an asset's value to the firm. However, the logical justification of this approach does not appear to be related directly to inflation accounting.

This is clear in the assumed case that the specific price of a firm's investment decreases while the general price level increases (see: Edwards and Bell, 1961, pp.19-21 for the deviation of individual prices from the general price index). As indicated above, under inflationary conditions, the specific price changes comprise relative price changes and general price changes. In a dynamic economy, regardless of inflation, relative price changes are normal and represent changes in the economic or real values of some goods and services relative to the others. Therefore, these relative price changes justify CCA as a method of accounting for them. Since CCA considers the specific price changes (including relative and inflationary changes), its proponents argue that it is a system of accounting for inflation (see: Sandilands Report, 1975, para.13). This is not true because the specific and general prices do not move in the same direction or even by the same rate and because CCA cannot account for the changes in the monetary items. Thus, there is a need to account for the two economic phenomena; the specific and the general price changes - where the accounting for both of them is necessary to account for the relative price changes.

The third approach may be termed 'real terms' accounting (or deflated CCA) as it uses both CCA and CPP. This approach was first developed by Edwards and Bell (1961) and supported by many others (see for example: Chambers, 1976 and Baxter, 1979). In this approach, distinctions are made between operating and holding activities and between the profit which is attributable to each activity. Operating profit is the difference between revenues and current operating expenses. Realized holding gains are the difference between operating and conventional accounting profits; unrealized holding gains are the difference between the current and historical costs of the held assets and realizable holding gains are the difference between the current cost of the held assets at the end of a period and their current cost at the beginning of that period or at the time of purchase if the assets are acquired in that interval. Business profit is operating profit plus the realizable holding gains. However, current cost data are restated in terms of the current purchasing power and holding gains are further divided into real and fictional holding gains. The latter are the amounts which are required to make the purchasing power adjustments. Since the current values of liabilities (a part from listed debt) and monetary assets are the same as their historical values, their unrealized monetary holding gains and losses are zero and are further divided into real and fictional - although they are not restated in terms of a general price level.

Accordingly, the above approach generates detailed information which can be used to report alternative accounting measures - e.g. conventional accounting income, operating income, business income and real business income (operating income plus real realizable holding gains). The alternative measures of income are believed to be useful for different purposes (Edward and Bell, 1961, pp.98-105 and Baxter, 1975, pp.23-4).

One can identify trends in operating (i.e. trading or recurrent) profits which represent the results of a firm's operating activities. Real business profit reflects, in addition to operating profit, the realizable results of a firm's holding activities (in terms of the relative price changes). The latter represents these real parts of holding gains and losses which have been realizable for the first time during a particular period, i.e. they reflect the net effect of both general and specific price movements on the firm's income for that particular period.

On the other hand, realizable profit and current exit values (net realizable vlaues) appear to be important for failure prediction studies. Realizable profit is defined as the difference between the exit values of a firm's assets at the end of a period and the corresponding value at the beginning of that period. Edwards and Bell (1961, pp.97-104) argue that when a firm's realizable profit falls below interest on current exit values (and is not expected to exceed it in the future), the firm should discontinue the business. Also, the changes in exit values reflect risk changes.

Finally, the usefulness of the above measures for one particular purpose may be empirically tested - and this is not possible for the lack of empirical data. As indicated in section 4.3 below, the usefulness of the income figures which are measured according to CCA and CPP have been tested empirically by adjusting historical cost data. However, it should be noted that although the above third approach is aimed at the perfection of accounting measures, they still cannot reflect the firm's future stream of earnings - which are reflected in Hicks's subjective concept of income and in the economic concept of capital - or its value as perceived by the capital market.

4.2.3 Flexibility of Accounting Practice

In addition to the above problems, conventional accounting includes a large number of alternative accounting practices which are all generally accepted. Therefore, in measuring income and financial position, the accountant is usually free to choose out of a number of generally accepted rules for his measurement. Inventory valuation methods, depreciation methods, accounting for research and development expenditure, deferred taxation, goodwill, mergers and acquitions and the subjective estimates that have to be made for some items (e.g. the useful life of fixed assets, bad debts, and the determination of the amount of any expected loss or contingent liability) are all domains for accounting flexibility (examples for alternative accounting methods are provided in Grady, 1965). This availability of the generally accepted alternative practices makes it possible to calculate widely different measures of income and financial position for the same firm for the same period of time. In this respect, Bird (1973, p.57) said:

> "Directors of companies are thus enabled to report whatever profit figure they wish within a very wide range, by choosing among the acceptable bases of reporting various transactions; and whicever they choose, the auditors must report that the accounts have been prepared in conformity with recognized professional standards".

The preparation of published financial statements is guided by two generally accepted accounting doctrines: consistency and full disclosure, which are hoped to reduce the effect of flexibility. According to the former the same accounting methods should always be employed and according to the latter any departure from the previously used methods should be fully disclosed in a note to the published financial statement. Thus the problem remains the same, the reliability and comparability of published financial statements (see: Keller, 1965).

The actual dimension of the flexibility problem is substantially less than it appears to be. In UK where there are strong professional accountancy bodies, it is expected that a narrow scope of flexibility is practised. In this respect, Lee (1976, pp.102-8) used empirical data gathered from various studies to show the limited scope of flexibility in practice. Moreover, the issuance of the statements of Standard Accounting Practice, from 1971, helps to reduce the dimension of accounting flexibility. However, there is evidence suggesting that standardization (as a compromise between flexibility and uniformity) satisfies the needs of all the interested parties. A discussion between the parties concerned with financial reporting (in a symposium held at Seaview, New Jersey in November 1968) revealed that the preparers of accounting information, on the one hand, are not seeking complete flexibility but they require the availability of different accounting treatments for the same economic event under the different circumstances and to allow management to choose, where available, the method which in its judgement best reveals the status of its firm. They also agreed that some ground rules are necessary to increase the usefulness of accounting reporting. On the other hand, it was revealed that the users of accounting information are not asking for rigid uniformity but they require that the appropriate practice ought to be stated and known by users and any choice of another practice ought to be disclosed and justified (Burton, 1969, pp.1-16). Although, this symposium was concerned with US accounting reporting, it is believed that its implications are valid for the UK as well.

Thus, standardization and the accounting doctrines of consistency and full disclosure are the accepted tools of treating the problems of accounting flexibility, as they appear to increase the reliability and comparability of accounting information. However, they only minimize the effect of flexibility and the user of accounting information would always have to assess the effect of any disclosed accounting change. As shown in section 4.3.1 below, the capital market appears to allow for any disclosed accounting change.

4.2.4 Accounting Disclosure

Disclosing and communicating the measured accounting information (the final output of accounting measurement) are two related concepts that need to be distinguished from each other for the purposes of defining the requirements of each of them and their present state in conventional accounting.

Accounting disclosure is concerend with both the quality and quantity of the information that can be transmitted or disclosed to the interested parties. Accounting communication is concerned with "how to convey this information in an understandable form which satisfies the users' needs?".

As such, accounting communication is also concerned with the quality and quantity of accounting information which can be usefully understood by its users, rather than which can be disclosed. Obviously, this concern of accounting communication does mean that it is concerned with the behavioural aspects of the recipients of accounting reports. It is only recently that the importance of accounting communication, with its behavioual aspects, has been emphasized over that of disclosure (see: Lee, 1971). However, this distinction, although not a clear-cut one, may indicate the need to consider both disclosure and communication.

The problem of disclosure is that a decision has to be made by a company's management as to the type, quantity and cost of accounting information that should be reported or made available to the interested parties. However, this problem is partially solved by the legal and institutional requirements for a minimum disclosure by companies for the benefit of external users, especially shareholders. In the UK, these requirements are governed by the Companies Acts 1948 and 1967, the Stcok Exchange's Listing Agreement, professional accountancy bodies and, also, the Prevention of Fraud Act 1958 and the City Code on Take-overs and Mergers which relies essentially on the Stock Exchange regulations (see: Benston, 1976, pp.14-37). Essentially, the company's annual balance sheet, profit and loss account, flow of funds statement, chairman's report, director's report and an independent auditor's report are published annually. However, these requirements do not resolve the whole problem because they only represent the required minimum of accounting disclosure. Thus, a company's management appears to have a freehand in deciding what else to disclose. This is not the case in practice because there is always the pressure of the interested parties (i.e. the market forces - especially shareholders and financial press and analysts) and the constraint of keeping the cost of the disclosed information within a particular limit. Therefore, one may conclude that the problems of accounting disclosure are concerned with satisfying the legal and institutional requirments and responding to the users' pressure while economizing on the costs of information. The latter two problems have been recently transformed to a problem of communication, according to the above distinction.

Accounting measurement and communication are highly interdependent. That is, what is to be communicated is a part or the whole of what has been measured and what is to be measured is at least that which is needed to be communicated (see: Bedford, 1973, p.3). In addition, the importance of accounting communication is related to the premise that the role of accounting information in a private enterprise economy is to help the proper allocation of national capital through the capital market by providing the decision makers with the information which is supposed to reduce his uncertainty about the future and promotes his decisions (see: Mahon, 1965). This implies that when the degree of uncertainty increases the decision maker requires more information and when his needs and objective change his required information also changes (see: Bedford, 1973, Chapter 1). Therefore, for accounting to maintain and to improve the performance of its role, accounting information service has to be improved in terms of communicating the needed information in a usefully understandable form. It has to cope with the continually changing and increasing needs and objectives of its users. Accordingly, much more attention is being given to accounting communication in order to improve the accounting information service and to keep improving the contribution of accounting to a society.

Accounting communication thus requires identifying the users of accounting information, their uses, their needed information, and the information load that maximizes their abilities to understand and process the reported information (see: Casey, 1980). Each of these requirements has been the basic theme of some works in accounting literature (e.g. Briggs, 1975 and Carsberg et al., 1974).

In conclusion, the nature and limitations of conventional accounting information have been discussed. As indicated above, conventional accounting measures are incomplete and outdated surrgoate representations of real world events or situations, the flexibility of accounting practice may affect the reliability and comparability of accounting information and accounting communication requires more consideration of the recipients' behavioural aspects. The effects of these limitations on accounting ratios which are the major variables in the empirical studies and financial analysis are considered below.

4.3 Accounting Limitations and Accounting Ratios

Despite the above limitations of conventional accounting information, the available empirical evidence indicates its usefulness. This finding is confirmed by the studies concerned with the area of failure prediction (see: Chapter 2) and some other areas (see for example: Lev, 1974 and Firth 1977 for a review of such studies). However, since conventional accounting information is incomplete, the users have to supplement it with other information, e.g. share prices, industry data, economy-wide data and other descriptive data. For example. Argenti (1976, Chapter 7) emphasizes the importance of the quality of management and that of visitng a company to meet its management, where a trained observer can gain valuable information about that company. That sort of information is not reflected by conventional accounting measures but is reflected by share price information, according to the efficient market hypothesis (see: Chapter 2). For this latter reason, share price information is beleived to be better indicator of a company's performance, where it reflects both accounting and non-accounting information. However, there is no strong evidence to suggest that the models incorporating share price variables perform better than the others. For example, Altman's model (1968) of predicting corporate failure included a market component in one of its variables (Market value equity to book value of total debt) but it did not perform better than other models (see: Chapter 2). This does not suggest that share price data cannot add to the power of purely accounting models because, in a failure prediction context, share prices may reflect the high expected repayment on liquidation more than they reflect the expected failure of a firm. The finding and argument of Gonedes (1973) can be used to support the effect of including a share price component. He found a low correlation between the accounting-based and market-based estimates of risk, which suggests that much of the information impounded in security prices is not reflected in accounting income numbers. In comparing this finding with that of other studies, i.e. Beaver et al., 1970 and Ball and Brown, 1968), he argued that the higher association found in the latter studies was due, mainly, to scaling the accounting income numbers by share prices which are also components of the market risk. However, a residual share price variable may perform better than only a share price component - where the former reflects an event which is specific to a company - but it has not been incorporated in any of known models.

As concerns the effects of accounting flexibility and inflation some empirical studies have been undertaken to test these effects and they are considered in the following subsection. The possibility of offsetting the effect of some of the conventional accounting limitations are considered in subsection 4.3.2 below.

4.3.1 The Empirical Effects of Accounting Limitations

Accounting ratios are the major variables of the empirical studies in accounting and they are expected to be affected by the limitations of conventional accounting. Simply, since ratios comprise accounting numbers in both the numerator and denominator, the quality of ratios will be dependent on the quality of published accounting data (as defined above). However, to the extent that the above limitations are common to all companies (e.g. in a cross-sectional sample) the user of accounting ratios has nothing to do with these limitations except to be always aware of them. Therefore, the impact of a change in an accounting method is of a considerable concern to any user of accounting information or ratios. If such a change is disclosed the user will have to adjust (as far as poosible) the reported figures to eliminate the impact of that change, and thus to make accounting figures comparable.

However, the user of accounting information, through ratio analysis, will be better aided and his problem of accounting changes will be reasonably solved if there are some guidelines regarding the impact of accounting changes on the ratios. In this concern, Holdren (1964) tested the impact of a change in the inventory valuation method, from FIFO to LIFO, on three accounting ratios - namely, current ratio, net profit to net sales, and inventory turnover ratio. He concluded that this change did not have significant impact on either current or net profit to net sales ratios but it resulted in a higher stock turnover ratio. He also noted that this impact differs from one industry to another and is not even uniform between companies in the same industry. Therefore, he recommended that comparisons should cover several years to offset the effect of any occasional change, which may occur.

In this same area, Derstine and Huefner (1974) investigated the impact of switching from FIFO to LIFO or vice versa on some risk-oriented accounting ratios for the purposes of investigating the impact of that accounting change on the interfirm comparability of accounting ratios and on the association between accounting and market measures of risk. Their study suggests that the switching to LIFO or FIFO methods has no significant effect on both the interfirm comparisons and the association between accounting and market measures of risk.

Comiskey (1971) and Archibald (1972) found that the switching-back from accelerated to straight-line depreciation has a significant effect on the reported earnings per share (EPS) and net income. In the first study, the price/earnings (P/E) ratio of the changers (the switching-back companies) declined after the change relative to that of the control group, i.e. the market was efficient in the sense that it recognized the artificiality of the increase in the EPS. The second study was not able to reach a definite conclusion regarding the capital market reaction to accounting changes, which seems not to be easily measurable (see: Archibald, 1972, Baskin, 1972, Eggleton et al., 1976, and more recently Brown, 1980).

The above studies suggest that the effects of changing accounting practice are either tolerable or insignificant. The capital market appears to allow for the effect of any disclosed change of accounting practice. However, further research is needed to add support to this conclusion.

As regards inflation, its impact on accounting figures has been studied in two instances; the relative predictability of alternative income models (Historic, CPP and Current Cost) and the reaction of a capital market to the information produced by using these models. In the first instance, Frank (1969) used historic - cost data for 76 companies in six industries and adjusted the data to reflect current cost income. His study suggested that current (replacement) cost income is not more useful than historical-cost income in terms of income predictions. It also suggested that reporting current income as supplementary information may be of assistance in predicting historical-cost income for only some industries - oil and perhaps chemicals.

Simmons and Gray (1969) used a simulation approach to test the predictability of the three income models (HC, CPP, CC) under different assumptions. They found that the most significant difference between the three methods in predicting income occurred in both the cases of no increase in unit sales and significant replacement of machinery. But generally, the three methods performed almost the same.

Buckmaster, Copeland, and Dascher (1977) used historical-cost data for a sample of 42 companies in four industries and adjusted the data according to the other two approaches. This study suggests that historical cost is the best predictor of future income followed by replacement cost and then general price-level adjusted historical cost, with the first two models consistently superior to the third. However, the finding of this study supported the impact of industry characteristics on the relative predictability of income models, where it was found that the best predicting income model varies among industries. Also, this study indicated that the relative predictability of the income models is not sensitive to the magnitude of the rate of price change, while the contrary was implied by Frank (1969).

A more recent study undertaken by Norton and Smith (1979) used historical cost data and adjusted them for the effects CPP changes for the purpose of comparing the prediction of bankruptcy based on accounting ratios computed from each of the two sets of data. By seleting bankruptcy as the object of prediction, this study avoided making any assumptions about the investor's earnings or his decision model which is one of the major shortcomings of the studies that were concerned with the prediction of future income. Discriminant analysis was used to fit a discriminant function for each of the two sets of data for each of four years before failure. The finding of this study was that CPP accounting data were "consistently neither more nor less accurate than historical data for predictions of bankruptcy".

In addition to Greenball's (1971) argument that accounting numbers of themselves can predict nothing, the results of the above studies "have been somewhat inconclusive - which is hardly surprising since the researchers have either unrealistically had to adjust real-world data with the advantage of hindsight, or instead have had to resort to sophisticated but artificial laboratory experiments" (Morris, 1975). The predictability of models using current cost data can be assessed only if CCA was actually introduced, because the real-world's current cost data may differ significantly than those produced by mrere adjustments of historical cost data.

As regards the capital market, some studies have been concerned with the effect of CPP on share prices.

Morris (1975) tested the impact of the CPP accounting information on the share prices, an alternative test of the usefulness of this information. The choice of the data which were published by Westwick was justified by two factors; first the data received a good deal of publicity; second although these data are subject to the comment quoted above, they were observed to be good approximations to the real-world data and what was needed for the purpose of the study was just "an aproximate indication of the size of the inflationary error". Using a simplified version of the market model, this study suggested that there was a little or negligible informational content in the publication of the inflation adjusted figures - either because the market had already made its adjustment or because it chose in general not to regard such information as being relevant when setting share prices.

Hillison (1979) investigated the relationship between, on the one hand, the movement of share prices and, on the other, each of the earnings per share computed from conventional accounting data and the earnings per share computed from CPP adjusted data. He found (for the test using the sign of the first difference in the two measures of earnings per share) an insignificant difference between conventional and CPP earnings per share and neither of them had significant association with the measure of the abnormal market return. For the second difference test, he found that conventional earnings per share exhibited a significantly stronger association with the measure of the abnormal market return.

Baran, Lakonishok, and Ofer (1980) computed three measures of accounting risk (accounting beta) for a set of historical cost data and for the same set after adjusting for the CPP changes. Then they correlated the three measures of each set of data with the market measure of risk (market beta). They found that the association between market beta and CPP adjusted betas was significantly higher than those observed between market and historical cost betas. Thus, it was concluded that CPP data contain information which is not included in historical cost data, and this was interpreted as an indication that investors adjust historical cost data to changes in the purchasing power of money and base their decisions on the restated data. This finding is consistent with that of Basu (1977).

Parker (1975) argued, as a representative of investment analysts who are investors or advisors to investors, that conventional accounting reports have over the years produced measures of earning per share which are good proxies of dividends per share, and that, although higher rates of inflation generally lead to higher rates of growth in earnings and dividends, investors learned (as the history of price/earnings ratios shows) to reduce the price-earnings relationship when inflation rates persisted at high levels (the investor cannot directly control earnings or dividends, but he can directly affect share prices). Thus, he further argued that CPP financial statements would fail to be helpful to any investor and would likely be harmful to less sophisticated investors.

The findings of the above mentioned studies lead to the conclusion that conventional accounting information can be used in empirical studies and, to the extent that there are problems, the inclusion of a residual market term in the model should improve its explanatory power.

4.3.2 Accounting Limitations and Methods of Analysis

The ability of methods of analysis to offset the effects of accounting limitations appears to be disputable. Lee (1976, p.144) argues that "no matter how good the techniques of analysing financial reports, the quality and reliability of the analysed data are only as good as the financial reports themselves". He emphasizes that although expert analysis can offset presentation faults after selecting the data, "the effect of measurement faults will be carried through to the analysed data, presentation faults can impede the selection of relevant data for analysis purposes". On the other hand, Taffler (1977b, pp.1-7 and 31-3) believes that "once a number of different facts of the firm are considered together {in a multivariate analysis} the published statement becomes an extremely valuable document for many fundamental decision purposes and different types of users". He also criticizes accountants for being concerned with individual numbers and with the materiality of an item or particular accounting treatment etc., in the abstract.

However, the fact of the situation may lie in between the above two extreme views. The statistical analysis of accounting information includes preparing the data and then applying the statistical techniques. The preparation includes adjusting the data to offset the effect of any disclosed accounting change, bounding the distributions of the data by replacing the extreme values with the limited values, and transforming the distributions of the data to approach normality. The latter two procedures may reduce the effect of any undisclosed accounting change (or disclosed - but adjustment is not possible) or extraordinary item. The application of multivariate statistical techniques has the advantage of allowing for the interaction between the independent variables, and thus it generates information which is not available elsewhere. Thus, it can be argued that as long as the data of all the considered set of companis are produced by their managements using conventional accounting and as long as the data are prepared as mentioned above, the multivariate analysis will minimize the effect of accounting limitations.

However, the validity of this argument does not justify any conclusion or recommendation about a specific accounting practice, as implied by Taffler's above criticism. Also, it is not valid to claim that accounting ratios largely discount the effect of inflation by virtue of their numerators and denominators both being affected by inflation (see: Taffler, 1977b). Inflation does not affect all the items of published financial statements in one direction or by the same amount. For example, inflation results in overestimated profit, undervaluated assets and a fixed monetary expression of liabilities and, thus, the ratios of profit to assets and profit to liabilities may inflate the effect of inflation rather than discounting it. Therefore, it can only be argued along the line of the above argument that as long as inflation is a common phenomenon, multivariate analysis may generate reasonabl results.

4.4 Company Accounts Data-Bank

The accounting information in the form of a computer file of UK quoted companies' accounts has recently been made available to British Academic Institutions. The history of the process of collecting and standardizing published accounts, in UK, dates back to 1950, "when the National Institute of Economic and Social Research began an investigation into the value, for the purpose of economic analysis, of company accounts published after the 1948 Companies Act". The Statistics Division of the Board of Trade (SDBT) prepared the data on punched cards for the five years following the Companies' Act, 1949-53, and has since then undertaken the task of putting published company accounts into the same standardized form which was adopted by Tew and Henderson (1959, pp.xvii-2). The SDBT, again, provided the data for the period 1948-1960 on punched cards for the project undertaken by Singh and Whittington. It is only through this last project that the data were reproduced on computer magnetic tapes (see: Singh and Whittington, 1968, p.13 and p.203). The data was rescued from "extinction" by Whittington, Meeks, and others who have over a period of ten years assembled it into a well organised database, which has recently been updated to include all company accounts up to April 1974 (see: London Business School, 1977, p.10.1). A copy of this latter database was obtained from London Business School for the purpose of this study, in the form of two lengthy 1600 b.p.i. magnetic tapes written in the IBM/360 binary language (with 32 bits a word). However, this data-bank comprises the financial accounts of mainly UK quoted companies, supplemented by 25 indicative variables representing biographical details for each company-year. The quantitative data include 150 variables representing a balance sheet, income appropriation account, sources and uses of funds statement and miscellaneous data (see: DABMUE, undated).

The major problem of using the obtained copy of the data-bank (DTI/ Whittington, henceforth) is that the magnetic tapes with the above specifications are not readable on ICL machines for two reasons; first the binary patterns of one machine are usually meaningless to another; second the size of the ICL word is only 24 bits and it would not be safe to transfer the 32 bits IBM word into ICL words. Fortunately, it was possible to convert the two binary tapes into 4 lengthy IBM formatted tapes by the IBM computer of the Department of Physics of the University of Liverpool. The IBM formatted tapes can be dealt with on ICL machines. However, it was not possible to convert the latter tapes directly into ICL magnetic tapes. Consequently, a computer program using a magnetic tape routine was used to read a number of the IBM blocks of data, convert each block into ICL characters, and then write them into a basic file. It was necessary to edit these basic files using the George Commands to make them readable. During the process of editing, it was decided to retain only the data which were considered necessary for the purpose of this study (appendix A represents the comparative layout of both the retained and original data). The edited files were then grouped into multiple files each of which contains the data of one industry. Finally, the multiple files were stored on one magnetic tape, using the newcopyout macro, and they can be read from this magnetic tape into multiple files using new-copyin macro. This process was a far more troublesome and time consuming and was eventually disappointing, especially as it had to be done on an individual basis as a once-off exercise.

The following are the limitations of the DTI/Whittington data-bank. First, its population is restricted to mainly large quoted companies which satisfy a size criterion. Second, the successive increases in the size criterion break the continuity of the data. This criterion was first introduced in 1961 and increased in 1970 (Department of

Industry, 1978, p.3). Therefore, if a company is of interest to a study and failed to satisfy an increased size criterion its data have to be continued from other sources. In this study, Ex Tel cards were used to complete the data of two companies. Third, the comparability of the data is violated by the changes of the Standard Industrial Classification (SIC) in 1958 and in 1968 (thus, a company may be reclassified because of a change in either its activities or the SIC), the increasing disclosure of accounting data either by legal and institutional requirements or voluntarily (e.g. disclosing turnover according to the companies act 1967) and the changes in the standardization procedures (e.g. provisions have been treated otherwise from 1964 onwards) (see: DABMUE, undated). Fourth, estimation has taken place in two instances; in deriving the sources and uses of funds statement from the other data and in adjusting the data for the change of accounting date (details are given in Singh and Whittington, 1968, appendix A). Fifth, missing values are not identified and they are given the zero value, thus, a user would have to distinguish for himself whether a zero identifies a missing value or an actual value of zero.

Fortunately, these limitations hardly affected this study. For the years up to 1963, provisions were added to the current liabilities for the purpose of computing accounting ratios and to offset the effect of changing the treatment of provisions by adding them (except the provision for pension liabilities which has been added to reserves) to trade and other creditors from 1964. The companies which have pension funds in their reserves for the period 1964-1968 are artifically in a better position. Pension funds are separately available from 1969 and thus they are subtracted from reserves where avialable. However, the provisions for pension liabilities appear much less frequently in British company accounts (see: Weaver, 1971, pp.35-8 and ICAEW, 1973, Survey of Published Accounts). Also, the values of equity capital and fixed assets of the companies which revalued their assets were adjusted by the amount of revaluation to improve the comparability between the companies.

In conclusion, the DTI/Whittington data-bank, by virtue of its long history and the participants in its production, appears to be the best available data-bank for academic purposes. Almost all the above limitations were anticipated and, as far as possible, provisions were made against them.

4.5 Share Price Data-Bank

Monthly share price and associated data for 2300 British companies quoted on the London Stock Exchange between 1955 and 1974 have recently been available to British academics in the form of a computer file called London Share Price Database (LSPD), which is produced by London Business School. A copy of this data-bank and a copy of the daily market index were obtained from the producer on a magnetic tape for each copy. The former tape is a formatted IBM tape while the latter is a binary IBM tape. Thus, only the latter tape has to be converted into a formatted IBM tape by the IBM computer of the Department of Physics of the University of Liverpool. This latter formatted IBM tape was converted into one ICL basic file which did not need any editing. The former tape was converted into ICL files following the same procedure which was used to convert the DTI/Whittington data-bank.

In preparing the data-bank, the data of only one share are recorded for each company (the share that represented the greater market value), prices in old pence were decimalised (into integer digits of new pence) with some subsequent loss of accuracy, and some prices are missing around February 1956. Apart from these minor limitations, the LSPD is fairly documented (see: London Business School, 1977) and it has been used in a published UK study (see: Franks et al., 1977). However, the effect of non-trading and the nature of the daily market index are considered in Chapter 3 and they are not limitations to the data-bank itself.

4 6 Concluding Remarks

The state of conventional accounting information was described in this chapter. Its measurement is based on actual financial transactions and assumes the stability of the monetary unit, recognizes only realized gains and any actual or potential losses and uses a set of alternative, generally accepted, accounting practices. This nature of conventional measurement resulted in the limitations of accounting information which were represented by the incompleteness of accounting measures of income and capital, the inability to allow for the effect of inflation, the flexibility of accounting practice and the problem of accounting communication. Conventional accounting measures are incomplete and outdated surrogate representations of real world events or situations. The share price data reflect information which cannot be reflected by conventional accounting information. Therefore, they may be used to improve the explanatory powers of the accounting-based models. Accounting for inflation is necessary to reflect the economic facts of general and specific price changes and to update and correct the accounting measures. The flexibility of accounting practice results in less comparable and less reliable information. Accounting communication requires more consideration of the behavioural aspects of the recipients of accounting reports. Previous empirical studies indicate the usefulness of accounting information and that effects of the limitations of accounting information on accounting ratios are either insignificant or tolerable (by adjusting for effect of disclosed accounting changes, by including additional data and by selecting the proper method of analysis). The behaviour of share prices indicates that the investors are not fooled by the changes of accounting practice or by the effect of inflation.

Finally, sources of this study's accounting and share price data, problems of preparing data-banks and the limitations of these data were described above.

Having considered this study's problem, objectives and hypotheses in the first chapter; reviewed the literature in the second; selected the methodology which hopefully can conclude this study satisfactorily in the third chapter - and presented the state of conventional accounting and the sources and limitations of the data in this chapter, the empirical results are presented in the following chapters.

CHAPTER V

VARIABLES SELECTION: EMPIRICAL RESULTS

CHAPTER V

Variables Selection: Empirical Results

5.1 Introduction

The purpose of this chapter is to report on the results of the statistical analysis which was undertaken to prepare the independent variables for the ultimate application in developing failure prediction models. The independent variables (see Chapter 3) include accounting ratios, industry-dummy variables and the economy-wide indicator.

As regards the preparation of accounting ratios, tests of normality and the descriptive statistics of each ratio's selected distribution (either the original or the transformed one) and the univariate comparisons between the mean values of each ratio for the failed and non-failed companies are reported in this chapter. The purpose of these comparisons is to gather some primary ideas about the ability of each ratio to discriminate between the two groups of companies (see Chapter 3). In addition, principal components analysis (PCA) is used to account for the effect of ratios' multicollinearity and to investigate the stability of accounting ratios (as measures of a firm's financial attributes) for the different periods of time and for the different groups of companies. Therefore, this chapter reports on the results of applying PCA to the data of the two groups of companies for the five years before failure (BF), the data of each group of companies for the five years BF, the data of the two groups of companies for each of the years BF and the data of each group of companies for each of the five years before failure. A comparison between these results indicates which are the stable ratios and groups of ratios.

As regards the environmental variables, Cluster analysis was undertaken to investigate the similarity between the industries and the possibility of clustering them around a few groups, three-groups discriminant analysis was undertaken to test the validity of the proposed classification of the 19 industries (represented in this study) into three functional groups (manufacturing, construction and distribution) and the FTA - market index was used to develop an economy-wide indicator.

The reported results indicate that: (1) the normality of some ratios' distribution can be improved by bounding the distributions and applying the relevant transformations; (2) there are significant differences between the mean values of some ratios for failed and non-failed companies for at least five years before failure and the ratios of the failed groups' deteriorate as the years of failure approaches; (3) the empirical grouping of accounting ratios differs from their a priori grouping and some ratios do not measure the same financial attributes for the different periods of time nor the different groups of companies; (4) there are some similarities between the considered 19 industries and the validity of their functional classification (into the above mentioned three groups) is confirmed by the three-groups discriminant analysis.

However, the preparation of accounting ratios, industry-dummy variables and the economy-wide indicators are each considered in one of the following sections.

5.2 Accounting Ratios

The primary considered list of accounting ratios comprises 96 ratios, see: tables B1 and B2 of Appendix B. 25 ratios were excluded because of missing values, i.e. they could not be computed for each company in the designed samples. A further 21 ratios were excluded because of non-normality before and after the transformations. Two of the remaining 50 ratios (ratios 94 and 96 which measure earnings variability) are not reported in what follows. They performed poorly on both principal components analysis and discriminant analysis.

5.2.1 The A priori Grouping of Ratios

The importance of the a priori grouping of accounting ratios is that it defines the ratios and the financial attributes they measure. Thus without a priori knowledge about each ratio and what it is supposed to measure, the interpretation of any empirical grouping will almost be impossible. On the other hand, the empirical grouping accounts for some aspects which cannot be accounted for by the a priori grouping - as shown in subsection 5.2.4 below.

Accounting ratios have been grouped according to the firm's financial attributes, on an a priori basis, into different numbers of categories - e.g., profitability and liquidity (see for example: Foster, 1978, p.28 and Horrigan, 1965).

However, Pinches, Mingo and Caruthers (1973) criticized the a priori groupings of ratios for their failure to take account of the empirical relationships existing between and among ratios. Foster (1978, p.184) added that these groupings have little explicit theoretical underpinnings. "There is little in economic theory that suggests that the liquidity, leverage, profitability and turnover categories constitute either a mutually exclusive or collectively exhaustive set of financial characteristics of a firm."

In this study, however, the primary considered list of accounting ratios covers a wider range of the firm's financial attributes and they are arranged into eight groups: profitability, liquidity, capital gearing, growth, prestige or importance of a company, size, risk and other ratios (see: Appendix B). These categories remained in effect after the exclusion of some ratios. However, the relationship between the a priori and empirical classifications is discussed in subsection 5.2.4 below.

5.2.2 <u>The Distributions and Transformations of Ratios</u>

As indicated in Chapter 3 (subsection 3.4.1.1), many accounting ratios are not expected to be normally distributed, but their transformations may approximate normality. Also, the linear discriminant function was found to perform better when the data are bounded from above and below.

Therefore, Shapiro' and Wilk's (1965) "W" and D'Agastino's (1971) "D" tests for normality (as defined in Chapter 3 - subsection 3.4.1.2) were applied to the ratios of each group of companies in both the analysis and hold-out samples. The two tests were programmed by the researcher to test for the normality of ratios and some forms of their transformations - at the same time, instead of testing the distribution of the ratios and subsequently each of their possible transformations (see: Appendix D for the computer program). The outlier values of each ratio were bounded (as indicated in Chapter 3) from above and below to the values of the ratio's mean plus and minus two standard deviations, respectively. The distributions of bounded ratios and their transformations were, as expected, more normal than the unbounded ratios (compare table C1 with table C2.1 of Appendix C). Therefore, the analyses in this and the following chapters are based upon the bounded ratios, except for the inter-temporal validation sample.

5.2.2.1 <u>Ratios' Transformations</u>

The purpose of transformation is to obtain more normal distributions of accounting ratios, which are the marginal distributions in a multivariate context. As stated by Gnanadesikan (1977, p.137) ".....even if a transformation of variables does not accomplish normality, it may often go a long way toward symmetrizing the data, and this can be a significant improvement of the data as a preliminary to computing standard statistical summaries such as correlation coefficients and covariance matrices."

Logarithmic, square root and reciprocal are generally the most common transformations and they are recommended in the literature (see: Chapter 3). These transformations cannot be used for the distributions which include zero values. In addition, the first two transformations cannot be used for the distributions which include negative values. Thus, a constant is added to the values of each ratio to make the transformations possible. Adding a constant does not change the distribution of a ratio. Geometrically it only has the effect of moving the point of origin from the zero point to the value of the constant. The values of 1, 0.5 and 0.375 have been proposed as the constant values which may improve normality when used in one of the above transformations (see: Zar, 1974, pp.184-8). In addition, the values of 2.25 and 3 have been tried. It should be noted that the logarithms in the base 10 and the base e produce the same transformed distributions, although the individual values are different.

5.2.2.2 Missing Values

When a ratio could not be computed because the concerned accounting data were not available, e.g., turnover, the ratio was assigned the value 9.999 as an indicator of a missing value. If the denominator of a ratio has a zero value, the ratio is assigned the missing value indicator (9.999) rather than the expected maximum value of the ratio. The latter value may appear to be the right numerical solution but it is not so in the context of accounting ratios - where it is not sensible, for example, to assign the maximum value of the liquidity ratio to a failed company only because its current liabilities are zero.

As regards the statistical analysis, the problem will exist only if the variables with some missing values cannot be excluded from the analysis. Therefore, the cases with missing values on some variables may either be excluded from the analysis (Listwise deletion method) or included in it. In the latter case,missing value can either be processed as the actual values or excluded only from the computations involving the corresponding variables (Pairwise deletion method) (see: Nie et al., 1975 for treating missing values under different statistical procedures). However, since any inclusion of cases with missing values affects the accuracy of the statistical analysis, their exclusion is the recommended treatment, especially in multi-variate analysis (see: Cooley and Lohnes, 1971, p.137). Following this latter treatment, the inclusion of variables which have some missing values for dfferent numbers of cases may reduce drastically the effective number of cases.

In this study, however, any ratio with any number of missing values is excluded from the subsequent analysis. This procedure leaves the number of cases unreduced because of missing values and leaves no case with a missing value. Thus, 25 of the 96 ratios, albeit some of them are normally distributed, were excluded at this stage (see: Appendix B).

5.2.2.3 Normality Tests and Descriptive Statistics

Sixteen distributions for each ratio were tested for normality. They are the distribution of the ratio and one set of three transformations (logarithmic, square root and reciprocal) for each distribution of the ratio plus one of the selected five constant values.

The selected distribution of each ratio is the closest one to normality for each group of companies for each of the five years before failure. Therefore, it is not necessarily the best distribution for each group-year.

The reason for this selection is that the same variable is used for the two groups of companies for a particular year and for combinations of years, thus, it must always keep the same form.

Tables 5.1a, 5.1b, 5.1c and 5.1d represent the statistics of 8 selected ratios for each group of companies for the fifth and the first years before failure, the statistics of all the 48 ratios appear in tables C2.1 to C2.5 of Appendix C. The 8 ratios were an arbitrary selection to represent the majority of the a priori groups of the primary list of ratios (see: Appendix B).

Column 3 of the tables represents the computed value of the 'D' test. D'Agostino (1971) provides a pair of critical values for each of five significance levels, see the footnotes on table 5.1a. If the computed value of D lies between the critical values of a particular level of significance, the null hypothesis of the population's normality is accepted. Column 4 of the tables represents the difference between the computed and the critical values of the 'W' test, the latter values are provided by Shapiro and Wilk (1965). Thus, the negative values of W in column 4 indicate departure from normality. However, a comparison between the results of D and W tests indicate that the W test is more sensitive to departure from normality than the D test.

The other columns of the tables represent the descriptive statistics of the distributions, i.e., mean (MN), standard deviation (STD), skewness (SKW) and Kurtosis (KUR). Using the tables in Pearson and Hartley (1976, pp.207-8) the coefficients of skewness and Kurtosis can provide test results similar to those of D and W tests.

However, tables 5.1a, 5.1b, 5.1c and 5.1d indicate that the degree of a ratio's normality differs for the same group of companies over the years as well as for the same year, before failure, between groups. The general trends of the untransformed distributions can be detected from tables 5.2a and 5.2b (and table C3 in Appendix C) which represent the results of W test for the bounded, but untransformed distributions of the ratios of each group for five years before failure. The distribution of the ratios of non-failed companies are more stable and closer to normality than that of failed companies. On the other hand, the distribution of failed companies' ratios departs increasingly from normality as the companies approach failure. The improvement achieved in the distribution of ratios by means of transformation can be revealed by comparing tables 5.1a, 5.1b, 5.1c and 5.1d with tables 5.2a and 5.2b - and the corresponding tables in Appendix C. This comprison also reveals that most of the transformed ratios have kept their general trends, albeit more normally distributed.

Column 2 of table C1 of Appendix C represents the form of the selected distributions of the 48 selected ratios, with which the subsequent analysis proceeds.

5.2.3 Univariate Comparisons Between Groups

Since. "in practice, a single overall multivariate analysis of data is seldom sufficient or adequate by itself and, almost always, it needs to be augmented by analysis of subsets of the responses, including univariate analysis of each of the original variables" (Gnanadesikan, 1977, pp.162-3), the following two univariate analyses, t-test for mean differences and profile analysis, are intended to reveal the difference between each ratio for the groups of companies. As indicated in Chapter 3, the mere comparison between the mean values of a ratio for the two groups of companies. e.g. profile analysis, is not indicative of the true differences between the two distributions. Therefore, the t-test is used to support the profile analysis. Each of the two tests is considered below.

Table 5.1a - Distribution of Selected Variables - Failed Companies (Year - 5)++

Variable No.	Name()	Form	D*	W**	MN	STD	SKW	KUR
7	EBIT/TCE	X	.2649	-.001	.041	.065	.347	.695
16	CA/CL	1.0/(X+0.5)	.2859	.034	.394	.181	-.125	-.836
38	FF/TCE	X	.2751	.034	.056	.069	.380	.157
49	FL/NCE	1.0/(X+3.0)	.2810	-.009	.314	.016	-.531	-.576
64	$\Delta NCE/NCE_{t-1}$	1.0/(X+3.0)	.2440	-.097	.332	.012	-.986	1.734
73	TrA	Ln(X+1.0)	.2845	.037	7.152	1.137	-.353	-.658
86	QA1/TCE	X	.2806	.017	.291	.120	.541	-.572
90	(NCE-FTR)/FA	SQ(X+1.0)	.2806	-.011	1.723	.263	.630	-.647

() See table 5A, p.183, for key to the ratios

Table 5.1b - Distribution of Selected Variables - Healthy Companies (Year - 5)

Variable No.	Name()	Form	D*	W**	MN	STD	SKW	KUR
7	EBIT/TCE	X	.2834	.045	.180	.061	.281	.486
16	CA/CL	1.0/(X+0.5)	.2691	-.004	.471	.141	1.181	1.846
38	FF/TCE	X	.2836	.055	.199	.057	.090	-.484
49	FL/NCE	1.0/(X+3.0)	.2444	-.194	.324	.013	-1.533	1.393
64	$\Delta NCE/NCE_{t-1}$	1.0/(X+3.0)	.2581	-.011	.327	.007	-.121	2.573
73	TrA	Ln(X+1.0)	.2490	-.093	7.949	.873	1.854	3.964
86	QA1/TCE	X	.2751	-.002	.412	.128	-.670	-.287
90	(NCE-FTR)/FA	SQ(X+1.0)	.2818	.031	1.783	.319	.492	-.503

++ n = 43 for (year - 5) and n = 44 otherwise

* Each significance level, α, is given a pair of critical values. If the calculated D is $\leq$ the first member of the pair, or $\geq$ the second, then the null hypothesis of population normality is rejected:

n	α = 0.20	α = 0.10	α = 0.05	α = 0.02	α = 0.01
42	.2743, .2854	.2717, .2861	.2691, .2867	.2659, .2871	.2636, .2874

Table 5.1c - Distribution of Selected Variables - Failed Companies (Year - 1)

Variable No.	Name()	Form	D*	W**	MN	STD	SKW	KUR
7	EBIT/TCE	X	.2690	-.004	-.040	.119	-.564	.349
16	CA/CL	1.0/(X+0.5)	.2608	.023	.514	.329	.072	2.742
38	FF/TCE	X	.2704	.019	-.011	.113	-.092	.538
49	FL/NCE	1.0/(X+3.0)	.2497	-.127	.303	.033	-1.799	4.049
64	ΔNCE/NCE$_{t-1}$	1.0/(X+3.0)	.2577	-.036	.350	.036	1.102	1.458
73	TrA	Ln(X+1.0)	.2831	.033	7.209	1.167	-.263	-.547
86	QA1/TCE	X	.2757	-.015	.291	.164	.820	-.034
90	(NCE-FTR)/FA	SQ(X+1.0)	.2779	.019	1.598	.317	.674	-.075

Table 5.1d - Distribution of Selected Variables - Healthy Companies (Year - 1)

Variable No.	Name()	Form	D*	W**	MN	STD	SKW	KUR
7	EBIT/TCE	X	.2844	.044	.207	.054	.289	-.598
16	CA/CL	1.0/(X+0.5)	.2762	.011	.454	.138	.851	.377
38	FF/TCE	X	.2838	.051	.222	.046	.041	-.485
49	FL/NCE	1.0/(X+3.0)	.2537	-.158	.328	.007	-1.253	.491
64	ΔNCE/NCE$_{t-1}$	1.0/(X+3.0)	.2771	.027	.315	.008	-.387	-.037
73	TrA	Ln(X+1.0)	.2564	-.065	8.456	.899	1.586	2.798
86	QA1/TCE	X	.2795	.041	.415	.139	-.352	-.114
90	(NCE-FTR)/FA	SQ(X+1.0)	.2690	-.006	1.882	.442	1.130	1.245

44 .2745, .2854 .2720, .2861 .2695, .2867 .2664, .2871 .2641, .2874

** The tabulated 1% point of W, which has been already subtracted from the calculated values, is 0.923 for n = 43 and 0.924 for n = 44.

Table 5.2a - W Statistic** for Untransformed Ratios - Failed Companies

Variable			Years before failure				
No.	Name	Form	-5	-4	-3	-2	-1
7	EBIT/TCE	X	-.001	0.04	0.020	0.004	-.004
16	CA/CL	X	-.270	-.233	-.365	-.366	-.306
38	FF/TCE	X	0.034	0.050	0.028	0.036	0.019
49	FL/NCE	X	-.020	-.021	-.014	-.209	-.271
64	$\Delta NCE/NCE_{t-1}$	X	-.125	0.004	-.506	-.087	0.014
73	TrA	X	-.087	-.106	-.102	-.112	-.155
86	QAI/TCE	X	0.017	0.038	0.000	0.011	-.015
90	(NCE-FTR)/FA	X	-.035	-.025	-.062	-.033	-.026

Table 5.2b - W Statistic** for Untransformed Ratios - Non-Failed Companies

Variable			Years before failure				
No.	Name	Form	5	4	3	2	1
7	EBIT/TCE	X	0.045	0.044	0.052	0.044	0.044
16	CA/CL	X	0.052	0.030	0.050	0.035	0.037
38	FF/TCE	X	0.055	0.052	0.053	0.057	0.051
49	FL/NCE	X	-.213	-.160	-.162	-.176	-.161
64	$\Delta NCE/NCE_{t-1}$	X	-.015	-.028	0.039	0.004	0.018
73	TrA	X	-.561	-.546	-.536	-.534	-.514
86	QAI/TCE	X	-.002	-.013	-.005	0.014	0.041
90	(NCE-FTR)/FA	X	0.000	0.012	0.000	-.041	-.087

5.2.3.1 The t-test of Significance

The significance of the difference between the means of the two populations on each ratio-year is tested using the t-test as reported in table 5.3 and table C4 in Appendix C. The t-test assumes that the observations are approximately normally distributed and are subject to a common variance (see: Thomas, 1973, pp.98-102 and Nie et al., 1975, pp.267-70). If the two populations are not subject to a common variance, t cannot be computed for the difference in sample means. However, an approximation to t may be computed. Since the variances of our two populations are not known, then an F-test of sample variances is performed for each ratio. Where the null hypothesis, H_o: $\sigma_1^2 = \sigma_2^2$, is accepted t is computed and otherwise approximate t is computed. All the computations have been made by the SPSS subprogram t-test. Tables 5.3 and C4 indicate that most ratios' means differ significantly between failed and non-failed companies.

Table 5.3 t-test, the 2-tail probability associated with t value ++

V. No.	Y = -5	Y = -4	Y = -3	Y = -2	Y = -1
7	0.000	0.000	*0.000	*0.000	*0.000
16	0.030	0.287	0.902	*0.552	*0.271
38	0.000	0.000	*0.000	*0.000	*0.000
49	0.002	0.000	*0.000	*0.000	*0.000
64	*0.026	*0.000	*0.208	*0.000	*0.000
73	0.000	0.000	0.000	0.000	0.000
86	0.000	0.000	0.000	0.001	0.000
90	0.341	0.180	0.109	0.013	0.001

++ Differences are significant if probabilities are less than α = .05.

* Probabilities associated with approximate t.

5.2.3.2 Profile Analysis

Profile Analysis was used by Beaver (1966) to outline the general relationships betwen the failed and non-failed companies. It is a graphic comparison between the mean values of the two groups of companies on each ratio. Figure 5.1 presents a plot of the mean values of the 8 selected ratios for the two groups of companies for five years before failure, Figure C1 in Appendix C presents a plot for each ratio. Figures 5.1 and C1 indicate that there is a difference, the same as the t-test, between the two groups of companies. Profile analysis has the advantage of showing the direction of the difference. The difference in the mean values is in the expected direction for the majority of ratios in all five years before failure (see: Figures 5.1 and C1). For some ratios, e.g., 52, 59 and 87, the difference in the mean values was not in the expected direction in the fifth year before failure. The difference in the mean values of liquidity ratios (16 through 22) is not in the expected direction. Failed companies appear to be more liquid than non-failed companies but, however, the difference between these ratios' means are not significant for most of the cases. Therefore, the differences displayed by profile analysis should be considered together with their significance as measured by the t-test. Finally, profile analysis may indicate the ratios which are measuring the same financial attribute, compare the groups of ratios (1, 2, 3, 7, 8, 10, 38 and 94), (5 and 6), (16, 17 and 18) and 48 and 51) in Figure C1 Appendix C.

5.2.4 Dimensionality of Accounting Ratios

Principal components analysis (PCA) was undertaken to account for the effect of ratios' multicollinearity, see Chapter 3. Since it reduces the dimension of p ratios to m components which are uncorrelated with each other and each of which groups a set of homogenous ratios, no more than one

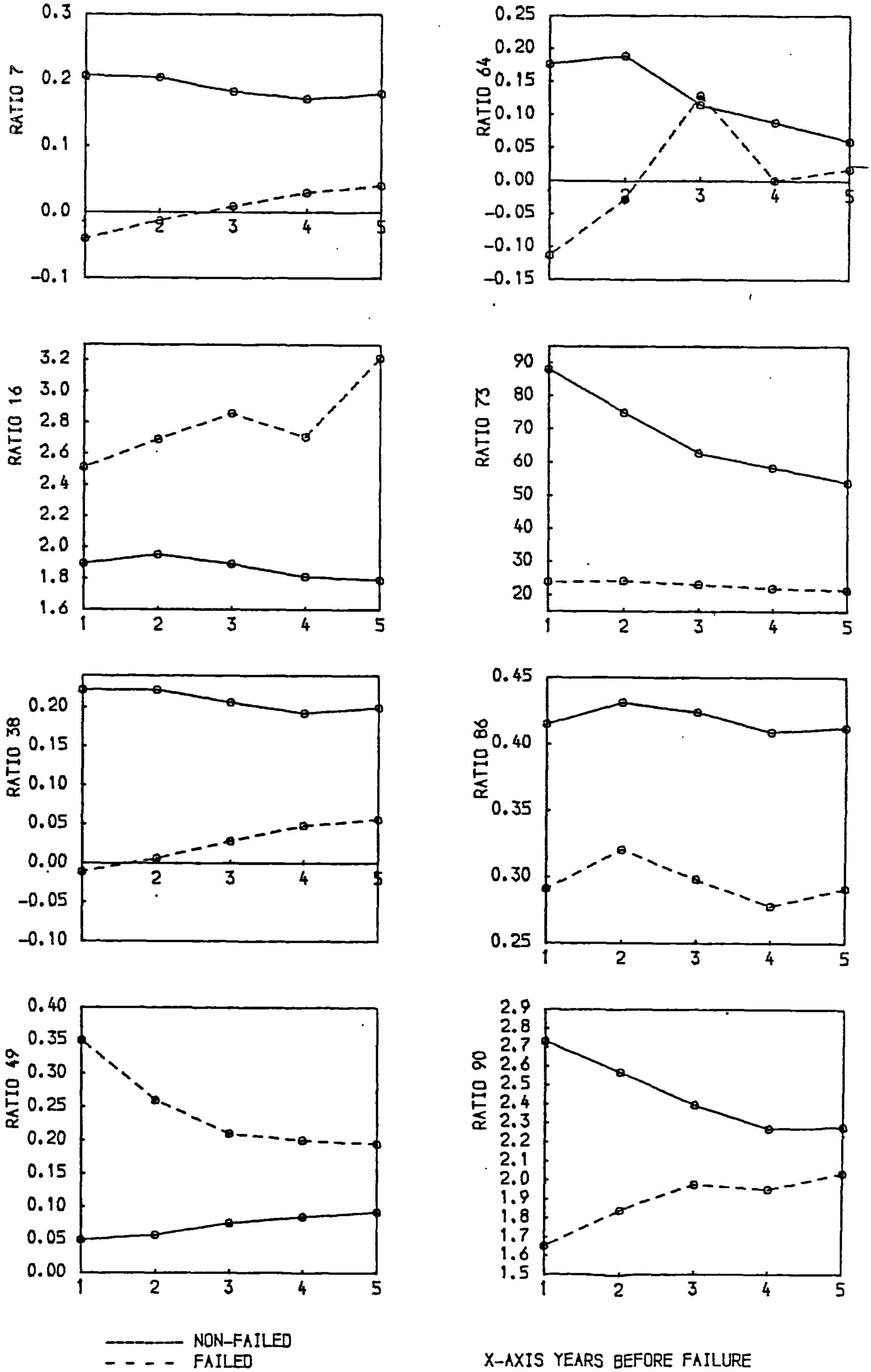


Figure 5.1 - Profile Analysis, Comparison of Mean Values

ratio from each component may be included in a multivariate model. However, if the analysis incorporates ratios of more than one financial year (BF) or of more than one group of companies, the stability of the resulting components for the different years and groups must be examined, see: hypothesis 5 of Chapter 1 - about the instability of ratios' groupings. If the components are not stable, e.g. some ratios may load on different components for the different years or groups of companies, any further analysis should be restricted to ratios which load consistently on the same components, otherwise multicollinearity may arise.

In the following, the empirical groupings of ratios are presented and compared with the a priori one and the hypothesis about their persistence is tested. In a primary run of PCA more than ten components were extracted by requiring that the eigenvalue of each component must be equal to or greater than 0.6. The examination of these components indicated that seven components are sufficient to convey most of the information contained in the set of our ratios. Thus, the number of extracted components, in the subsequent analysis, was controlled by requiring that the eigenvalue of each component must be equal to or greater than 1.0, which resulted in at least seven components. Only accounting ratios which had component loadings of .70, the square of which is approximately 50%, or greater are reported in the tables below. The loading of each ratio on the concerned component represents the correlation coefficient between the ratio and the component. The square of the loading of a ratio on a certain component is the variance of the ratio that is accounted for by the component. Ratios with less than 50% variance, which is approximately .70 loading, accounted for by a component were considered too weak to report (see: Pinches et al., 1973 and 1975 and Taffler, 1977a). Table 5a presents key to the ratios of principal component analysis while the key to all the ratios and their computation are in Appendix B.

5.2.4.1 Empirical Grouping of Ratios

Principal components analysis of the selected 48 ratios across the 88 companies (44 companies of each group representing both the analysis and hold-out samples) for the five year period resulted in the identification of seven groups, components, of financial ratios, table 5.4. The seven components account for 83.4% of the information contained in the original 48 ratios. The ratios which loaded on each component suggest an interpretation and a name for each component. Thus, the seven components are named: profitability, liquidity, assets' position or intensiveness, size, capital gearing, growth and payout. A comparison with the a priori classification of table B1, in Appendix B, indicates that although many of the groups were anticipated, two of the empirical groups and the empirical classification of some ratios were not expected. The payout and retention ratios, the complementary ratios no.5 and 6, defined a separate empirical group while ratio 5 is classified in the literature as either profitability ratio (for example see Lev, 1974, p.21) or gearing ratio (see: Lee, 1976, p.211). The group of 'other ratios' of table B1 were empirically represented by the third component, Assets' Position or Intensiveness, while there is no such a priori group of ratios. The ratios of this group are mainly concerned with the structure (or position) of a firm's assets, e.g., the proportion of current assets to total assets and the coverage of fixed assets from the long-term capital. The other five groups of table 5.4 were expected with some variations in the ratios included in each group. Funds flow ratios were grouped as profitability ratios while most of them are intended as measures of a firm's liquidity. This finding is consistent with those of Taffler (1977a, 1977b) and Pinches et al (1973 and 1975). Yet, a further explanation of this finding may be possible within the analysis below. The value added ratio loaded on profitability, a variation from Taffler's finding (1977a), because some of the constituent items of the numerator of

Table 5.4 Varimax rotated principal components - 88 Companies for 5 years BF

R. No.	Ratio Name	Component Loadings 1	2	3	4	5	6	7	
1	EBIT/Adj TCE1	.90							
2	EBIT/NCE	.93							
3	PBT/TrA	.90							
7	EBIT/TCE	.91							
8	EBIT/Adj TCE2	.92							
10	PBT/NCE	.93							
11	PBT/PhA	.84							
12	ODG/EqC	-.70							Profitability
35	FF/CL	.70							
36	FF/TL	-.76							
37	FF/QA1	.75							
38	FF/TCE	.91							
39	FF/NW	.88							
69	VA/Adj TCE	.90							
84	FF/NCE	.92							
16	CA/CL		.88						
17	QA1/CL		.91						
18	QA2/CL		.78						
22	NWC/CL		.88						
52	TL/TA		.84						Liquidity
53	TL/EqC		-.86						
54	NW/TL		.88						
59	EqC/TCE		-.84						
87	NWC/TCE		-.73						
85	CA/TCE			.92					
89	EqC/FA			.75					Assets Position or Intensiveness
90	(NCE-FTR)/FA			.81					
71	TCE				.93				
72	NCE				.94				Size
73	TrA				.91				
77	FA				.86				
48	Adj TL1/EqC					.87			
49	FL/NCE					.85			Capital Gearing
51	Adj TL2/EqC					.82			
58	FL1/EqC					.82			
64	$\Delta NCE/NCE_{t-1}$						.71		
65	$\Delta TCE/TCE_{t-1}$						.89		Growth
66	$\Delta TrA/TrA_{t-1}$						.89		
5	OD/NE							.97	Pay-out
6	Rt/NE							-.97	
	% Variance explained	35.8	21.3	7.0	5.9	4.9	4.6	3.7	83.4

Table 5.A Key to Principal Components Analysis Ratios

Item	Description
EBIT	Earnings before Interest and Tax
PBT	Profit before Tax
NE	Net Earnings
OD	Ordinary Dividends, Net
ODG	Ordinary Dividends, Gross
Rt	Retention
CA	Current Assets
QA1	Quick Assets = Current Assets - Inventory
QA2	QA1 - Debtors
QA3	QA2 - Bank Overdrafts
NTCG	Net Trade Credit given (debtors-creditors)
Inv	Inventory
NWC	Net Working Capital
FF	Funds Flow
TL	Total Liabilities
Adj TL1	(TL - Bank Overdrafts - Creditors)
Adj TL2	(Adj TL1 - Minority Interest)
BO	Bank Overdrafts
FL	Long-term debt
FLBO	(FL + BO)
NW	Net Worth
FL1	(FL - Minority Interest)
EqC	Equity Capital
CL	Current Liabilities
TCE	Total Capital Employed
NCE	Net Capital Employed
TrA	Trading Assets
Adj TCE1	(TCE - BO - Creditors)
Adj TCE2	(TCE - BO)
PhA	Physical Assets
FA	Fixed Assets
TA	Total Assets
S & W GNA	Singh' and Whittington's measure of net assets' growth.

our ratio were not available, see Chapter 4. The liquidity group included four ratios (52, 53, 54 and 49) which are perceived as measures of capital gearing and a further ratio (87) which should have been grouped as one of the assets' position ratios.

However, the above findings were further questioned and tested as to the extent to which they apply to each group of companies, separately.

Table 5.5 presents the components, ratios and component loadings for all ratios that loaded at .70 or greater for either all, non-failed or failed companies. The components are presented in the same order of the analysis of all companies but the order of a component in any set of components is determinable by the percentage variance it explains. The percentage of total information accounted for by each set of components is reported at the end of the table. Table 5.5 indicates that although the seven groups of all companies' ratios were identified for the two groups of failed and non-failed companies, the components did not keep their rank for each group of companies. This change of the relative importance of each component is not significant as long as each component measures one of the firm's financial attributes. What is important is that some ratios have changed their classification between the two groups of companies, i.e., they measure a financial attribute for the failed companies and another attribute for the non-failed companies. For example, two of the funds flow ratios (35 and 36) measure profitability for all and failed companies, with .64 load of ratio 35 for failed companies, while they measure liquidity for the non-failed companies, with the two highest loads on component two. The inclusion of these two ratios, 35 and 36, in the liquidity component for the non-failed group of companies may explain why liquidity is the most important component for this group of companies and why some funds flow ratios are assigned on a priori basis to the liquidity group of ratios.

Table 5.5 - Varimax Rotated Principal Components - For 5 years BF.

R.No.	Ratio Name	Component Loadings		
		All Companies	Non-Failed	Failed
Component One - Profitability				
1	EBIT/Adj TCE1	.90	.95	.90
2	EBIT/NCE	.93	.98	.92
3	PBT/TrA	.90	.72	.93
7	EBIT/TCE	.91	.74	.91
8	EBIT/Adj TCE2	.92	.76	.92
10	PBT/NCE	.93	.97	.92
11	PBT/PhA	.84	.56	.89
12	ODG/EqC	-.70	-.55	-.42
35	FF/CL	.70	.19	.64
36	FF/TL	-.76	-.24	-.71
37	FF/QA1	.75	.41	.82
38	FF/TCE	.91	.75	.89
39	FF/NW	.88	.79	.83
69	VA/Adj TCE	.90	.90	.86
84	FF/NCE	.92	.95	.88
Percentage variance explained by Component		35.8	22.1	34.0
Component Two - Liquidity				
16	CA/CL	.88	-.64	.87
17	QA1/CL	.91	-.71	.91
18	QA2/CL	.78	-.79	.82
19	QA3/CL	.56	-.75	.61
22	NWC/CL	.88	-.66	.87
35	FF/CL	-.39	.95	-.31
36	FF/TL	.36	-.91	.29
52	TL/TA	.84	-.86	.80
53	TL/EqC	-.86	.86	-.83
54	NW/TL	.88	-.84	.84
59	EqC/TCE	-.84	.86	-.80
87	NWC/TCE	-.73	.51	-.72
Percentage Variance explained by Component		21.3	35.6	20.1

Table 5.5 (continued)

R.No.	Ratio Name	Component Loadings		
		All Companies	Non-Failed	Failed
Component Three - Assets' Position or Intensiveness				
56	NW/FA	-.20	.85	-.11
85	CA/TCE	.92	-.95	.92
87	NWC/TCE	.60	-.81	.60
89	EqC/FA	.75	.90	.68
90	(NCE-FTR)/FA	.81	.93	.78
Percentage Variance explained by Component		7.0	10.4	5.5
Component Four - Size				
71	TCE	.93	.97	.94
72	NCE	.94	.99	.96
73	TrA	.91	.95	.91
77	FA	.86	.81	.87
Percentage Variance explained by Component		5.9	8.6	5.9
Component Five - Capital Gearing				
48	Adj TL1/EqC	.87	.74	.91
49	FL/NCE	.85	.90	.90
51	Adj TL2/EqC	.82	.73	.85
58	FL1/EqC	.82	.86	.90
Percentage Variance explained by Component		4.9	6.3	7.7
Component Six - Growth				
64	$\Delta NCE/NCE_{t-1}$	.71	.62	.68
65	$\Delta TCE/TCE_{t-1}$	.89	.90	.87
66	$\Delta TrA/TrA_{t-1}$	.89	.90	.88
Percentage Variance explained by Component		4.6	3.1	3.2
Component Seven - Pay-out				
5	OD/NE	.97	.93	-.97
6	Rt/NE	-.97	-.93	.97
Percentage Variance explained by Component		3.7	4.2	4.7
Percentage Variance explained by 7 Components		83.4	90.2	81.2

Another example is that ratio 56 (NW/FA) measures assets position for the non-failed companies while it measures something else for all and failed companies. However, the components representing size, capital gearing and payout are consistent and stable between the two groups of companies.

The conclusion to be drawn from the above analyses is that a consistent and stable grouping of accounting ratios for all types of companies is empirically achievable. One such grouping can be based on table 5.5. A list of grouped accounting ratios which consistently measure the same attributes for all types of companies, two types were considered above, can be prepared by excluding all the ratios, in table 5.5, that loaded less than .70 for any group of companies. Such a list presents the ratios that can be theoretically interpreted and that account for the effect of multicollinearity.

However, the above analyses were based on the data of the five years. The next subsection tests whether the above findings hold for each year of data and tests the persistence of the findings over the years.

5.2.4.2 Persistence of Empirical Groupings

The persistence of ratios' grouping and of ratios' classification over the groups is evaluated in terms of consistent loadings and groups. As shown below, unstable loadings may or may not be associated with a change of ratio's group.

Principal components analysis was undertaken for all, failed and non-failed companies for each year of data. Table 5.6 presents the components, ratios and component loadings for ratios that loaded at .70 or greater in any of the five years before failure for all the companies, taken together. It indicates that the components of size, capital gearing and payout are very stable over the five years. Each accounting ratio grouped by each of the three components loaded very high on the component for each of the

Table 5.6 Varimax Rotated Principal Components - All Companies for each year BF

R.No.	Ratio Name	Y = -1	Y = -2	Y = -3	Y = -4	Y = -5
Component One-Profitability						
1	EBIT/Adj TCE1	.90	.94	.95	.96	.96
2	EBIT/NCE	.94	.95	.97	.97	.97
3	PBT/TrA	.86	.92	.95	.90	.95
7	EBIT/TCE	.86	.93	.96	.91	.95
8	EBIT/Adj TCE2	.88	.94	.96	.93	.95
10	PBT/NCE	.94	.95	.97	.97	.97
11	PBT/PhA	.79	.86	.89	.83	.88
12	ODG/EqC	-.43	-.75	-.85	-.78	-.85
35	FF/CL	.66	.68	.76	.72	.74
36	FF/TL	-.71	-.67	-.83	-.77	-.84
37	FF/QA1	.69	.85	.67	.84	.69
38	FF/TCE	.82	.94	.96	.93	.96
39	FF/NW	.90	.90	.93	.95	.90
64	Δ NCE/NCE$_{t-1}$	-.87	-.69	-.34	-.50	-.32
65	ΔTCE/TCE$_{t-1}$	-.81	-.70	-.21	-.12	-.21
66	ΔTrA/TrA$_{t-1}$	-.81	-.67	-.19	-.10	-.15
67	S & W GNA	-.89	-.85	-.41	-.69	-.37
69	VA/Adj TCE	.81	.96	.96	.97	.96
84	FF/NCE	.86	.96	.97	.98	.97
Percentage Variance explained by Component		41.8	40.0	34.8	34.6	32.6
Component Two - Liquidity						
16	CA/CL	-.87	.82	.85	.73	.85
17	QA1/CL	-.92	.93	.89	.83	.91
18	QA2/CL	-.82	.82	.77	.83	.79
19	QA3/CL	-.21	.71	.56	.71	.70
20	NTCG/CL	-.13	.71	.72	.58	.64
22	NWC/CL	-.92	.88	.87	.76	.86
52	TL/TA	-.83	.80	.81	.80	.76
53	TL/EqC	.92	-.82	-.83	-.81	-.77
54	NW/TL	-.86	.84	.86	.83	.81
59	EqC/TCE	.83	-.79	.81	-.80	-.76
87	NWC/TCE	.70	-.71	-.67	-.56	-.63
Percentage Variance explained by Component		17.8	24.2	25.1	24.8	26.3

Table 5.6 continued

R.No.	Ratio Name	Y = -1	y = -2	Y = -3	Y = -4	Y = -5
Component Three - Assets' Position or Intensiveness						
56	NW/FA	-.06	-.68	-.81	-.85	-.83
85	CA/TCE	.85	.95	.94	.91	.94
86	QA/TCE	.72	.60	.47	.58	.57
87	NWC/TCE	.55	.63	.70	.78	.73
89	EqC/FA	.74	.78	.83	.85	.84
90	(NCE-FTR)/FA	.78	.84	.88	.91	.90
Percentage of Variance explained by Component		7.3	6.9	8.4	7.6	8.7
Component Four - Size						
71	TCE	.93	.90	.93	.94	.93
72	NCE	.87	.91	.96	.96	.97
73	TrA	.91	.88	.91	.92	.91
77	FA	.88	.83	.84	.88	.86
Percentage Variance explained by Component		6.4	4.4	5.4	5.7	5.9
Component Five - Capital Gearing						
48	Adj TL1/EqC	.85	.90	.88	.90	.92
49	FL/NCE	.73	.87	.87	.83	.88
51	Adj TL2/EqC	.83	.87	.86	.89	.90
58	FL1/EqC	.72	.81	.85	.79	.84
Percentage Variance explained by Component		4.8	6.6	6.3	6.5	6.6
Component Six - Growth						
56	NW/FA	.90	.25	-.07	-.03	.14
64	$\Delta NCE/NCE_{t-1}$	-.14	.49	.86	.71	.83
65	$\Delta TCE/TCE_{t-1}$	-.14	.62	.93	.96	.90
66	$\Delta TrA/TrA_{t-1}$	-.13	.61	.94	.93	.89
67	S & W GNA	-.10	.25	.83	.03	.78
Percentage Variance explained by Component		3.9	3.5	4.6	4.5	4.7
Component Seven - Pay out						
5	OD/NE	-.84	.87	-.98	.95	-.97
6	Rt/NE	-.84	-.86	.98	-.95	.98
Percentage Variance explained by Component		4.3	3.8	3.9	4.0	3.6
Percentage Variance explained by 7 Components		86.4	89.5	88.4	87.7	88.4

five years. Moreover, the three components exhibited the same pattern they had exhibited when the analysis was based upon all the five years of data for all, failed,and non-failed companies, see table 5.5. Component six, growth, is the least stable one. The ratios of this component started to change their group in the second year before failure and all of them have clearly become profitability ratios in the first year before failure. A comparison with table 5.5 indicates that this behaviour of growth ratios cannot be indicated when the analysis is based upon the five years of data. Ratio 56 (NW/FA) also changed its group, Assets Position, and loaded highly on component six in the first year before failure. Profitability, liquidity and assets position are reasonably stable components. Apart from the ratios of growth, the component of profiatbility exhibited a pattern similar to that of table 5.5. Ratios 12 and 35,36 and 37(funds flow ratios) are the least stable ratios of this component. The above evidence, see table 5.5, suggests that the behaviour of ratios 35 and 36 is explainable by the fact that the two ratios loaded on profitability for failed companies and on liquidity for non-failed companies. However, this is examined below. Liquidity component exhibited a pattern similar to that of table 5.5 with the addition of ratios 19 and 20 which are not stable over the years. Ratio 87 which was not stable between the two groups of companies, see table 5.5, is also unstable over the years. It loaded highly on liquidity for the first two years before failure and on assets position for the last three years. Component three, assets' position or intensiveness, included ratios 56, 86, and 87 which are not stable over time.

Whether the above findings hold for each group of companies is examined in tables 5.7 and 5.8 below. These tables also represent a break down to the analysis in table 5.6, which may explain the behaviour of its components and ratios.

Tables 5.7 and 5.8 present the components, ratios and component loadings for ratios that loaded at .70 are greater in any of the five yeras before failure for non-failed and failed companies, respectively.

The examination of tables 5.7 and 5.8 indicates that they retain some features of table 5.5, viz liquidity is the most important component - in terms of the variance it explains - for non-failed companies, and ratios 35 and 36 are liquidity ratios for the non-failed companies while they are profitability ratios for failed companies. Ratio 56 loaded consistently on component three, assets position, for the non-failed companies while it changed this group for failed companies in the first year before failure and loaded on component six, this is the same behaviour as in table 5.6 and it may explain why this ratio appeared to measure something else for failed companies in table 5.5. In addition, some ratios which loaded consistently high on profitability in the analyses of tables 5.5 and 5.6 are either unstable - 3, 7 and 8 - or not included, 11, for non-failed companies. However, some of these ratios, 3, 7 and 11, loaded on liquidity for the same group of companies. Ratio 12 loaded on profitability for the non-failed companies while it did not for the failed companies. Component five, capital gearing, was unstable for the non-failed companies, except for ratios 49 and 58. Some of the previously identified liquidity ratios - 50, 52, 53 and 59, loaded for one year on capital gearing for failed companies while the previously identified ratios of gearing remained stable for that group of companies. These aspects of ratios grouping, especially for the non-failed companies were hindered either by processing all the five years of data or by taking the two groups together.

Component six, growth, exhibited a pattern similar to that of table 5.6 for the failed companies, i.e., ratios of growth loaded on profitability for two years before failure, with lower loads in the second. The difference

Table 5.7 - Varimax Rotated Principal Components - Non-Failed Companies for each year BF

R.No.	Ratio Name	Y = -1	Y = -2	Y = -3	Y = -4	Y = -5
Component One - Profitability						
1	EBIT / Adj TCE1	.94	.94	.96	.95	.96
2	EBIT/NCE	.98	.98	.98	.97	.98
3	PBT/TrA	.75	.81	.77	.67	.63
7	EBIT/TCE	.76	.85	.80	.68	.65
8	EBIT/Adj TCE2	.79	.87	.82	.70	.66
10	PBT/PhA	.96	.96	.96	.97	.98
12	ODG/EqC	-.66	-.67	-.77	-.72	-.57
38	FF/TCE	.76	.85	.79	.70	.68
39	FF/NW	.88	.81	.80	-.75	.78
48	Adj TL1/EqC	-.75	-.68	-.51	-.46	-.21
51	Adj TL2/EqC	-.74	-.68	-.50	-.46	-.22
69	VA/Adj TCE	.84	.85	.88	.92	.92
84	FF/NCE	.94	.92	.92	.94	.97
Percentage Variance explained by Component		22.5	22.2	22.5	24.3	22.6
Component Two - Liquidity						
3	PBT/TrA	-.57	-.47	-.57	.69	.70
7	EBIT/TCE	-.62	-.49	-.57	.70	.70
11	PBT/PhA	-.53	-.48	-.55	.65	.70
17	QA1/CL	.66	.74	.68	-.70	-.65
18	QA2/CL	.78	.76	.79	-.79	-.81
19	QA3/CL	.73	.76	.79	-.77	-.78
22	NWC/CL	.66	.70	.63	-.65	-.55
35	FF/CL	-.95	-.93	-.93	.95	.88
36	FF/TL	.94	.92	.89	-.91	-.81
52	TL/TA	.90	.90	.85	-.86	-.71
53	TL/EqC	-.90	-.90	-.86	.85	.71
54	NW/TL	.87	.88	.83	-.84	-.71
59	EqC/TCE	-.90	-.90	-.85	.86	.71
Percentage Variance explained by Component		36.3	37.8	38.7	38.5	36.7

Table 5.7 continued

R.No.	Ratio Name	Y = -1	Y = -2	Y = -3	Y = -4	Y = -5
Component Three - Assets Position or Intensiveness						
16	CA/CL	.67	.65	.71	-.67	.70
22	NWC/CL	.66	.64	.69	-.65	.70
56	NW/FA	.90	.85	.85	-.81	.80
85	CA/TCE	-.96	-.95	-.94	.92	-.94
87	NWC/TCE	-.82	-.80	-.82	.79	-.82
89	EqC/FA	-.93	-.92	-.89	.85	-.86
90	(NCE-FTR)/FA	-.94	-.94	-.93	.91	-.93
Percentage Variance explained by Component		10.3	9.4	8.8	7.7	8.3
Component Four - Size						
71	TCE	.96	.96	.96	.97	.97
72	NCE	.99	.99	.99	.99	.96
73	TrA	.95	.95	.95	.96	.96
77	FA	.77	.81	.82	.83	.84
Percentage Variance explained by Component		7.5	6.6	6.8	8.2	6.8
Component Five - Capital Gearing						
48	Adj TL1/EqC	.51	.48	.68	.71	.91
49	FL/NCE	.82	.85	.87	.85	.90
50	FLBO/NCEBO	.59	.62	.69	.63	.70
51	Adj TL2/EqC	.51	.47	.67	.70	.90
58	FL1/EqC	.82	.84	.84	.84	.86
Percentage Variance explained by Component		4.9	4.5	5.9	4.0	9.4
Component Six - Growth						
64	$\Delta NCE/NCE_{t-1}$	.13	.00	.40	.36	.81
65	$\Delta TCE/TCE_{t-1}$	.84	.36	.94	.88	.84
66	$\Delta TrA/TrA_{t-1}$	.80	.32	.93	.88	.83
67	S & W GNA	.02	.07	.16	.23	.75
Percentage Variance explained by Component		1.9	2.2	3.9	2.9	3.9
Component Seven - Pay out						
5	OD/NE	.87	.79	.90	.90	-.93
6	Rt/NE	-.87	-.79	-.90	-.90	.93
64	$\Delta NCE/NCE_{t-1}$	.83	.85	.78	.62	-.16
65	$\Delta TCE/TCE_{t-1}$	.38	.83	.17	.19	.01
66	$\Delta TrA/TrA_{t-1}$	.32	.83	.11	.09	.03
67	S & W GNA	.67	.74	.76	.51	-.23
Percentage Variance explained by Component		6.4	8.5	4.5	5.9	3.0
Percentage Variance explained by 7 Components		89.8	91.2	91.2	91.5	90.8

Table 5.8 - Varimax Rotated Principal Components - Failed Companies for each year BF

R.No.	Ratio Name	Component Loading				
		Y = -1	Y = -2	Y = -3	Y = -4	Y = -5
Component One - Profitability						
1	EBIT/Adj TCE1	.90	.95	.95	.96	.96
2	EBIT/NCE	.95	.96	.95	.96	.96
3	PBT/TrA	.90	.95	.97	.91	.97
7	EBIT/TCE	.89	.96	.96	.95	.97
8	EBIT/Adj TCE2	.89	.96	.96	.96	.97
10	PBT/NCE	.95	.96	.96	.96	.96
11	PBT/PhA	.87	.92	.94	.98	.94
35	FF/CL	.53	.56	.76	.71	.82
36	FF/TL	-.62	-.61	-.84	-.78	-.88
37	FF/QA1	.61	.88	.90	.87	.89
38	FF/TCE	.70	.96	.98	.95	.98
39	FF/NW	.88	.77	.93	.96	.95
64	$\Delta NCE/NCE_{t-1}$	-.84	-.65	-.47	-.36	-.46
65	$\Delta TCE/TCE_{t-1}$	-.79	-.65	-.37	.02	-.39
66	$\Delta TrA/TrA_{t-1}$	-.78	-.60	-.40	.03	-.29
67	S & W GNA	-.86	-.85	-.55	-.69	-.46
69	VA/Adj TCE	.66	.96	.96	.97	.95
84	FF/NCE	.75	.96	.96	.97	.96
Percentage Variance explained by Component		38.3	37.0	34.1	35.2	32.2
Component Two - Liquidity						
16	CA/CL	-.88	.75	.81	.65	.90
17	QA1/CL	-.93	.92	.89	.82	.96
18	QA2/CL	-.85	.83	.82	.88	.83
19	QA3/CL	-.16	.77	.63	.78	.77
20	NTCG/CL	-.05	.70	.69	.47	.70
22	NWC/CL	-.92	.83	.85	.70	.90
50	FLBO/NCEBO	.75	-.61	-.60	-.50	-.54
52	TL/TA	-.88	.66	.75	.63	.72
53	TL/EqC	.94	-.68	-.77	-.64	-.73
54	NW/TL	-.88	.72	.80	.69	.80
59	EqC/TCE	.88	-.66	-.75	-.63	-.72
87	NWC/TCE	.74	-.68	-.60	-.43	-.62
Percentage Variance explained by Component		18.8	6.8	8.6	9.4	26.4

Table 5.8 continued

Component Three - Assets Position						
21	Inv/CL	-.04	-.34	.53	.73	-.51
56	NW/FA	-.07	-.62	.85	.90	-.88
85	CA/TCE	.90	.95	.89	.79	.92
87	NwC/TCE	.53	.60	.74	.84	.73
89	EqC/FA	.57	.67	.83	.85	.84
90	(NCE-FTR)/FA	.69	.79	.90	.94	.90
Percentage Variance explained by Components		5.5	8.6	7.2	7.2	7.3
Component Four - Size						
71	TCE	.95	.92	.93	.95	.93
72	NCE	.90	.94	.97	.97	.96
73	TrA	.93	.88	.90	.92	.91
77	FA	.88	.85	.83	.87	.85
Percentage Variance explained by Components		8.6	5.5	5.9	6.6	5.9
Component Five - Capital Gearing						
48	Adj TL1/EqC	.82	.95	.94	.94	.96
49	FL/NCE	.71	.95	.96	.93	.96
50	FLBO/NCEBO	.30	.68	.63	.79	.69
51	Adj TL2/EqC	.81	.93	.93	.94	.95
52	TL/TA	-.24	-.70	-.58	-.71	-.65
53	TL/EqC	.21	.68	.55	.71	.64
58	FL1/EqC	.73	.92	.95	.93	.93
59	EqC/TCE	.24	.70	.58	.71	.65
Percentage Variance explained by Component		3.7	25.2	24.8	20.4	9.3
Component Six - Growth						
56	NW/FA	-.90	.29	-.13	-.04	.05
64	$\Delta NCE/NCE_{t-1}$	.08	.48	.79	.80	.76
65	$\Delta TCE/TCE_{t-1}$	.07	.65	.87	.96	.83
66	$\Delta TrA/TrA_{t-1}$	.05	.68	.86	.96	.86
67	S & W GNA	.02	.08	.75	-.02	.74
91	(Dep. + Amo)/FA	-.70	-.03	.04	-.23	-.07
Percentage Variance explained by Comparison		5.8	1.8	4.1	5.6	4.6
Component Sevon - Pay-out						
5	OD/NE	-.82	.88	-.97	.94	-.96
6	Rt/NE	.82	-.85	.97	-.94	.97
12	ODG/EqC	.70	-.57	-.26	-.03	.18
Percentage Variance explained by Component		6.5	4.3	3.9	4.1	3.2
Percentage Variance explained by 7 Component		87.2	89.1	88.5	88.6	88.9

for the non-failed companies was that growth ratios loaded on the payout component for the first two years before failure. However, the plots, in figure C1 Appendix C, of the mean values of growth ratios for five years indicate that there is a considerable change in the mean values of these ratios for the first two years before failure for both failed and non-failed companies.

As concluded above, a list of grouped accounting ratios which consistently measure the same financial attributes for different types of companies for different years can be prepared by excluding all the ratios, in tables 5.7 and 5.8, that loaded at less than .70 for any group of companies in any year. In our case the group of growth ratios will be excluded and the origianl number of 48 ratios will be drastically reduced. However, the resulting list can be of general use, but for the purpose of our, and the similar statistical analysis a reference should always be made to the results of the corresponding principal components analysis. For example, if the discriminant analysis, in the next chapter, is based on the five years of data, the selection of the independent variables should be guided by table 5.5. If the discriminant analysis is based on the data of a given year, the selection of ratios should be guided by the results of principal components analysis of that given year.

However, the above empirical classification of accounting ratios did not incorporate the ratios that did not load at .70 or greater on any of the extracted components. Some of these ratios for a given set of components, e.g., the components of all or a group of companies for all or any of the five years of data, were moderately loaded on more than one component. Two problems arise about these moderately loading ratios. The first problem is their interpretation and the second is concerned with their application if they prove to be of high predictive power. As regards the first problem, these ratios can be interpreted as measuring more than one financial attribute, more than one theoretical dimension (see: Nie et al., 1975, p.475). As regards their application, it means that a search should always be made for the best predicting ratios, either in the previous studies or within a certain set of ratios. In this respect it has been stated that:

> "If prediction rather than description (or representation) is the goal, researchers and analysts may find it desirable to select financial ratios employed in previous empirical studies even though they are less descriptive of the financial ratio groups identified in the present study." (Pinches et al., 1975, p.304).

The discriminant model developed by Taffler (1977b) presents an example of using a ratio which loaded moderately on two components, one of which was already represented by a highly loaded ratio. This situation gives rise once again to the problem of multicollinearity. However, the inclusion of two ratios measuring the same financial attribute, the highly and moderately loading ratios, does not necessarily mean the presence of multicollinearity, see the discussion in Chapter 3.

5.3 The Industry Dummy Variables

As indicated in Chapter 3, 19 of the UK 23 industries, classified according to the 1969 Standard Industrial Classification, are represented in this study by the sampled companies (see: table 5.9 below). For the purpose of this study the 19 industries are reclassified into three functional groups - manufacturing, construction and distribution. This broad classification is first tested empirically and then used to define a set of industry dummy variables. The empirical tests included cluster analysis to test the similarity between the industries at different levels and three-groups discriminant analysis to test the separation among the three groups of our broad classification (see: Chapter 3 - subsection 3.4.2.1).

Table 5.9 Standard Industrial Classification - for 19 Industries*

S. No.	Industry No.	Industry Name +
1	10	Mining and Quarrying
2	21	Food
3	23	Drink
4	26	Chemicals & Allied Industries
5	31	Metal Manufacture
6	33	Non-Electrical Engineering
7	36	Electrical Engineering
8	37	Shipbuilding & Marine
9	38	Vehicles
10	39	Metal Goods N.E.S.
11	41	Textiles
12	44	Clothing and Footwear
13	46	Bricks, Pottery, Glass, Cement, etc.
14	47	Timber, Furniture, etc.
15	48	Paper, Printing & Publishing
16	49	Other Manufacturing Industries
17	50	Construction
18	81	Wholesale Distribution
19	82	Retail Distribution

* See Table A2 in Appendix A for more detailed classification.

\+ The proposed broad classification groups industries 81 and 82 into the distribution group, industries 10 and 50 into the construction group and the rest of the 19 industries into the manufacturing group.

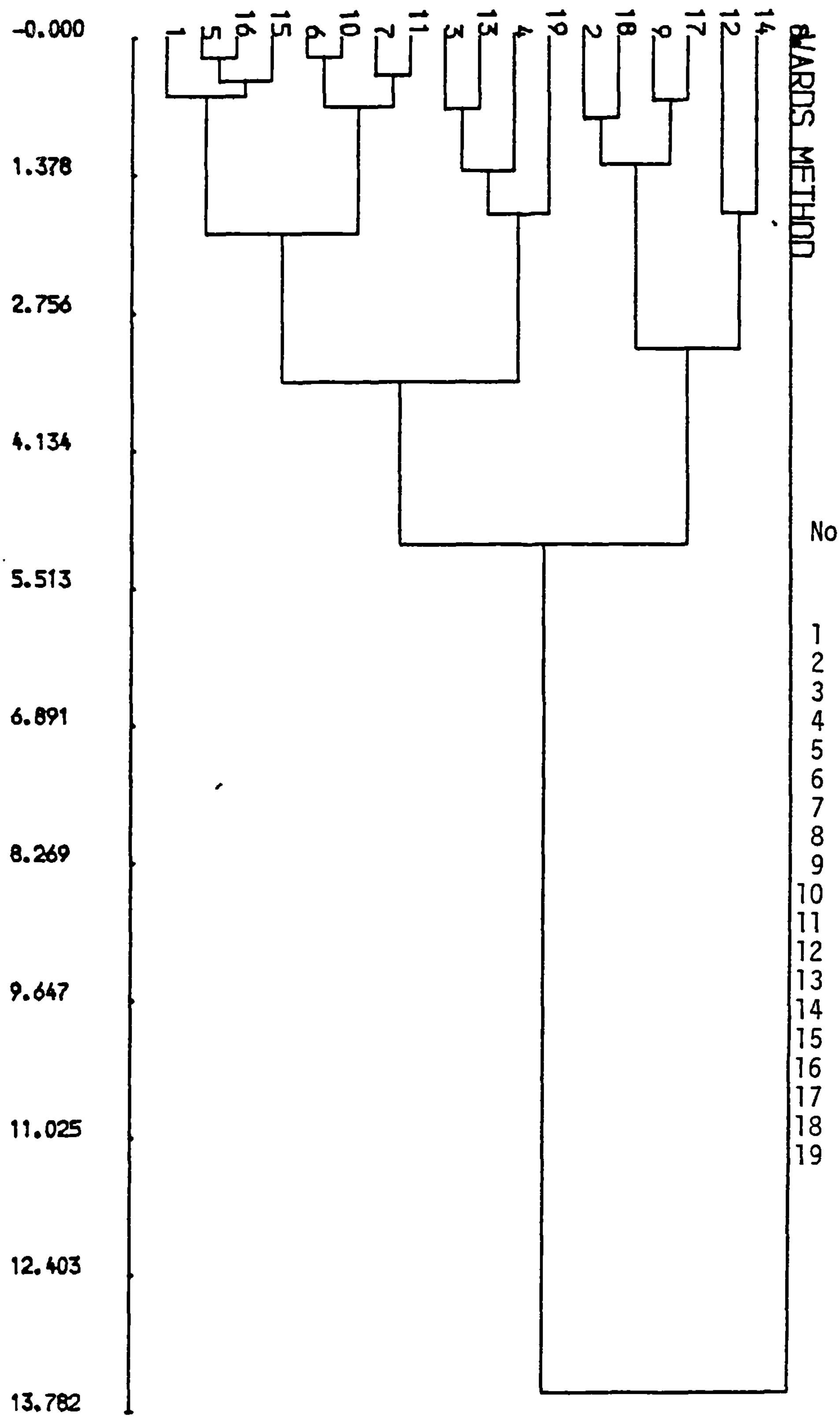
5.3.1 The Similarity Between Industries

As indicated in Chapter 3, the output of the cluster program (see: Trasi, 1978, CLUSTAN 1A package) is presented in this study in graphical form - dendrogram. In figure 5.2 the industries are clustered on the basis of their aggregated data for the year 1973 and using the standardized values of all the first 91 ratios of Appendix B1. The scale on the left-hand side in figure 5.2 indicates the level of similarity between industries. The figure shows that only some pairs of industries can be clustered at the higher level of similarity and then at a lower level the pair of industries may cluster with another industry or pair of industries. This process of clustering continues until all the industries are grouped in one cluster at the lowest level. The similarity among the industries at the higher levels indicates the validity of classifying them into broad groups while the similarity among the clusters at the lower level (before the lowest) indicates the difference between the broad groups of industries - and, thus, the need to account for the industry effect.

However, cluster analysis was performed on the industries' data for each of four years prior to 1973 using all the 91 ratios, selected ratios and the standardized values of all and the selected ratios. The clusters of these sets of analyses were different from each other and none of them confirmed our broad classification. Figure 5.3 shows the clusters of the same set of data using the unstandardized variables. Cluster analysis, however, is not concerned with testing an a priori grouping - discriminant analysis is.

5.3.2 The Separation Among the Three Groups

Multiple Discriminant Analysis is the statistical technique which is concerned with testing the validity of an a priori classification by classifying the individuals into their a priori groups upon the basis of



No.	SIC Industry No.
1	10
2	21
3	23
4	26
5	31
6	33
7	36
8	37
9	38
10	39
11	41
12	44
13	46
14	47
15	48
16	49
17	50
18	81
19	82

Fig. 5.2 Hierarchical Clustering of 19 Industries Using the Standardized Ratios

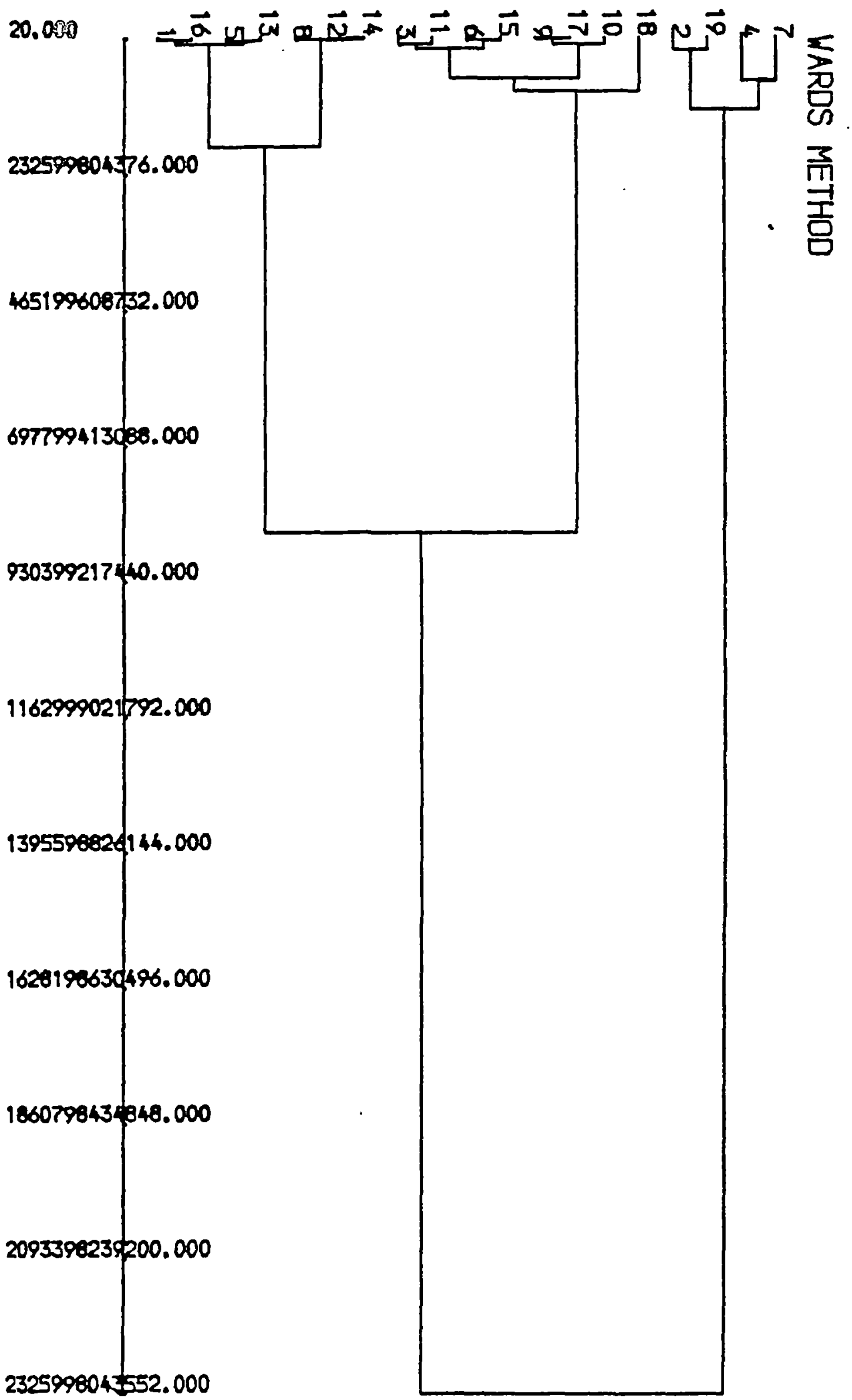


Fig. 5.3 Hierarchical Clustering of 19 Industries Using the Unstandardized Ratios

their attributes (see: Chapter 3). Therefore, three-groups discriminant analysis was undertaken to test the separation among the three groups. The ratios of the 19 industries for all the five years (1969-1973) were used in the analysis (i.e., the number of cases is 19 x 5 = 95). The following two functions incorporating five variables were able to correctly classify 94 out of the 95 cases (the number of discriminant functions is determined by either the number of groups minus 1 or the number of variables whichever the less):

$$Z_{i1} = -50.995+39.965(R12)+10.583(R53)+60.605(R59)+0.642(R79)+4.425(R81)$$

$$Z_{i2} = 25.265-22.079(R12)-8.648(R53)-31.118(R59)-.329(R79)+1.397(R81)$$

Where: Z_{iG} is the z-score of the ith case using function G and R12, R53, R59, R79 and R81 are the ratios number 12, 53, 59, 79 and 81 in Appendix B, with ratio 79 divided by 100,000. The functions are statistically of high significance and the relative contribution of the first is 84% while that of the second is 16% (as measured by the percentage eigenvalue of each function to the total of both of them). As mentioned previously, the two functions classified correctly 94 out of all the 95 cases; the misclassified case was industry 37 (Shipbuilding & Marine) for the year 1973 which was classified as group 2 (construction) instead of group 1 (manufacturing). Since this classification of the original data is known to be biased upwards, Lachenbruch's hold-out test was used to test the classifying powers of the two functions together. This test resulted in the misclassification of one additional case which is industry 38 (vehicles) for the year 1971. Thus, 93 out of 95 cases were classified correctly according to this hold-out test, i.e., the two functions have classifying power of 98% (93/95). However, each of the two misclassified industries was correctly classified four times using the data of its other four years.

The above findings indicate that the three groups of the broad classification are well separated. This separation is shown in figures 5.4 and 5.5. In figure 5.4, the first function is represented on the horizontal axis and the second on the vertical axis. The centroid of each group is represented by an asterisk and the numbers represent the cases from each group (1 for manufacturing 2 for construction and 3 for distribution). This figure shows that the cases of each group are clustered around the group-centroid. The misclassified case (from 1 in 2) appears to be closer to group 2 than group 1. Figure 5.5 presents a territorial map for the three groups showing the centroid of each group.

Since our three groups are different from each other they may be used to represent the industry effect.

5.3.3 The Selected Set of Dummy Variables

According to the above broad industrial classification the following set of three dummy variables is constructed to represent the industry factor.

	D1	D2	D3
Industry number = 50 or 10	1	0	0
Industry number > 80	0	1	0
Industry number < 50 > 10	0	0	1

Since we must drop one from the set of dummy variables, because our models in the next chapter compute an intercept term (see: Johnston, 1972, p.180), the third variable was finally selected to be dropped, after experimenting with variables 1 and 2, 1 and 3, and 2 and 3. Thus in the analysis of the next chapter D1 refers to either industry 10 or 50 and D2 refers to either industry 81 or 82.

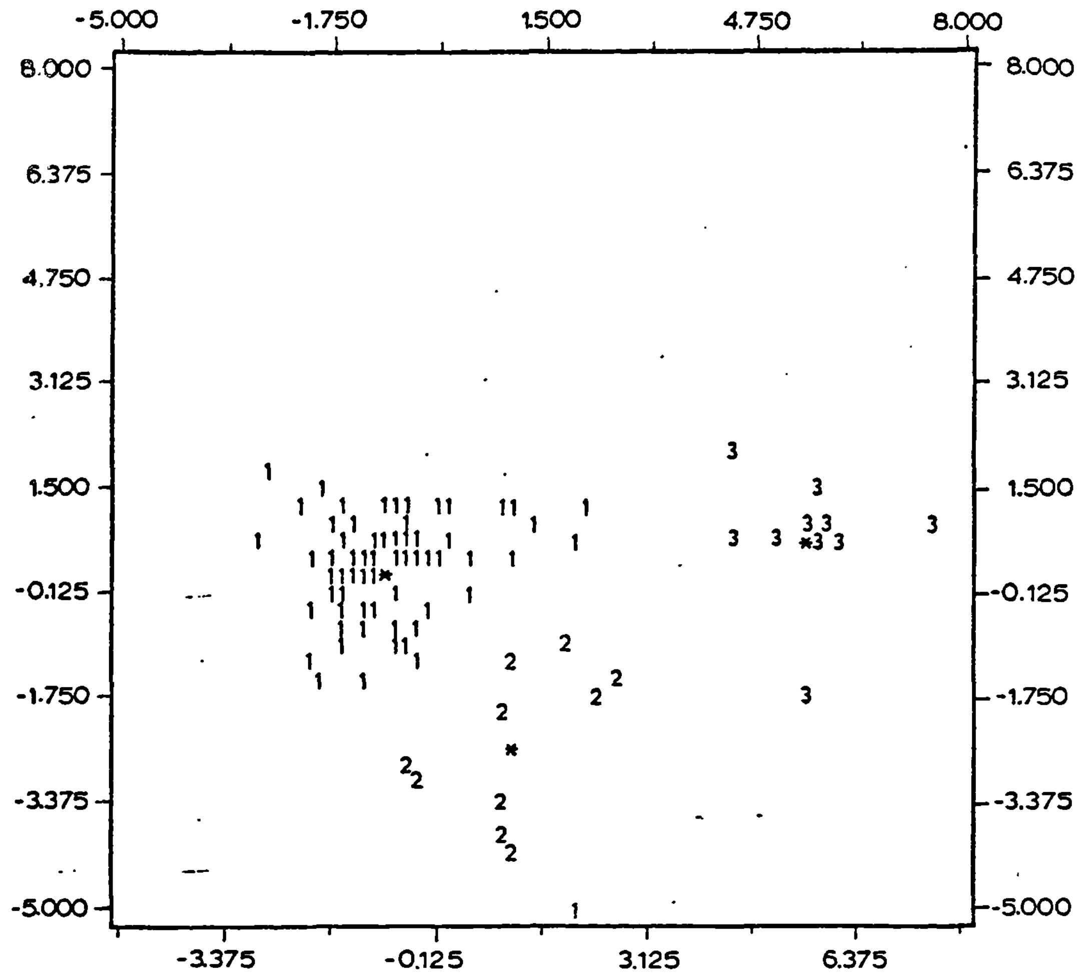


Fig 5.4 A Scatterplot of the Cases and the Centroid of each group

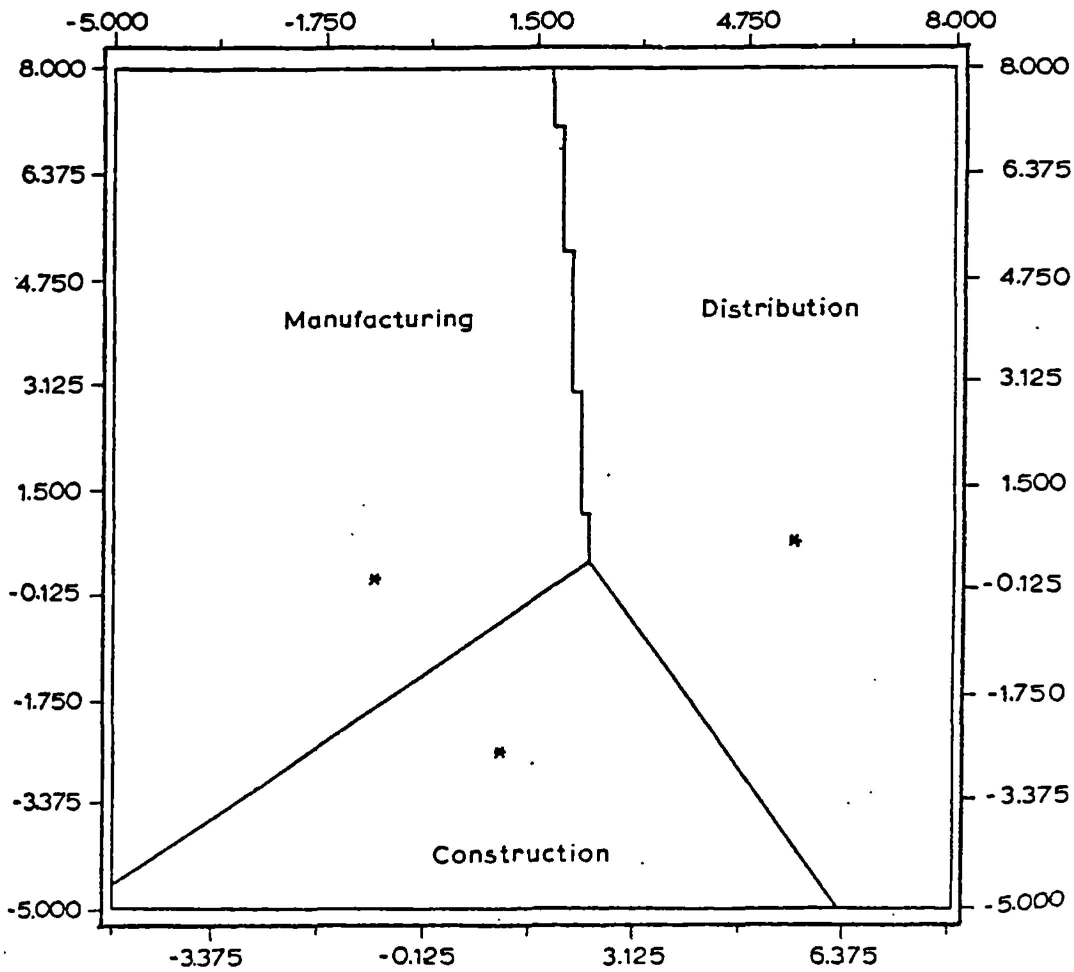


Fig 5.5 Territorial map of the three groups discriminant scores

5.4 The Economy-Wide Indicator

As indicated in Chapter 3, the standard deviation of the Financial Times Actuaries (all share) Index (FTA) for the working days of each company's financial year is used as the economy-wide indicator. Accordingly, a list of opening and closing dates for each company's accounting year was prepared for all the companies in our three samples. For each distinct year, the daily market index for the corresponding days was copied to a new file, through a program written by the researcher. The resulting sets of data, each of which reprsents the market index for the working days of an accounting year, were processed by the SPSS to compute the standard deviation for each set. Finally the standard deviation for each accounting year of each company was added to the corresponding set of accounting ratios (see: Chapter 3).

5.5. Concluding Remarks

This chapter has been concerned with the statistical preparation of the independent variables of the failure prediction models. Therefore, accounting ratios, industry dummy variables and economy-wide indicator are each considered in a separate section.

The preparation of accounting ratios included testing the normality of each ratio's distribution and a number of its possible transformations, univariate comparisons between the mean of each ratio for the two groups of companies and the dimensionality of ratios. The results of this section indicate that some ratios are normally distributed and many are not. The distribution of some of the non-normally distributed ratios can approach normality by transformation. However, the distributions of the ratios of non-failing companies are generally closer to normality than those of the failing companies. Of the 96 ratios considered in this study, 48 were excluded because of missing values (25), non-normality before and after transformations (21) and poor performance on the subsequent analysis (2). For the selected distributions of each of the remaining 48 ratios, the results of the two statistical tests of normality and the descriptive statistics are reported in this chapter.

The results of the univariate comparisons (using the t-test and profile analysis) indicate that there is a difference between some ratios of failing and non-failing companies for as far back as five years before failure and that the ratios of failing companies deteriorates as the year of failure approaches. These results confirm hypotheses 1 and 2 of Chapter 1 - that symptoms of failure can be seen several years before it occurs and that these symptoms are reflected in the firm's accounting ratios.

The results, of the principal components analysis indicate the difference between the a priori and the empirical grouping of accounting ratios and the instability of some accounting ratios for the different groups of companies (failing and non-failing) and for the different periods of time (i.e. one such ratio may measure a financial attribute for failing companies or year t and measure another attribute for non-failing companies or year t + 1). The stability of accounting ratios for failing and non-failing companies has not been tested before. These findings confirm hypothesis 5 of Chapter 1.

As for the industry dummy variables, the cluster analysis indicates the validity of classifying the 19 industries (represented in this study) into a small number of groups, The three-groups discriminant analysis indicates the differences between and among the three groups of our functional classification (manufacturing, construction and distribution). Therefore, this three-groups' classification has been used to define the industry dummy variables.

The standard deviation of FTA index for the working days of each company's accounting year is used as an economy-wide indicator.

The above results of the variables' preparation exercise pave the way for the development of the models reported in the next chapter.

CHAPTER VI

FAILURE PREDICTION MODELS: EMPIRICAL RESULTS

CHAPTER 6

Failure Prediction Models: Empirical Results

6.1 Introduction

The present chapter reports on the two selected models which possess the highest power in classifying companies and predicting corporate failure. It also reports on the comparison between the empirical results of applying multiple discriminant analysis (MDA) and Multiple regression analysis (MRA).

The first of the two reported models (Model 1) is developed upon the basis of the data of the fifth year before failure (BF), i.e. these data were used for the purposes of searching for the best discriminating variables and computing their coefficients. Therefore, this model has the advantages of capturing the early sumptoms of failure and, thus, predicting failure for the fifth year BF better than the models of the subsequent years (see: hypothesis 4 of Chapter 1). Since, symptoms of failure are more violent for each subsequent year including the first BF, this model should predict failure with increasing efficiency for each of the years from the fifth to the first BF. Accordingly, it performs for each of the five years BF better than the models of the subsequent years BF. It should be noted, however, that none of the previous studies has attempted to develop such a model.

The second model (Model 2) is developed upon the basis of the data of the first year BF (as are the models of the previous studies - see: Chapter 2). Although this model appears to perform almost better than those of the previous studies, it does not outperform Model 1 even for the first year BF which is the year of Model 2. This finding is explained by the fact that Model 1 discriminates between failing and non-failing companies upon the basis of the early symptoms of failure while Model 2 discriminates between them upon the basis of the latest severe symptoms of the first year BF. The severity of the latter may not be the same for all the companies in the first year before failure.

However, each of the above two models was developed using MDA and the analysis sample (of the concerned year BF). The fitted discriminant function (DF1) was then subjected to the tests of applicability (see: Chapter 3). A second function (DF2) was fitted to the same model using the data of both the analysis and hold-out samples (the combined sample) and was also subjected to the tests of applicability.

As concerns MRA, the experimental runs indicated that the stepwise procedure of both MDA and MRA selected the same accounting ratios. Therefore, MDA was used for the development of the models because the output of the discriminant subprogram includes a classification of the companies, in the analysis and other samples, which can be readily used to evaluate the fitted functions. However, two regression functions (RF1 and RF2) were fitted to each model using the analysis sample and the combined sample.

Thus, two discriminant functions and two regression functions for each of the two models and the results of their tests are reported in what follows. The mean discriminant scores of the functions for the five years before failure are graphically compared in figures 6.1 and 6.2.

the findings of this chapter establish the usefulness of accounting information on its own, as measured by the ability of ratio-based models to predict corporate failure. A comparison with the findings of the next chapter appears to establish the usefulness of accounting indicators relative to share price information, in the context of corporate failure.

6.2 Discriminant Models

As indicated in chapter 3, the SPSS discriminant subprogram allows the user to select one of five crtieria for the stepwise inclusion of the variables. Each of these criteria was tried in the earlier runs and the ratios were similarly ranked by each criterion. Therefore, the first criterion (Wilks) was used in all subsequent runs.

According to this method the entry criterion for each independent variable is the overall multivariate F-ratio for the test of difference among the group centroids. The variable which maximizes the F-ratio also minimizes Wilks lambda, a measure of group discrimination (see: Nie, et al., 1975, p.447).

As indicated before, the stepwise procedure is not capable of selecting the best discriminating variables and it may select a large number of variables which satisfy the inclusion's criteria. Some of these selected variables may be measuring the same financial attribute. However, it provides the computed F-statistic, the computed value of the stepwise entry criterion and the tolerance level for each of the considered variables and the standardized coefficients for each variable included in the fitted function. Therefore, these statistics together with the results of principal components analysis (see: Chapter 5), were used for selecting different combinations of variables to be processed by the stepwise procedure. Some of these selected combinations included more than one ratio from the same group in the hope that the stepwise procedure would select one of them. Where a computed function incorporated more than one ratio which was loaded on the same component, the ratio with the lower value on the above mentioned statistics was excluded - and in some other cases the functions were recomputed more than once excluding a variable each time. It should be noted that the variables with very low tolerance (the default value in the subprogram is 0.001) may cause mathematical problems and thus they should not be included in the analysis (see: Nie, et al., 1975, p.453).

This process of selecting the variables was used for the development of a failure prediction model for each of the five years BF, for the five years together, for each of the first and last four years BF and for the middle three years before failure. The purposes of developing all these 9 models were to reveal how early the symptoms of failure are reflected in the accounting ratios of failing companies, to test hypothesis 4 of Chapter 1 and to investigate whether the multi-year models are more efficient than the single-year models.

The best performing model was that of the fifth year BF. Otherwise, the multi-year models performed about as well as the single-year models. That based on the first year BF was amongst a group of second best performing models, but it is reported for the purposes of comparing it with that of the fifth year BF and with those of previous studies.

Finally, Altman, Haldman and Narayanan (AHN) (1977, footnote 14) pointed out two alternative strategies of temporal-type bankruptcy modelling. The first includes developing a model for each of the years before failure while the second includes fitting functions to the model of the first year BF using the data of each of the years prior to the first BF. They were interested in the latter approach and found that the function of the first year BF performed for all the years better than the functions of the years prior to the first BF.

The fact is that the two approaches are not alternatives. The first approach includes, for each year, the search for the best valiables which discriminate between failed and non-failed companies upon the basis of the symptoms of failure which are reflected by the data of the specific year.

As long as these symptoms are not constant for each of the years BF, the functions of the years BF other than that of the model should not perform as well as the function of the model's year BF. Moreover, the lower performance of the functions of the other years BF may be partially due to the instability of some of the model's variables over time or between groups.

Accordingly, the models reported below are each developed for a specific year BF and their functions are fitted to the data of the same specific year.

6.2.1. Model 1: The Fifth Year's Model

The following model was finally selected to predict corporate failure using accounting ratios of any year up to the fifth BF. It was first developed using the analysis sample of the fifth year BF, 21 companies (22 for each other year) of each group. The model was then subjected to six tests, reported below, including classifying the companies in the hold-out sample, 22 companies of each group. According to the split sample procedure, the coefficients of the model were re-estimated using the combined sample. The re-estimated coefficients were tested using Lachenbruch's "leaving-one out" test, see Chapter 3. The purposes of this latter procedure are to test the coefficients which may be recommended for practical applications and to make the optimum use of the available data, i.e., to overcome the two shortcomings of the split sample procedure.

However, the development of this model implements a test of hypothesis 4 of chapter 1 and is based on and supported by two facts. The first is the implication of the univariate finding that there is a difference between the accounting ratios of the failed and non-failed companies for at least five years before failure and that the ratios of the failed companies deteriorate as the year of failure approaches (see: Chapter 5). These findings imply that the severity of the symptoms of failure increases for each of the years from the fifth to the first BF. The second fact is that the essence of failure prediction is the establishment of a combination of selected characteristics which can discriminate between failing and no-failing companies (see: Chapter 3). Therefore, if a failure prediction model is developed upon the basis of the data of the fifth year BF, the established characteristics will capture the early symptoms of failure and the model's efficiency will be increasing for each of the years subsequent to the fifth BF - because of the increasing severity of the symptoms of failure for each of these years.

As shown below, this model gives a five year early warning and its power increases as companies approach failure. The two functions, based upon the analysis and combined samples, are presented and evaluated in what follows:

First: The model's function fitted to the analysis sample is:

$$Z_i = -5.36+16.79(V07)+3.81(X17)+4.24(V86)-1.70(D1)+0.23(D2)$$

where:

V07 is the Return on Total Capital Employed, measured by the earnings before interest and tax divided by the total capital employed (total assets). This variable was one of the most important variables in a number of previous studies (e.g., Altman, 1968 and 1973, Altman and Loris, 1976, Altman, et al., 1977 and Taffler 1977a). It measures the overall performance of a company and is a key factor in solving a company's financial problems. Thus a company with a poor rate of return and financial problems is expected eventually to fail.

X17 is the Quick Ratio of Liquidity, measured by current Assets less inventory divided by current liabilities (including bank overdafts). This ratio was transformed into the form "1/(x+1)" to improve the normality of its distribution. It measures the ability of a company to meet, out of its current assets less inventory, its current liabilities including bank overdrafts when they come due. Beaver's (1966), Taffler's (1977a) and Parosh' and Tamari's studies found that short-term solvency is less important than long-term solvency, capital gearing (see: Taffler, 1977a and Tamari, 1978, pp.132-3). Altman (1968) and AHN (Altman, et al., 1977) found that liquidity, as measured by working capital to total assets (our ratio number 87, which is not a stable measure of liquidity) and current ratios, was one of their important variables. Our models of the first and second years before failure indicate that capital gearing is more important than liquidity. Thus, it can be said that, according to our results, liquidity is more important for the years which are more remote from failure.

V86 is the Ratio of Quick Assets to Total Assets. Although this ratio has the denominator of the above first ratio and the numerator of the second, it is not a measure of a specific financial attribute. Generally, this ratio loaded moderately on both components three (assets position or intensiveness) and eight. The latter was not identified as an important component because no ratio loaded highly on it. Ratio 86 loaded highly only on component three for the first year before failure for the analysis of the combined failed and non-failed companies (see: table 5.6 of Chapter 5). It was one of Taffler's (1977a) important ratios and it loaded highly on his component of quick assets position. However, Taffler's ratio did not include the near cash assets in its quick assets definition and his principal components analysis was concerned with the combined failed and non-failed companies for the first year before failure. This ratio indicates the relative share, to the total assets, of liquid assets on the one hand and of the fixed assets and inventory on the other. The higher this ratio is the more liquid the company would appear to be, given a certain level of current liabilities, and the less will be the total costs of holding fixed assets and inventory.

D1 is an Industry Dummy Variable, which has the values of 1.0 for either industry 10 (Mining and Quarrying) or industry 50 (Construction) and 0.0 otherwise. The inclusion of this variable is consistent with the observation that the companies of the UK construction industry are more failure prone than others. It indicates that the z-scores of construction companies, failed and non-failed, are generally less than those of other companies in the above model.

D2 is another Industry Dummy variable, which has the values of 1.0 for either industry 81 (Wholesale) or industry 82 (Retail) and 0.0. otherwise. The positive sign of this variable's coefficient indicates that the z-scores of companies in industries 81 and 82 are generally higher than those of other companies.

The positive coefficients of the above model's accounting ratios indicate that the three ratios act in the same direction so that the higher the value of each of them the more solvent is the company. The two industry dummy variables represent an adjustment to the z-scores of companies in the industries defined by these dummy variables. However, the relationships between all the five variables are represented by the within groups correlation matrix which is displayed in table 6.1. This table shows that the highest correlation coefficient is (-.69). As stated in Chapter 3, it was found that any negative correlation among the independent variables increases their discriminating power. Table 6.2 reprsents the relationship between the three ratios of the above model and the principal components of each of the five years before failure which were defined for all companies, failed and non-failed, in the previous chapter. It shows that ratio numbers 7 and 17 loaded consistently highly on the components of profitability and liquidity, respectively. Also, ratio number 86 loaded moderatly, except for the first year before failure where the loading was .72, on the component of assets position. Tables 5.7 and 5.8 of the previous chapter show that the first two ratios exhibited the same behaviour for failed companies but not exactly the same as for non-failed companies. Again, the principal components analysis (see: Chapter 5) is concerned with the descriptive ability of each accounting ratio, while the emphasis in developing the MDA model is placed on the predictive ability of a set of ratios. However, since the derivation of the discriminant function uses some values which are pooled over the samples of the two groups (see for example: Cooley and Lohnes, 1971, p.246 and Johnston, 1972, p.337), it seems reasonable to refer to the results of the principal components analysis of all companies, failed and non-failed.

As mentioned above each discriminant function was subjected to the following six tests:

Test (1): The statistical significance of the discriminating function can be measured by the F-statistics (see: Chapter 3, subsection 3.3.2.1 for a discussion and defnitions). The value of the computed F is 7.03 while the tabulated value for $F_{5,36} \approx 5.29$ for $\alpha = 0.001$ (see: Abramwitz and Stegun, 1972, table 26.9). Thus, the overall discriminating power of the above function is highly significant. However, the statistical significance is not a good indicator of the efficiency of a discriminant function.

Test (2): The relative importance of each independent variable can be measured by one of three methods (the standardized coefficients, Mosteller' and Wallace's measure and the conditional deletion method) which are discussed in chapter 3 (see: subsection 3.3.2.2).

Table 6.1 Within Groups Correlation Matrix, Model 1 - Function 1

Variables	V07	X17	V86	D1
X17	-.32			
V86	.31	-.69		
D1	.24	-.08	.04	
D2	-.12	.21	-.14	-.06

Table 6.2* Correlation between the Model's Ratios and Components, Model 1

Variables	Components	Correlation between variables and components				
		Y = -1	Y = -2	Y = -3	Y = -4	Y = -5
V07	Profitability	.86	.93	.96	.91	.95
X17	Liquidity	-.92	.93	.89	.83	.91
V86**	Assets Position	.72	.60	.47	.58	.57

* Abstracted from table 5.6 of the previous chapter.

** This variable loaded also on component eight, undefined component, at .26, .53, .68, .55, and .50 for the first through the fifth years before failure,respectively.

Table 6.3 Relative Importance of Each Independent Variable, Model 1 - Function 1

Variable	Standardized Coefficients	Mosteller & Wallace's %	Conditional Deletion	D^2-Excluding a variable	
				Value	% of overall D^2***
V07	1.709	76	1	1.907	51
X17	0.678	4	2	3.263	88
V86	0.609	17	3	3.448	93
D1	-0.263	2	4	3.597	97
D2	0.091	1	5	3.705	99.6

*** The value of the overall variables D^2 is 3.7198

Table 6.3 presents the above three measures of the variables' relative importance and the D^2 (the Mahalanobis's distance between the centroids of the two groups - as defined in subsection 3.3.2.1) for five functions each of which excludes one of this model's five variables. As argued in Chapter 3, although the method of Mosteller and Wallace (the third column of table 6.3) appears to measure the relative contribution of each variable to overall D^2, it cannot measure the contribution of the interaction between the set of variables nor reveal its effect on their individual contributions. This can be indicated by comparing the third and last columns of table 6.3. For example, the third column shows that the contribution of ratio V07 to the D^2 of the five variables' function (D^2_5) is 76%, while the last column shows that the D^2 of the four variables' function which exclude ratio V07 is 51% of D^2_5. Therefore, 49% of D^2_5 appears to be attributable to the inclusion of ration V07 together with the other four variables. This 49% is due presumably to the contributions of both ratio V07 and its interaction with the other four variables. Thus, one may conclude that unless we have some way of segregating the effect of the interaction between the variables, it is not possible to measure the percentage contribution to the overall D^2 and, therefore, the three measures reported in table 6.3 may be considered as only ranking the variables. However, the variables are ranked the same by columns 2 and 4 of table 6.3.

Test (3): Cross validation test uses the model to classify the failed and non-failed companies of the hold-out sample, which is the second half of our split sample. Tables 6.4 and 6.5 present the classification matrices which are the results of applying the model to each of the analysis and hold-out samples. The cut-off point is zero because of the assumed equality of prior probabilities and costs of misclassification (see: Chapter 3).

Table 6.4 Classifying the Analysis Sample, Model 1 - Function 1*

Actual Groups	Classified as:		
	Failed	Non-Failed	Total
Failed	21	0	21
Non-Failed	0	21	21
Total	21	21	42

Table 6.5 Classifying the Hold-out Sample, Model 1 - Function 1*

Actual Groups	Classified as:		
	Failed	Non-Failed	Total
Failed	18	4	22
Non-Failed	0	22	22
Total	18	26	44

* For an explanation of classification matrices and the measures derivable from them, see Chapter 3.

Table 6.4 indicates that the model resulted in 100% correct classifications for the analysis sample. This proportion correctly classified may be due to true differences between the groups, sampling errors - as a result of using the sample means and variance as a proxy of the population parameters - and intensive search for the variables that work best for the sample (see: subsection 3.3.2.3 of Chapter 3). To eliminate the upward classification bias due to both sampling and search biases, the model is used to classify the companies in the hold-out sample.

Table 6.5 shows that the model correctly classified 91% of all the companies in the hold-out sample. Four failing companies were misclassified - i.e., type I error of 9% (4/44) - and all the non-failing companies were correctly classified, i.e., 0% type II error. The percentage of group 1, failing companies, correctly classified is 82% and the percentage of group 2, non-failing companies, is 100%. Also, 100% of the companies classified as group 1 and 85% of those classified as group 2 are correctly classified. However, the correct classifications of the companies in group 1 and of those classified as group 1 are considered the most important measures of a discriminant function's efficiency, in this type of study (see: Chapter 3).

These results indicate that the first function of the fifth year's model appears to possess a high power (91%) in classifying failing and non-failing companies five years BF.

Test (4): The inter-temporal validation test is concerned with testing the predictive power of the model by using it to classify the companies in an inter-temporal validation (prediction) sample which is concerned with a period of time subsequent to that of the analysis and hold-out samples. Table 6.6 presents the classification matrix of our inter-temporal validation sample, 9 companies of each group. It shows that the model correctly classified 94% of all the companies in the precition sample, i.e., it has a predictive power of 94%. Only one failing company was misclassified, i.e., type I error of 6% (1/18). The group memberships of 89% of failing companies and 100% of non-failing companies were correctly predicted. Also the group memberships of 100% of companies classified as group 1 and 90% of companies classified as gropu 2 were correctly predicted.

Table 6.6 Classifying the Prediction Sample, Model 1 - F 1

Actual Groups	Classified as:		
	Failed	Non-Failed	Total
Failed	8	1	9
Non-Failed	0	9	9
Total	8	10	18

Accordingly, the performance of the above first function appears to indicate the efficiency of the fifth year's model (94%) in predicting failure as early as five years before it occurs. However, the small size of the inter-temporal validation sample should be noted.

Test (5): Evaluating the expected performance (EP) on a random sample and the expected cost (EC) of using the model. This test serves two objectives. It allows for the effects of the population's prior probabilities and costs of misclassification and compares the performance of a discriminant function (DF) with that of the proportional chance criterion (prop.) see: Chapter 3). Taffler (1977a and 1977b) has estimated the population's prior probability odds (failing to non-failing) for the UK companies at 1:10 and at 1:7 respectively. Using these estimates and the the classifications of the hold-out sample (table 6.5), the expected performance on a random sample and the expected cost of using the model can be evaluated as follows (see subsection 3.3.2.4 for definitions).

(a) Evaluating the expected performance:

(1) For prior probability odds of 1:10

$$EP_{DF} = 0.091(18/22) + 0.91(22/22) = 0.98$$

$$EP_{Prop.} = (0.091)^2 + (0.91)^2 = 0.84$$

(2) For prior probability odds of 1:7

$$EP_{DF} = 0.125(18/22) + 0.875(22/22) = 0.98$$

$$EP_{Prop.} = (0.125)^2 + (0.875)^2 = 0.78$$

Accordingly, the above function is expected to perform very well on a random sample drawn from the UK population of companies and it performs better than the proportional chance criterion.

(b) Evaluating the expected cost of using the DF.

(1) For priorprobability odds of 1:10.

$EC_{DF} = 0.091(4/22)\ C_1 + 0.91(0/22)\ C_2$

$EC_{Prop.} = 0.091 \times 0.91\ (C_1 + C_2)$

The DF would be superior to the proportional chance criterion if and only if $EC_{DF} < EC_{Prop.}$ i.e., if

$$0.0165\ C_1 < 0.0828\ C_1 + 0.828\ C_2.$$

Solving this inequality without quantifying C_1 and C_2 gives the following inequality $C_1 > -1.25\ C_2$. The latter indicates that the DF outperforms the proportion chance model even if C_1 (the cost of misclassifying a failing company) is less than C_2 (the cost of misclassifying a non-failing company).

(2) For prior probability odds of 1:7

$EC_{DF} = 0.125(4/22)\ C_1 + 0.875(0/22)\ C_2$

$EC_{Prop.} = 0.125 \times 0.875\ (C_1 + C_2)$

Following the above steps

$$0.0227\ C_1 < 0.1094\ C_1 + 0.1094\ C_2$$

and, thus $C_1 > -1.26\ C_2$.

Accordingly, the results of this test indicate that this model is expected to classify a random sample with a very high efficiency (98%) and it performs better than the proportional chance model. They also indicate that the expected cost of using this model for decision-making is significantly lower than that of using the proportional chance model, even if C_1 was less than C_2. However, C_1 is believed to more than 30 times greater than C_2 (see: Chapter 2).

Test (6): In addition to the above tests the model was used to classify the companies in each of the three sample - analysis, hold-out and inter-temporal validation - upon the basis of their variables for each of the four years subsequent to the fifth before failure.

Table 6.7 presents the classification matrices for each of the three samples of each of the four years subsequent to the fifth BF. Table 6.8 presents some efficiency measures based upon the classifications of table 6.7. Both tables 6.7 and 6.8 indicate that the model generally performs better as companies approach failure with minimum efficiency equal to those of the year of the model, the fifth BF.

Thus, this model, in the above first function, appears to possess consistently high classifying and predicting powers over the five years period. In this way, the model appears to improve our ability to predict corporate failure and, therefore, it appears to represent an improvement over all the models of the previous studies.

As mentioned above, the coefficients of the model were re-estimated using the combined sample, both analysis and hold-out samples. This second function of the model and the above tests are presented below.

SECOND: The model's function fitted to the combined sample is:

$$Z_i = -4.86+13.5(V07)+3.11(X17)+4.80(V86)-0.97(D1)+0.68(D2)$$

Where:

V07, X17, V86, D1, and D2 are as presented previously. The within groups correlation matrix based upon the data of the combined sample are presented in table 6.9. It shows similar relationships between the variables with some different correlation coefficients. The relationship between the three accounting ratios of the model and the principal components of the previous chapter is the same as presented in table 6.2 and as discussed above.

Table 6.7 Classification Matrices for the three samples of each year subsequent to the fifth year BF, Model 1 - Function 1

Samples		Analysis			Hold-Out			Inter-temporal V		
Years Prior to Failure	Actual Groups	Classified			Classified			Classified		
		Failed	Non-Failed	Total	Failed	Non-Failed	Total	Failed	Non-Failed	Total
4	Failed	21	1	22	20	2	22	9	0	9
	Non-Failed	0	22	22	0	22	22	0	9	9
	Total	21	23	44	20	24	44	9	9	18
3	Failed	20	2	22	22	0	22	9	0	9
	Non-Failed	0	22	22	1	21	22	0	9	9
	Total	20	24	44	23	21	44	9	9	18
2	Failed	20	2	22	22	0	22	8	1	9
	Non-Failed	0	22	22	0	22	22	0	9	9
	Total	20	24	44	22	22	44	8	10	18
1	Failed	21	1	22	21	1	22	8	1	9
	Non-Failed	0	22	22	0	22	22	0	9	9
	Total	21	23	44	21	23	44	8	10	18

Table 6.8 Efficiency Measures based upon table 6.7

Year before failure	4			3			2			1		
Efficiency Measure+	A*	Ho*	ItV*	A	Ho	ItV	A	Ho	ItV	A	Ho	ItV
1-Total %	98	95	100	95	98	100	95	100	94	98	98	94
2.% G1 correctly classified	95	91	100	91	100	100	91	100	89	95	95	89
3.% G2 correctly classified	100	100	100	100	95	100	100	100	100	100	100	100
4.% correctly classified G1	100	100	100	100	96	100	100	100	100	100	100	100
5.% correctly classified G2	96	92	100	92	100	100	92	100	90	96	96	90

* A stands for the analysis sample, Ho stands for the hold-out sample, and ItV stands for the inter-temporal validation sample.

+ For the definition of these measures, see Chapter 3.

This function was also subjected to the above six tests and the results are as follows:

Test (1): The statistical significance of the computed function:
The computed F-statistic for this function is 11.06 while the tabulated value for $F_{5,80} \approx 4.65$ for $\alpha = 0.001$ (see subsection 3.3.2.1). Thus, this function possesses a highly significant discriminating power.

Test (2): The relative importance of each independent variable is shown in table 6.10. Generally, the explanation of table 6.3 applies to table 6.10. The latter indicates that the variables are similarly ranked by all the methods, which was not the case in table 6.3.

Table 6.9 Within Groups Correlation Matrix, Model 1 - Function 2

Variable	V07	X17	V86	D1
X17	-.19			
V86	.20	-.68		
D1	.50	.09	-.08	
D2	-.17	.28	-.16	-.05

+ The comment on table 6.1 applies to this table as well.

Table 6.10 Relative Importance of Each Independent Variable, Model 1 - Function 2

Variable	Standardized Coefficients	Mosteller & Wallace's %	Conditional Deletion	D^2-excluding a variable Value	% of overall D^2*
V07	1.267	69	1	1.530	57
X17	0.537	2	3	2.494	92
V86	0.660	22	2	2.434	90
D1	-0.146	2	5	2.674	99
D2	0.284	5	4	2.607	96

* The value of the overall variables D^2 is 2.702

Test (3): Cross Validation Test:

According to the split sample procedure there is no cross validation test to the re-estimated coefficients of the model. To avoid the drawbacks of the split sample procedure, wasting the data and using untested parameters, the Lachenburch's "leaving-one out" method was used to test the model's second function (see: Chapter 3). According to the "leaving-one out" method 86 functions, which is the number of cases in the combined sample, were computed using 85 cases for each function, i.e. excluding a different case for each function. The excluded case for each function was then classified by the function.

Table 6.11 presents the misclassified companies by the "leaving-one out" method compared with those misclassified by applying the second function to the combined sample (which is the analysis sample in this case) and with those misclassified by applying the first function to the hold-out sample.

Table 6.11 Misclassified Companies, Model 1 - Function 2

Companies		Classified		
Serial No.	Actual Group	Lachenburch's "leaving-one out"	Combined Sample by second function	Hold-out Sample by first function
29	1	2	2	2
36	1	2	2	2
38	1	2	2	2
39	1	2	2	2
41	1	2	2	1

Table 6.11 shows that the classifications by the Lachenbruch's test are exactly the same as the classifications by the re-estimated coefficients for the analysis (combined) sample. Also, these classifications include only one additional misclassified company relative to those of the first function.

These findings indicate that the re-estimated coefficients do not include upward bias. This bias appears to be peculiar to the analysis sample, the first half of the split sample.

Table 6.12 presents the classification matrix for the companies in the combined sample using the re-estimated coefficients as well as the Lachenbruch's hold-out test. It shows that the second function of the fifth year's model correctly classified 94% of all the companies in the combined sample. Five failing companies were misclassified - i.e. type I

Table 6.12 Classification of Combined Sample*, Model 1 - Function 2

Actual Groups	Classified as:		
	Failed	Non-Failed	Total
Failed	38	5	43
Non-Failed	0	43	43
Total	38	48	86

* By the re-estimated coefficients as well as the leaving-one-out" method.

error of 6% (5/86) - and all the non-failing companies were correctly classified - i.e. 0% type II error. The percentage of group 1, failing companies correctly classified is 88% and the percentage of group 2, non-failing companies, is 100%. Also, 100% of the companies classified as group 1 and 90% of those classified as group 2 are correctly classified.

These results indicate that the above second function appears to possess a high power (94%) in classifying failing and non-failing companies as early as five years before failure.

Test (4): Inter-Temporal Validation Test:

Table 6.13 presents the classifications made by the model's second function to the inter-temporal validation sample. It shows that the function correctly classified 94% of all the companies, 89% of failing companies, 100% of non-failing companies, 100% of companies classified as group 1 and 90% of the companies classified as group 2. Thus, this model appears to have a predictive power of 94% forits two functions (see: Table 6.6).

Table 6.13 Classifying the Inter-Temporal Validation Sample, Model 1 - Function 2

Actual Groups	Classified as: Failed	Non-Failed	Total
Failed	8	1	9
Non-Failed	0	9	9
Total	8	10	18

<u>Test (5)</u>: Evaluating the function's expected performance on a random sample and the expected cost of using it in decision-making. Using the classifications of table 6.12 and the estimate of prior probability odds at 1:10, this evaluation can be made as follows (see test 5 of the first function):

(a) Evaluating the expected performance

$$EP_{DF} = 0.091\ (38/43) + 0.91\ (43/43) = 0.99$$

$$EP_{Prop.} = (0.091)^2 + (0.91)^2 \qquad = 0.84$$

Thus, the expected performance on a random sample of this function is better than that of the proportional chance criterion.

(b) Evaluating the expected cost of using the second DF of Model 1

$$EC_{DF} = 0.091\ (5/43)\ C_1 + 0.91\ (0/43)\ C_2$$

$$EC_{Prop.} = 0.091 \times 0.91\ (C_1 + C_2)$$

The DF would be superior to the proportional chance criterion if and only if $EC_{DF} < EC_{Prop.}$, i.e., if

$$0.0106\ C_1 < 0.0828\ C_1 + 0.0828\ C_2 \qquad \text{or,}$$

$$C_1 > -1.147\ C_2$$

This latter inequality indicates that the expected cost of using the second function of the fifth year's model for decision-making is less than that of using the proportional chance model even if C_1 was less than C_2.

Test (6): In addition to the above tests the second function was used to classify the companies in each of the two samples (combined and inter-temporal validation) using their variables for each of the four years subsequent to the fifth BF. The resulting classification matrices are presented in table 6.14. Table 6.15 presents some efficiency measures based upon the classifications of table 6.14. These tables show that the second function of Model 1 possesses consistently high classifying and predicting powers. Therefore, this model in its two functions appears to improve our ability to predict corporate failure and, thus, it appears to represent an improvement over the models of the previous studies. However, the results presented in the next section appear to add support to the efficiency of this model and its basic hypothesis (see hypothesis 4 in chapter 1).

6.2.2 Model 2: The First Year's Model

The following model was developed upon the basis of the data of the first year before failure. The purpose is to compare its results with the previous model and then to compare them with those of previous studies. (In fact all the models in previous studies are first year's models except those of Deakin (1972 and 1977) and Blum (1974) which were a priori defined by a number of accounting ratios and then different functions were fitted to the data of the different periods BF or to those of the second year BF (Deakin (1977) - see Chapter 2).

Table 6.14 Classification Matrices of the Two Samples of Each Year Subsequent to the Fifth BF, Model 1 - Function 2

Samples		Combined			Inter-Temporal Validation		
Years prior to Failure	Actual Groups	Classified			Classified		
		Failed	Non-Failed	Total	Failed	Non-Failed	Total
4	Failed	40	4	44	8	1	9
	Non-Failed	1	43	44	0	9	9
	Total	41	47	88	8	10	18
3	Failed	40	4	44	8	1	9
	Non-Failed	3	41	44	0	9	9
	Total	43	45	88	8	10	18
2	Failed	40	4	44	8	1	9
	Non-Failed	1	43	44	0	9	9
	Total	41	47	88	8	10	18
1	Failed	42	2	44	8	1	9
	Non-Failed	0	44	44	0	9	9
	Total	42	46	88	8	10	18

6.15 Efficiency Measures Based Upon Table 6.14

Year Before Failure	4		3		2		1	
Efficiency Measures+	C *	ItV *	C	ItV	C	ItV	C	ItV
1. Total %	94	94	92	94	94	94	98	94
2.% G1 correctly classified	91	89	91	89	91	89	95	89
3.% G2 correctly classified	98	100	93	100	98	100	100	100
4.% correctly classified G1	98	100	93	100	98	100	100	100
5.% correctly classified G2	91	90	91	90	91	90	96	90

* C stands for the combined sample and Itv stands for the inter-temporal validation sample.

+ For the definition of these measures, see Chapter 3.

The presentation of this section follows exactly that of the previous one, thus:

FIRST: The Model's function based upon the analysis sample is:

$Z_i = -7.4865+11.7718(V38)+18.0758(X49)+0.4729(V85)-1.4543(D1)+0.3438(D2)$

Where :

V38 is the ratio of Funds Flow to Total Capital Employed, where funds flow is measured as the operating profit before tax, interest and depreciation. This ratio was not selected as one of the best predictors in any of the previous studies. However, the analysis in the previous chapter indicates that this ratio is one of the important measures of profitability, in terms of a high loading on profitability for different years and for the different groups of companies. Measures of profitability have always been the best predictors of corporate failure in most previous multivariate studies (the second best in Beaver's study (1966)) and in our previous model (see: ratio V07 above).

X49 is the ratio of Long-term Debt to Net Capital Employed. This ratio was transformed to the form "1/(x+3)" to improve the normality of its distribution. It is one of the more stable measures of capital gearing and it shows the ability of a company to pay its long-term debts, when they come due. The high values of this ratio imply heavy financial charges, poor ability of rising long-term (loan and equity) capital and low probability of capital repayment on a liquidation. Therefore, it is believed that the measures of gearing are concerned with the evaluation of a company's risk (see: Lee, 1976, p.209). Almost all the previous studies, see chapter 2, include a measure of capital gearing. Our previous model included a measure of liquidity (X17) instead of gearing. Thus, it was pointed out that gearing may be more important for the years which are less remote from failure. This does not mean that measures of gearing are not important for the other years but it means that measures of gearing develop a greater discriminating power as companies approach failure.

V85 is the ratio of Current Assets to Total Capital Employed. This ratio is one of the more stable measures of assets position or intensiveness. It was one of the constituting ratios of the models developed by Deakin (1977) and Marais (1979). It conveys information about the distribution of a company's financial resources between current and fixed assets. Low values of this ratio imply high fixed charges and, given a certain level of current liabilities, low level of liquidity. But a firm with a high value of this ratio could still have a high proportion of fixed to operating costs if (for example) it leased the fixed assets it uses (which would not appear in its balance sheet).

Lev (1974a) measured the operating leverage by the ratio of fixed to variable operating costs and used the relationship between sales, fixed and variable costs to derive a measure of a company's return on common stock. Using the latter measure, Lev found a positive association between operating leverage and a stock's riskiness. Ratio 85 can be regarded as an inverse measure of operating leverage and, thus, inversely associated with riskiness.

D1 and D2 are as previously defined.

The relationships between the above five variables are represented by the within groups correlation matrix in table 6.16. As stated above, negative correlation coefficients increase the discriminating power of the set of independent variables. The relationship between the three ratios of the above model and the principal components defined for all the companies for each year before failure, see Chapter 5, is presented in table 6.17. Each of the three ratios loaded highly on the corresponding component for all (as shown in table 6.18) failed and non-failed companies (see tables 5.7 and 5.8 of Chapter 5).

The above first function of the first year's model was subjected to the six tests as follows:

Test (1): The statistical significance of the computed function: The computed F-statistic for this function is 6.97 while the tabulated value for $F_{5,38} \approx 5.21$ for $\alpha = 0.001$ (see: subsection 3.3.2.1 of Chapter 3). Thus, this function possesses a highly significant discriminating power.

Test (2): The relative importance of each independent variable is shown in table 6.18. Generally, the explanation of table 6.3 applies to table 6.18.

It was argued in Chapter 3 (subsection 3.3.2.2) that the relative contribution of each independent variable (according to the measure of Mosteller and Wallace) must be positive and all the contributions must sum up to unity. The intermediate results of developing the above model (Model 2) add support to this argument. Two different models were selected before the above one was chosen. The first of the two models included ratio X18, which is the quick assets less debtors to current liabilities in the form of 1/(x+.375), instead of ratio V85. Although the sum of the relative contribution, using Mosteller and Wallace's method, of the variables was 1, the sum of the positive contributions was 1.04 and the contribution of ratio X18 was -.04, because the sign of the difference between group 2 and group 1 means of ratio X18 was negative while its discriminant coefficient was positive (as for the other ratios). When the coefficients were recomputed (excluding ratio X18) the sum of relative contribution of the new function's variables was less than unity. The second of the two models included ratio V87, which is net working capital to total capital employed, instead of ratio V85. The relative contributions of this model's variables were similar to those of the first model, although different in magnitude. The problem

Table 6.16 Within Groups Correlation Matrix, Model 2 - Function 1

Variable	V38	X49	V85	D1
X49	-.24			
V85	-.12	-.002		
D1	.34	-.39	.13	
D2	-.11	.03	.05	-.08

Table 6.17* Correlation between the Model's Ratios and Components, Model 2

Variable	Component	Correlation between Variables & Components				
		Y = -1	Y = -2	Y = -3	Y = -4	Y = -5
V38	Profitab-ility	.82	.94	.96	.93	.96
X49	Gearing	.73	.87	.87	.83	.88
V85	Assets position	.85	.95	.94	.91	.94

* Abstracted from table 5.6 of the previous chapter.

6.18 Relative Importance of Each Independent Vriable, Model 2 - Function 1

Variables	Standardized Coefficients	Mosteller & Wallace's %	Conditional Deletion	D^2-Excluding a variable	
				Value	% of overal D2+
V38	1.74	81	1	1.253	35.8
X49	.48	13	2	3.224	92.2
V85	0.09	1	5	3.486	99.7
D1	-.31	4	3	3.373	96.4
D2	.13	1	4	3.467	99.1

+ The value of the overall variables D^2 is 3.498

with this second model was that the sign of the discriminant coefficient of ratio V87 was negative while the difference between its two groups means was positive.

Accordingly, a variable with negative contribution should not be accepted and the process of searching for the best discriminating variables should be continued until a balanced model (i.e. that which satisfies the above conditions) is developed.

Test (3): Cross Validation Test:

Tables 6.19 and 6.20 present the classification matrices made by applying the model to the analysis and hold-out samples, respectively.

Table 6.19 Classifying the Analysis Sample, Model 2 - Function 1

Actual Group	Classified as:		
	Failed	Non-Failed	Total
Failed	21	1	22
Non-Failed	0	22	22
Total	21	23	44

Table 6.20 Classifying the Hold-out Sample, Model 2 - Function 1

Actual Group	Classified as:		
	Failed	Non-Failed	Total
Failed	21	1	22
Non-Failed	0	22	22
Total	21	23	44

* For an explanation of classification matrices and the measures derivable from them, see Chapter 3.

Table 6.19 shows that the model correctly classified 98% of all the companies in the analysis sample. As mentioned above, this classification may be biased upward because of the sampling error and the intenstive search for the best discriminators. However, table 6.20 shows that the model correctly classified also 98% (the same as for the analysis sample) of all the companies in the hold-out sample. Only one failed company was misclassified, i.e. 2% type I error and 0% type II error. More importantly, the model correctly classified 100% of the companies classified as group 1, failed companies, which is 95% of the actual failed companies. Also 96% of the companies classified as group 2, non-failed group, were correctly classified, which is 100% of the actual non-failed group. Thus, our first year's model, in its first function, possesses a very high classifying power.

Test (4): The inter-temporal validation test:
Table 6.21 presents the classifications made by the model's first function to the inter-temporal validation sample. It shows that the function correctly classified 100% of all, of failed, of non-failed, of classified failed and of classified non-failed companies. Thus, the first function of the first year's model has a predictive power, upon the basis of our small prediction sample, of 100%.

Table 6.21 Classifying the Prediction Sample - Model 2 - F 1

Actual Group	Classified as:		
	Failed	Non-Failed	Total
Failed	9	0	9
Non-Failed	0	9	9
Total	9	9	18

Test (5): Evaluating the function's expected performance on a random sample and the expected cost of using it in decision-making. Using the classifications of table 6.20 and the estimate of prior probability odds at 1:10, this evaluation can be made as follows (see test 5 of the first function of the fifth year's model):

(a) Evaluating the expected performance

$EP_{DF} = 0.091\ (21/22) + 0.91\ (22/22) = 0.997$

$EP_{Prop.} = (0.091)^2 + (0.91)^2 = 0.84$

Thus, the expected performance of this function on a random sample is significantly better than that of the proportional chance model.

(b) Evaluating the expected cost of using the first DF of Model 2

$EC_{DF} = 0.091\ (1/22)\ C_1 + 0.91\ (0/22)\ C_2$

$EC_{Prop.} = 0.091 \times 0.91\ (C_1 + C_2)$

The DF would be superior to the proportional chance criterion if (and only if) $EC_{DF} < EC_{Prop.}$, i.e. if

$$0.0041\ C_1 < 0.0828\ C_1 + 0.0828\ C_2 \qquad \text{or,}$$
$$C_1 > -1.052\ C_2$$

This latter inequality indicates that the expected cost of using the first function of model 2 for decision-making is less than that of using the proportional chance model even if C_1 was less than C_2.

Test (6): In addition to the above tests this function was used to classify the companies in each of the three samples using their variables for each of the four years prior to the first BF. The purposes of this procedure are to compare this model's first function with that of the previous one and to reveal an indication about the span of time within which a predicted failed company is expected to collapse. It is not intended as an additional hold-out test (see the comments on Altman's models in Chapter 2).

Table 6.22 presents the classification matrices for each of the four years prior to the first before failure. Table 6.23 presents some efficiency measures which are computed from the classifications of table 6.22. The former table shows that the model possesses very high classifying and predicting powers. It performed better than all the models of the previous studies, especially for the years which are more remote from failure. The total efficiency of our model, on the hold-out sample, was 98, 100, 98, 89, and 84% for each of the years 1 to 5 before failure. This high efficiency of the model can be explained by the nature of the constituting variables and by our method of sampling. Each constituting ratio is a very stable measure of a company's financial attribute, see table 6.17 above. It measures the same attribute for failed and non-failed groups of companies, for different years and for the combined companies and years, see Chapter 5. Also the industry dummy variables add to the power of the model, see section 6.4 below. As mentioned in Chapter 3, our companies were selected from the extreme cases, failed and healthy companies, to minimize the overlap between the two groups.

The comparison between this model and the previous one is made after the presentation of this model's second function. According to table 6.23, about 73% of the failed companies in the hold-out sample were correctly classified in the fifth year BF. This indicates that a predicted failed company may collapse after a period of five years. Thus, although the model is developed upon the basis of the data of the first year BF, a predicted failed company may not be expected to collapse after one or even two years from the date of the data used in the prediction. Therefore, it has been a common conclusion that the lower the z-score the more close the company is to collapse. However, this point is considered further in subsection 6.2.4.

Table 6.22 Classification Matrices for the three samples of each year prior to the first BF., Model 2 - Function 1

Years prior to first BF	Actual Groups	Analysis Classified			Hold-Out Classified			Inter-temporal val. Classified		
		Failed	Non-Failed	Total	Failed	Non-Failed	Total	Failed	Non-Failed	Total
5	Failed	20	1	21	16	6	22	8	1	9
	Non-Failed	0	21	21	1	21	22	0	9	9
	Total	20	22	42	17	27	44	8	10	18
4	Failed	20	2	22	18	4	22	9	0	9
	Non-Failed	0	22	22	1	21	22	0	9	9
	Total	20	24	44	19	25	44	9	9	18
3	Failed	19	3	22	21	1	22	9	0	9
	Non-Failed	0	22	22	0	22	22	1	8	9
	Total	19	25	44	21	23	44	10	8	18
2	Failed	18	4	22	22	0	22	8	1	9
	Non-Failed	0	22	22	0	22	22	1	8	9
	Total	18	26	44	22	22	44	9	9	18

Table 6.23 Efficiency Measures Based Upon Table 6.22

Year BF	5			4			3			2		
Efficiency Measure	A*	HO*	ItV*	A	HO	ItV	A	HO	ItV	A	HO	ItV
1. Total %	98	84	94	95	89	100	93	98	94	91	100	89
2.% G1 correctly classified	95	73	89	90	81	100	86	95	100	82	100	89
3.% G2 "	100	95	100	100	95	100	100	100	89	100	100	89
4.% correctly classified G1	100	94	100	100	95	100	100	100	90	100	100	89
5.% " G2	95	78	90	92	84	100	88	96	100	85	100	89

* See table 6.8 for notation.

SECOND: The Model's function based upon the combined sample is:

Z_i = -6.1729+11.4303(V38)+14.0743(X49)+.5537(V85)-1.5652(D1)+.9828(D2)

Where:

V38, X49, V85, D1 and D2 are as defined above. The relationship between the variables is presented by the within groups correlation matrix, based upon the data of the combined sample, in table 6.24. The relationship between the model's three ratios and the principal components of the previous chapter is presented in table 6.17. The following are the results of the six tests.

Test (1): The statistical significance of the computed function: The computed F-statistic for this function is 14.16 while the tabulated value for $F_{5,82} \approx 4.64$ for $\alpha = 0.001$ (see subsection 3.3.2.1 of Chapter 3). Thus, this function possesses a highly significant discriminating power.

Test (2): The relative importance of each independent variable is shown in table 6.25. Generally, the explanation of table 6.3 applies to table 6.25.

The ranking by Mosteller and Wallace's measure is more stable than the others. However, D2 achieved a higher rank than that of the first function.

Table 6.24 Within Groups Correlation Matrix, Model 2 - Function 2

Variable	V38	X49	V85	D1
X49	-.08			
V85	.09	.19		
D1	.25	-.21	.17	
D2	-.25	-.04	-.03	-.05

Table 6.25 Relative Importance of Each Independent Variable, Model 2 - F 2

Variable	Standardized Coefficients	Mosteller & Wallace's %	Conditional Deletion	D^2-Excluding a variable: Value	D^2-Excluding a variable: % of overall D^2*
X38	1.66	79	1	1.290	38.2
V49	.37	10	3	3.204	94.9
V85	.10	2	5	3.361	99.6
D1	-.29	3	4	3.257	96.5
D2	.41	6	2	3.118	92.4

* The value of the overall variables D^2 is 3.375.

Test (3): Cross Validation Test:

The discussion on this test for the previous model's second function applies to this function as well. Table 6.26 presents the misclassified companies by Lachenbruch's "leaving-on-out" test compared with thos misclassified by applying this function to the combined sample, which is the analysis sample in this case, and with those misclassified by applying the first function to the hold-out sample. It shows that the function performed exactly the same for reclassifying the original companies, i.e., those which were used

Table 6.26 Misclassified Companies, Model 2 - Function 2

Companies		Classified		
Serial No.	Actual Group	Lachenbruch's Leaving-one-out"	Combined Sample by 2nd function	Hold-out Sampling by 1st function
10	1	2	2	2
22	1	2	2	1
32	1	2	2	2

to compute the coefficients, and for Lachenbruch's hold-out test. Similar to the previous model's second function, only one additional case was misclassified by the re-estimated coefficients compared with the first function's misclassifications.

Table 6.27 presents the classification matrix for the results of Lachenbruch's hold-out test which is the same for the combined sample. It shows that this model, in its second function, correctly classified 97% of all companies, 93 of failed companies, and 100% of non-failed companies. It also correctly classified 100% of the classified failed companies and 94% of the classified non-failed companies. Only three failed companies were misclassified, i.e., type I error of 3% (3/88) and all non-failed companies were correctly classified, i.e., 0% type II error. Thus, this second function of the first year's model (Model 2) has a high ex post discriminating power.

Table 6.27 Classification of Combined Sample*, Model 2 - Function 2

Actual Groups	Classified as:		
	Failed	Non-Failed	Total
Failed	41	3	44
Non-Failed	0	44	44
Total	41	47	88

* By the re-estimated coefficients as well as the "leaving-one-out" method.

<u>Test (4)</u>: Inter-Temporal Validation Test:

Table 6.28 presents the classifications made by this model's second function to the inter-temporal validation sample. It shows that the model correctly classified 94% of all the companies, 89% of failed companies, 100% of non-failed companies, 100% of companies classified as group 1 and 90% of companies classified as group 2. Therefore, our model has a predictive power, upon the basis of our small prediction sample, of 94%.

Table 6.28 Classifying the Prediction Sample, Model 2 - F2

Actual Group	Classified as:		
	Failed	Non-Failed	Total
Failed	8	1	9
Non-Failed	0	9	9
Total	8	10	18

Test (5): Evaluating the function's expected performance on a random sample and the expected cost of using it in decision-making. Using the classifications of table 6.27 and the estimate of prior probability odds at 1:10, this evaluation can be made as follows (see test 5 of the first function of the fifth year's model):

(a) Evaluating the expected performance

$EP_{DF} = 0.091\ (41/44) + 0.91\ (44/44) = 0.994$

$EP_{Prop.} = (0.091)^2 + (0.91)^2 = 0.84$

Thus, the expected performance of this function on a random sample is significantly better than that of the proprtional chance criterion.

(b) Evaluating the expected cost of using the second DF of Model 2.

$EC_{DF} = 0.091\ (3/44)\ C_1 + 0.91\ (0/44)\ C_2$

$EC_{Prop.} = 0.091 \times 0.91\ (C_1 + C_2)$

The DF would be superior to the proportional chance criterion if (and only if) $EC_{DF} < EC_{Prop.}$ i.e., if

$0.0062\ C_1 < 0.0828\ C_1 + 0.0828\ C_2$ or,

$C_1 > -1.081\ C_2$

This latter inequality indicates that the expected cost of using the second function of model 2 for decision-making is less than that of using the proportional chance model even if C_1 was less than C_2.

Test (6): In addition to the above tests this function was used to classify the companies in each of the combined and inter-temporal validation samples using their variables for each of the four years prior to the first BF. The resulting classification matrices are presented in table 6.29. Table 6.30 presents some efficiency measures based upon the classifications of table 6.29. These tables show that the second function of model 2 possesses very high classificating and predictive powers. The total efficiency of this function, on the Lachenbruch's test and on the prior years' data, is 97, 92, 93, 91 and 91% for each of the years 1 to 5 before failure. The factors explaining the high efficiency of the model's first function applies to this function as well.

6.2.3 A Comparison between the Two Models

The purpose of comparing the model of the fifth year BF (Model 1) with the model of the first year BF (Model 2) is to test hypothesis 4 which states that "accounting ratios of the earliest year or years before failure can predict failure better than those of the subsequent years". The comparison is made between the two functions of each of the two models and includes the two important measures of efficiency (total efficiency and the correct classifications of the failed companies - group 1) and the mean z-scores of each function for the five years before failure. The comparison between the measures of efficiency is made in table 6.31. This table shows that the first functions of each of the two models performed the same for the first two years BF and that Model 1 outperformed Model 2 for the years 3 to 5 BF. As regards the second function of each of the two models, table 6.31 shows that Model 1 outperformed Model 2 for each of the years BF, even for the first year BF which was the year of Model 2. Therefore, the results of this comparison confirm the validity of hypothesis 4 above.

Table 6.29 Classification Matrices of the two samples of each year prior to the first BF., Model 2 - Function 2

Samples		Combined			Inter-temporal validation		
Years prior to Failure	Actual Groups	Classified			Classified		
		Failed	Non-Failed	Total	Failed	Non-Failed	Total
5	Failed	35	8	43	8	1	9
	Non-Failed	0	43	43	0	9	9
	Total	35	51	86	8	10	18
4	Failed	36	8	44	8	1	9
	Non-Failed	0	44	44	0	9	9
	Total	36	52	88	8	10	18
3	Failed	38	6	44	8	1	9
	Non-Failed	0	44	44	1	8	9
	Total	38	50	88	9	9	18
2	Failed	37	7	44	8	1	9
	Non-Failed	0	44	44	1	8	9
	Total	37	51	88	9	9	18

Table 6.30 Efficiency measures based upon table 6.29

Year before failure	5		4		3		2	
Efficiency measure	C *	ItV *	C	ItV	C	ItV	C	ItV
1. Total	91	94	91	94	93	89	92	89
2.% G1 correctly classified	81	89	82	89	86	89	84	89
3.% G2 correctly classified	100	100	100	100	100	89	100	89
4.% correctly classified G1	100	100	100	100	100	89	100	89
5.% correctly classified G2	84	90	85	90	88	89	86	89

* See table 6.16 for notations.

Figures 6.1 and 6.2 compare the mean z-scores of the two discriminant functions of each model (M1 DF1, M1 DF2, M2 DF1 and M2 DF2) as well as the regression functions of the two models (M1 RF1, M1 RF2, M2 RF1 and M2 RF2) for each of the five years BF. In figure 6.1 the mean z-scores are plotted using the same scale on the Y axis to indicate the differences in the magnitude of the functions' mean z-scores. In figure 6.2 different scales are used on the Y axis to allow for a clear display of the difference between the mean z-scores of the two groups of companies for each function. Figures 6.1 shows that the difference between the mean z-scores for the two groups of companies is greater for the functions of model 1 for each of the five years BF. However, figure 6.2 indicate that the mean z-scores are well separated by all the functions for each of the five years BF. The mean z-scores of the non-failing companies display an improved trend especially from the third to the first year before failure. A similar trend was displayed by Taffler's (1977a) sound companies and was attributed to the changes in the British economy between 1969 and 1973, which is the same period in this study. It appears more likely that this trend is due to the method of sampling our healthy (non-failing) companies, which are the companies that kept their rank among the top companies throughout the five years (see: section 3.5.2 of Chapter 3).

However, the above comparisons indicate that Model 1 performs better than Model 2 and achieves greater separation between the centroids of the two groups of companies for each of the five years BF. The previously reported results and table 6.31 indicate that Model 2 appears to be a very powerful model. According to the prediction sample, the two models possess high predictive powers. The second functions of the two models performed the same for each of the five years BF, but the first function of Model 1 performed better than that of Model 2 for the same periods. However, this sample is very small - 9 failed and 9 non-failed companies - and only the

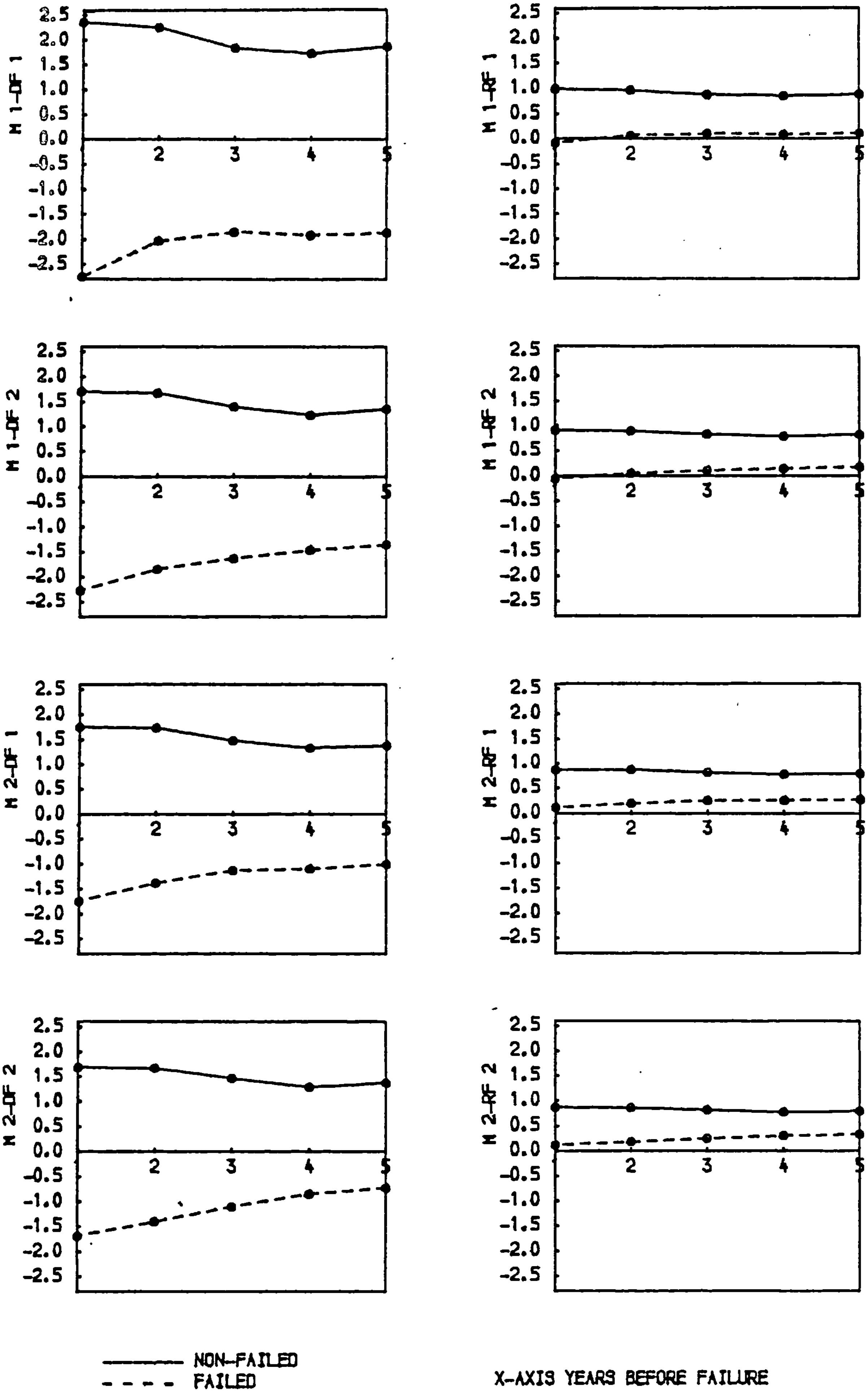


Fig. 6.1 Comparison bewteen Two Models' Discriminant and Regression Functions

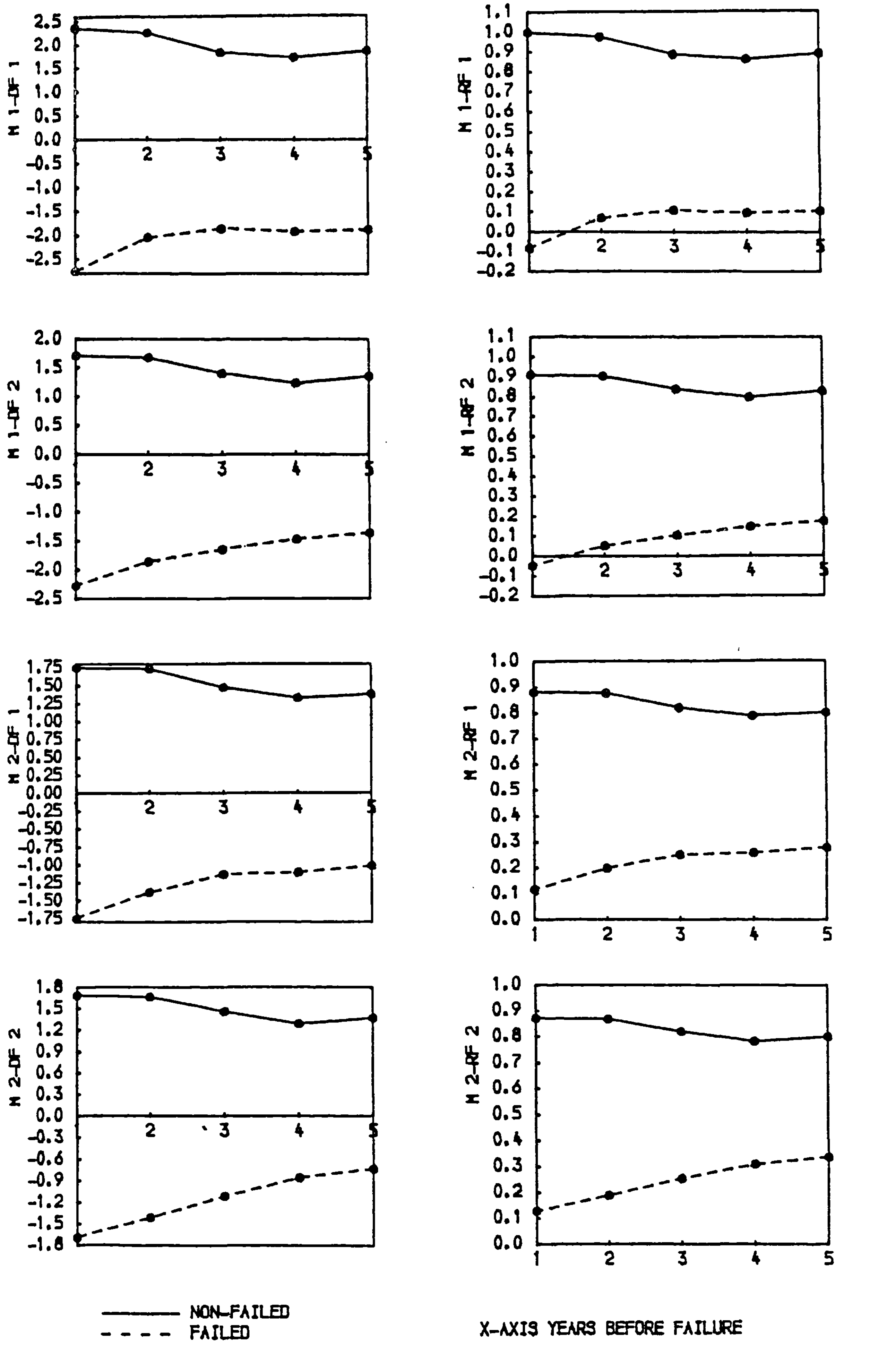


Fig. 6.2 Comparison between Two Models' Discriminant and Regression Functions

failed companies are concerned with a period of time which is subsequent to those of both the analysis and hold-out samples. Therefore, the two models are not compared upon the basis of the prediction sample because the comparison may not be indicative. However, the first two functions are compared by the results of the hold-out sample and the second two functions are compared by the results of Lachenbruch's test. Recall that the results of this latter test were the same as the results of using the re-estimated coefficients to reclassify the combined sample which was not the case in the other studies (see: Taffler, 1977b and Altman et al., 1977).

Since Model 2 is a first year's model it can be cmpared with the models of the previous studies. As previously indicated Model 2 performed, on our data, better than any of the models of the previous studies, on their data.

Table 6.31 Comparison between the Functions of the Two Models

Year before failure	5		4		3		2		1	
Efficiency measure	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
First function										
1. Total %	91	84	95	89	98	98	100	100	98	98
2. G1 correctly classified	82	73	91	81	100	95	100	100	95	95
Second function										
1. Total %	94	91	94	91	92	93	94	92	98	97
2. G1 correctly classified	88	81	91	82	91	86	91	84	95	93

The superiority of Model 1 over Model 2 can possibly be explained by the fact that (as previously mentioned) the former captures the financial characteristics of failed companies five years before failure while the latter captures the financial characteristics of the first year before failure. One might expect the financial characteristics, as reflected by accounting ratios, of failed companies five years before failure are different than those of the first year before failure. Since several accounting ratios of failed companies deteriorate as the year of failure approaches (see Chapter 5), the separation between failed and non-failed companies increases as the year of failure approaches. Therefore, Model 1 performs better as the year of failure approaches (years subsequent to the year of the model, -5) and the efficiency of Model 2 decreases for the years which are more remote from failure (years prior to the year of the model, -1). However, both are more efficient at predicting failure at year -1 than at year -5.

Intuitively one might well expect a priori the economic characteristics of firms which will ultimately fail to be somewhat different five years before bankruptcy than just twelve months prior to that event, and the difference between the discriminating ratios of the two models can possibly be explained in such a way.

Thus the financial characteristics captured by the two models are different, evidenced by the fact that the best discriminating ratios for the two sets of financial characteristics are not the same. For instance, Model 1 included a liquidity ratio while Model 2 included a capital gearing ratio, thus it was argued that measures of capital gearing developed greater discriminating power as the companies approach failure (see: Subsection 6.2.2.). This is supported by the plot of the means of ratios 17 and 49 for failed and non-failed companies in Figure 1 of Appendix C.

6.2.4 Interpreting the Models' Results

As mentioned before, the essence of failure prediction is to establish a combination of selected characteristics which can discriminate between failing and non-failing companies (this combination is expressed in terms of z-scores and a cut-off point). For a specific company, failure is predicted if its combination resembles the combination of the failed firms, otherwise success may be predicted. Therefore, the only true indication of classifying a company as failing or predicted failing is that is financial characteristics resemble those of the failed group of companies.

However, it appears useful to enquire about the span of time within which it seems to be possible to predict the collapse of a company. As indicated before, the first year's model of this study and those of the previous studies have correctly classified a proportion of failed companies upon the basis of the data of the fifth year BF. This indicates that although the models are based on the data of the first year BF, a prediction of failure can often apparently be successfully made as early as 5 years before failure. However, the lower than the critical value is a company's z-score the more likely the company is to collapse shortly. This rule is valid on average, but it may not be valid for a particular company (the z-scores of some classified failed companies were changing up and down throughout the five years period).

If the first year's model can correctly classify failed companies up to the fifth year BF (i.e., 4 years prior to the years of the model), it is reasonable to assume that the fifth year's model can predict failure for some years prior to the fifth BF. This assumption can be supported by the large separation between the mean z-scores of the two groups of companies as shown in Figures 6.1 and 6.2. In addition, Argenti's (1976, Chapter 8) trajectories of failure indicate that the process of failure may last well over ten years. Therefore, if the fifth year's model is used, it may prove possible to predict correctly a failing company more than 5 years before its eventual collapse. In this way model 1 gives a warning earlier than that of model 2.

6.3 Regression Functions

For the purpose of comparing the empirical results of applying the discriminant and regression analyses, two regression functions corresponding to those of the discriminant analysis were fitted to each of the above two models. The computed cut-off point for each of the four functions was 0.5 (see: equation 3.11 of Chapter 3). It resulted in exactly the same classifications as those of corresponding discriminant functions. Moreover, applying the method of Mosteller and Wallace to determine the relative importance of each independent variable resulted in exactly the same values as those of the corresponding discriminant functions.

6.3.1 The Fifth Year's Model

First: The following is the function fitted to this model using the analysis sample:

$Z_i = -.630+3.5384(V7)+.8036(X17)+.8943(V86)-.3589(D1)+.0482(D2)$

where: V7, X17, V86, D1 and D2 are as previously defined.

Second: The following is the regression function fitted to this model using the combined sample:

$Z_i = -.6706+3.2553(V07)+.7508(X17)+1.1565(V86)-.2329(D1)+.164(D2)$.

6.3.2 The First Year's Model

First: The following is the regression function fitted to this model using the analysis sample:

$Z_i = -1.1311+2.5648(V38)+3.9384(X49)+.103(V85)-.3169(D1)+.0749(D2)$

where: V38, X49, V85, D1, are as previously defined.

Second: The following is the regression function fitted to this model using the combined sample:

$Z_i = -.8617+2.5214(V38)+3.1047(X49)+.1221(V85)-.3453(D1)+.2168(D2)$

The above regression functions fitted to the two models performed similarly to the corresponding discriminant functions. Thus, the comparison between the regression functions of the two models shows they give the same indications as the corresponding discriminant functions, although the coefficients, the scores and the cut-off points are different - see figures 6.1 and 6.2.

The relationship between the coefficient of determination R^2 of a regression function (in the case of two groups dependent variable) and the Mahalanobis's distance D^2 was defined in chapter 3 by equation (3.23) as:

$$D^2 = \frac{R^2}{1 - R^2} \quad \frac{(n_1 + n_2)\ (n_1 + n_2 - 2)}{n_1\ n_2}$$

Once D^2 is computed the significance of the regression function can be tested by the F-statistic which is test (1) of the above discriminant functions. However, the above equation was used to compute the regression functions' D^2 and it was found that the square root of the right hand side of the above equation is exactly equal to the discriminant functions' D^2, as defined by equation (3.9) of chapter 3.

Accordingly, the widely available regression programs can be used instead of the discriminant programs in the cases of two groups dependent variables.

6.4 Conclusions

The above reported results confirm some of the hypotheses of chapter 1 and achieve some of the objectives of this study (see: Chapter 1).

First, hypotheses 1 and 2 state that symptoms of corporate failure can be seen several years before it occurs (thus failure is predictable) and these symptoms are reflected in the firm's accounting ratios. The results of the univariate analysis of chapter 5 confirm these two hypotheses where a difference was found to exist between several ratios of failed and non-failed companies for at least five years before failure, with the ratios of failed companies deteriorating as the year of failure approaches. The significance of this latter finding (as recognized in this study) is that the severity of the symptoms of failure increases as the year of failure approaches.

However, the above univariate finding is the basis of all the failure prediction models. As previously indicated, the essence of failure prediction models is the establishment of a combination of selected characteristics which can discriminate between failing and non-failing companies (which are different from each other according to the univariate finding). As argued in chapter 1, since the difference between the two groups of companies was found to exist for at least five years BF, there is no reason why failure prediction models should be based only on the data of the first year BF. Therefore, hypothesis 4 was formulated to state that models based on the data of the earlier year(s) BF (for which the difference between the groups of companies is observable) can predict failure better than those based on the data of subsequent years.

The results reported in this chapter confirm hypotheses 1, 2 and 4, see the comparison between the fifth year's model and the first year's model in subsection 6.2.3 above.

Hypothesis 3 states that industry and economy-wide indicators can improve the predictability of the models based on accounting ratios. The results of this chapter confirm the importance of the industry factor, where the industry dummy variables incorporated in the reported most efficient models. This does not indicate that the economy-wide factors is not important. One or more of three explanations are possible for the fact that the economy-wide indicator was not one of the constituting variables of the reported models. First, the selected indicator (the standard deviation of the FTA index over the working days of each company's financial year) did not reflect the general state of the economy (see: subsection 3.4.2.2 for some alternative indicators). Second, the economy-wide effect may have been picked up by the industry dummy variables (where the two indicators are expected to be interrelated - see: subsection 3.4.2.2). Third, a vector variable, $\underline{x}$, incorporating the economy-wide indicator performed reasonably well but less well than the reported models. In fact, this was the case in this study, but there is a possibility for the former two explanations. The process of developing a model is iterative in nature and only the best performing models are selected. As argued before (subsection 3.4.2.2), the variables which are not included in the reported models are not necessarily unimportant. There is the possiblity that if another set of variables was considered some of our unselected variables might be included in a selected model.

As regards the objectives of this study, the principal one has been partly achieved and some of the secondary ones have been fully achieved (see the objectives in Chapter 1).

First, the efficient performance of the two selected models appears to suggest the usefulness of accounting information in the context of failure prediction. The content of accounting information and its usefulness relative to the share price information, in the context of corporate failure, are the subject of the next chapter.

Second, the results of this chapter appear to suggest that the fifth year's model (Model 1) improves considerably our ability to predict corporate failure (secondary objective No. 1), the performance of the regression functions is exactly the same as that of the discriminant functions (secondary objective No.2) and several hypotheses were confirmed (secondary objective No.4).

CHAPTER VII

THE MARKET MODEL: EMPIRICAL RESULTS

CHAPTER 7

The Market Model: Empirical Results

7.1 Introduction

The purpose of this chapter is to report on the results of testing the hypothesis that 'an efficient capital market, using other information besides that derived from published accounts, may anticipate corporate failure well before a model employing accounting information alone can do so' (see: Chapter 1).

The market model was used to obtain evidence from monthly London Stock Exchange (LSE) share prices of abnormal returns to shareholders in a sample of UK failing companies. The results of analysing these abnormal returns (residuals) provide evidence regarding the ability of share price information to impound accounting and non-accounting information which are specific to the failing companies and the ability of the market to anticipate corporate failure within a certain span of time.

Therefore, a comparison between the results of this chapter and those of the previous one completes the test of the above hypothesis, indicates the content of accounting information and establishes the relative usefulness of the latter.

The results of this chapter suggest that the market on average began to anticipate failure five years before its announcement. Thus, these results seem to support the efficiency of the LSE in the pricing of equities in anticipation of public information about forthcoming failure. The comparison between this finding and those of the previous chapter indicates that both the stock market and failure prediction models can identify failing companies as far back as five years before failure (BF). Thus, accounting information appears to have a content for the capital market, i.e. appears to be useful according to the previously identified second aspect of usefulness (the content of information - see Chapter 1). However, the behaviour of the share prices of failing companies indicates that investors may have regarded these companies as having temporary financing problems, while the failure prediction models indicate that the financial characteristics of failing companies resemble those of failed companies. Therefore, failure prediction models appear to offer investors a useful piece of information which may affect their attitudes towards the securities of the classified failing companies. Thus, accounting information (as used in this study) appears to be potentially useful relative to the share price information.

However, the results of estimating the parameters of the market model, investigating changes in systematic risk of failing companies, the residual analysis and a comparison between these results and those of the previous chapter are each considered in one of the following sections.

7.2 Estimating the Parameters α and β

The logartihmic form of the market model was defined in Chapter 3 as:

$$\text{Log}_e\, R_{it} = \alpha_i + \beta_i\, \text{Log}_e\, R_{mt} + u_{it}$$

The securities and market returns R_{it} and R_{mt} were computed after allowing for the effect of securities' non-trading, following the definitions and procedure presented in Chapter 3. (See Appendix E1 for the computing program). The coefficients $\hat{\alpha}_i$ and $\hat{\beta}_i$ were estimated by regressing the relevant monthly returns of each security R_{it} (but excluding monthly returns for a given interval of time before failure announcement dates) on the market index R_{mt}. As indicated in Chapter 3, the expected values of the residuals u_{it} of the months close to the event of a study are known to be non-zero and, thus, violate the regression assumptions about the residual term. Therefore, these months (intervals of time) must be excluded from the sample of estimating the model's parameters. "Failure to exclude this data could result in biased estimates of the parameters. The initial choice of interval is arbitrary, but the interval is adjusted on the basis of the resulting estimate of abnormal residuals" (Frank, et al., 1977). The results of the exclusion procedure and the estimates of the model's parameters are considered in the following two subsections.

7.2.1 Excluding Months with Abnormal Returns

The exclusion procedure, which is described in subsection 3.2.2.1 of Chapter 3, comprises the following calculations: First, the parameters of the model were estimated for each security using all available data. Second, the sample regression residuals for each security were computed for each month including that of failure announcement, month zero. The price relatives of any month whose reisudal was out of the range of plus or minus 2 standard deviations from the mean of the distribution of the residuals of this first regression were excluded from the estimating sample (see Appendix E2 for the computing program). Third, the coefficients $\hat{\alpha}_i$ and $\hat{\beta}_i$ were re-estimated using the new estimating sample, i.e. the original sample excluding the price relatives of the months with outlier residuals on the first regression. Fourth, the coefficients of the second regression were used to compute the residuals of all the available data for each security. The residuals were then cross sectionally averaged (AR) and the cumulative average residual (CAR) and the abnormal performance index (API) were computed (see Appendix E3 for the computing program).

Table 7.1 presents the AR,CAR and API computed over the periods of 7 and 6 years, respectively. The purpose of presenting CAR and API for two different periods of time is to show that, although the values of the

Table 7.1 Residual Analysis for the Exclusion Procedure

Month++ m	Sample Size n	AR*	7 Years Period + CAR*	API*	6 Years Period + CAR*	API*
-29	20	-0.0014	0.0626	0.8707	-0.0115	0.8686
-28	20	0.0024	0.0650	0.8847	-0.0091	0.8774
-27	20	-0.0260	0.0390	0.8445	-0.0351	0.8464
-26	20	0.0452	0.0842	0.8601	0.0101	0.8656
-25	20	0.0141	0.0983	0.8598	0.0242	0.8604
-24	20	-0.0326	0.0657	0.8412	-0.0084	0.8434
-23	20	-0.0076	0.0581	0.84195	-0.0160	0.8515
-22	20	0.0060	0.0641	0.8519	-0.0100	0.8578
-21	20	-0.0146	0.0495	0.8421	-0.0246	0.8509
-20	20	-0.0422	0.0073	0.8199	-0.0668	0.8236
-19	20	0.0141	0.0214	0.8099	-0.0527	0.8122
-18	20	-0.0163	0.0051	0.7903	-0.0690	0.7932
-17	20	-0.0971	-0.0920	0.7051	-0.1661	0.7370
-16	20	0.0532	-0.0388	0.7057	-0.1129	0.7287
-15	20	-0.0649	-0.1037	0.6900	-0.1777	0.7262
-14	20	-0.0068	-0.1104	0.6591	-0.1845	0.7018
-13	20	-0.0166	-0.1270	0.6384	-0.2011	0.6756
-12	20	-0.0111	-0.1381	0.6349	-0.2122	0.6727
-11	20	·0.0081	-0.1300	0.6178	-0.2041	0.6590
-10	20	0.0098	-0.1201	0.6127	-0.1942	0.6582
- 9	20	-0.0316	-0.1517	0.603	-0.2258	0.6464
- 8	20	-0.0134	-0.1651	0.5723	-0.2392	0.6132
- 7	20	-0.0395	-0.2046	0.5551	-0.2787	0.5976
-6	20	-0.0271	-0.2317	0.5336	-0.3057	0.5816
-5	20	-0.0649	-0.2965	0.5128	-0.3706	0.5713
-4	20	0.0464	-0.25017	0.5122	-0.3243	0.5763
-3	20	-0.0582	-0.3084	0.4859	-0.3825	0.5528
-2	20	-0.0256	-0.3340	0.4498	-0.4081	0.5096
-1	20	-0.0775	-0.4115	0.3914	-0.4856	0.4393
0	19	-0.4632	-0.8747	0.2365	-0.9488	0.2882

*AR is the monthly average residual for the n securities, CAR is the cumulative average residual, and API is the abnormal performance index.

\+ CAR and API are computed overthe entire periods of 7 and 6 years respectively. Only the last 30 of their values are presented above.

++ Months, m, are numbered relative to the month of failure announcement, m=0.

two measures are sensitive to the change in the period of time over which they are computed, a clear pattern can be identified and, thus, the period of abnormal returns can be selected. Table 7.1 shows a decreasing neagive CAR and a decreasing API starting from month (-17) for both the 7 and 6 years of periods of cumulation. Although the values of CAR started to be negative in month (-24) for the six years cumulation, these negative values were decreasingly less than -0.1 from month (-17). Also, it should be noted that the trend displayed by the API is more consistent than that displayed by the CAR.

Accordingly, the period of the last 18 months of data, including month zero, (i.e. from month -17 to month 0, the month of failure announcement), was excluded from each sample of estimating the model's parameters, α and β, for each company. (This period was also excluded from the three periods used to investigate changes in systematic risk of failing companies, see section 7.3 below).

However, the above method of exclusion reflects a recognition of the fact that the residuals may be abnormal in periods other than those close to the failure date, but it does not exclude abnormal returns which are not outliers (see: Franks, et al., (1977)). The above application of the exclusion method appears to have the advantage of objectively determining the excluded period without having to start with an arbitrary choice.

7.2.2 Summary Statistics of the Estimated Parameters

The parameters of the market model were estimated for each security using all the available data except those of the last 18 months in the time-series of price relatives of each security. Table 7.2 presents the estimated parameters for each of the 20 companies in our sample. Table 7.3 presents some descriptive statistics for the estimated values of α_i, β_i and r_i, where r_i is the correlation between monthly rates of return on

Table 7.2 Values of the Estimated Parameters

S.N.	LSPD* No.	Company Name	Values of $\hat{\alpha}$	$\hat{\beta}$	$\hat{r}$
1	503	Bee Hive Spinning	0.0198	1.0055	0.9936
2	1548	Devas Routledge (Hldgs)	0.0105	1.0029	0.9982
3	1671	Dreyfus & Co.	0.0170	1.0116	0.9926
4	2376	Handley Page	-0.0083	0.9939	0.9979
5	3140	Lines Bros	-0.0017	0.9990	0.9980
6	3509	Metal Traders LD	0.0128	0.9996	0.9955
7	4058	Pickles (Robert)	0.0201	1.0152	0.9781
8	4382	Rolls Royce	-0.0054	0.9943	0.9940
9	5612	Whiteside (H.S.) & Co.	0.0276	1.0216	0.9935
10	302	Associated Motor Cycles	-0.0232	0.9904	0.9886
11	1468	Crowley Russell & Co.	-0.0179	0.9934	0.9976
12	3571	Minton Hollins	0.0154	1.0061	0.9953
13	3617	Morgan Brewery	-0.0017	0.9985	0.9973
14	3790	North British Locomotive Co	-0.0084	1.0145	0.9892
15	5665	Wilson Lovatt & Sons	-0.0008	1.0012	0.9917
16	969	Bydand Ltd	0.0077	1.0035	0.9935
17	3576	Mitchell Construction	0.0157	1.0113	0.9969
18	4481	St Martin Preserving Co.	0.0206	1.0280	0.9878
19	4765	Smiths Food Group	0.00741	1.0081	0.9900
20	5476	Wardle & Davenport	-0.0067	0.9966	0.9914

* London Share Price database

Table 7.3 Some Descriptive Statistics for the Estimated Parameters

Parameter	Mean	Standard Deviation	Extreme Values Minimum	Maximum	Skewness
$\hat{\alpha}$	0.005	0.014	-0.023	0.028	-0.349
$\hat{\beta}$	1.005	0.010	0.990	1.028	0.711
$\hat{r}$	0.993	0.005	0.978	0.998	-1.572

security i (i.e., $Log_e R_{it}$) and the approximate monthly rates of return on the market portfolio (i.e., $Log_e R_{mt}$). The value of this correlation coefficient is the value of beta weight, the standardized coefficient of $\hat{\beta}$, and its square is the coefficient of determination, R^2. The former indicates the effect of the independent variable, R_{mt}, on the dependent variable, R_{it}, and the latter indicates the proportion of variation in R_{it} explained by R_{mt}. Tables 7.2 and 7.3 indicate that there are very strong relationships between the market and monthly returns on individual securities, the mean value of r_i is 0.993 (the square of which is 0.986). The statistics of table 7.3 are, generally speaking, similar to those of previous studies. For example, the mean value of $\hat{\beta}$ in a US study, (Fama, et al., (FFJR) 1969) using the same logarithmic form of the market model was 0.894 with a maximum value of 1.95, for a sample of 622 securities. Cunningham (1973) estimated the mean value $\hat{\beta}_i$ for a sample of 950 UK stocks using the logarithmic form of the market model at 0.908, 0.973, and 0.876 for the periods of 1965-70, 1965-67 and 1968-70, respectively.

However, it appears interesting to investigate the behaviour of failing companies' systematic risk for various periods prior to the 18 months before failure.

7.3 The Changes of Failing Companies' Systematic Risk, $\hat{\beta}$s

The estimated coefficient, $\hat{\beta}$, of the market model reflects a security's systematic risk, i.e. it indicates the extent to which the security's return is subject to the systematic variability of the market return. The higher the value of $\hat{\beta}$ the more risky is the security (see for example: Lev, 1974, pp.189-90 and Fama, 1976, pp.106-7).

However, the risk of a failing company's security might be expected to increase as the company approaches failure, in the sense that investors will be reluctant to buy or hold the security of a company which is presumably thought to be increasingly likely to fail. Thus one might expect the price of the security will be marked down in the market, and this should be reflected in a residuals analysis (see Section 7.4).

Thus, the problem is whether the investors' attitude, towards the securities of failing companies, affects the estimates of the companies' systematic risk, $\hat{\beta}$, i.e., the relationship between the security's returns, R_{it} and the market's returns, R_{mt}. According to the market model's statistical assumption of a stationary joint distribution of R_{it} and R_{mt} (see Fama, 1976, pp.112-19), the $\hat{\beta}$ should not be changed for the same security from period to period.

Thus, to test whether the failing companies' $\hat{\beta}_s$ change, the time series of each security's returns prior to the 18 months before failure announcement (from month -17 to month 0) were divided into three periods: Period 1 included 30 months from -91 to -62, Period 2 included 22 months from -61 to -40, and Period 3 included 22 months from -39 to -18. For each of these periods, each security's returns were regressed on the corresponding market returns to estimate the period's β_s.

Table 7.4 presents the three estimates of each company's $\hat{\beta}$ and table 7.5 shows the summary statistics of each period's $\hat{\beta}_s$. The former table shows changing $\hat{\beta}_s$ for the sample companies. However, the latter table seems to indicate an increasing trend of the mean estimated β.

This finding appears to be in conflict with the above assumption of a stationary relationship between R_{it} and R_{mt}, but this is not really the case. The coefficients of determination, R^2s, for all the β estimates of table 7.4 are well over 0.9 except in period 3 for cases No. 5, 6 and 16 where R^2s are 0.012 (as noted on table 7.4), 0.77 and 0.83, respectively. Therefore, the above changes of $\hat{\beta}_s$ can possibly be explained by the unreliable size of the estimating samples (30, 22 and 22 months). The empirical evidence (referred to by Fama, 1976, p.132) indicates that with monthly data, the optimal estimation period is apparently five to seven years; and for other periods a security's $\hat{\beta}$ may change. Accordingly, Fama (1976, p.132) argues that "it seems that, at least for individual securities, we must learn to live with substantial uncertainty about the values of β_i. For many purposes, the problem is not serious. When we conduct tests requiring estimates of β_i, it is often possible to work with estimates for portfolios rather than individual securities, and it turns out that $\beta_{p's}$ of portfolios can be estimated far more reliably than those of individual securities."

However, the analysis of residuals in the following section seems to indicate the ability of the stock market to anticipate corporate failure.

7.4 Analysis of the Residuals

Using the estimated coefficients for $\hat{\alpha}$ and $\hat{\beta}$ present in table 7.2 the residuals of the market model were computed for each security for the

Table 7.4 β Estimates Over Three Periods

S.N.	LSPD* No.	Company Name	Estimates of β Period 1	Period 2	Period 3
1	503+	Bee Hive Spinning	0.9787	1.0257	0.9947
2	1548	Devas Routledge (Holdings)	1.0141	0.9962	1.0026
3	1671	Dreyfus & Co	1.0205	0.9815	1.0814
4	2376	Handley Page	0.9985	0.9791	1.0237
5	3140	Lines Bros	0.9982	1.0054	- ++
6	3509	Metal Traderrs LD	0.9993	1.0008	1.0937
7	4058	Pickles (Robert)	0.9876	0.9817	1.1652
8	4382	Rolls Royce	0.9945	1.0125	0.9791
9	5612+	Whiteside (H.S.) & Co	0.9954	1.0812	1.0334
10	302	Associated Motor Cycles	0.9617	1.0180	0.9859
11	1468	Crowley Russell & Co	-	0.9994	0.9715
12	3571	Minton Hollins	-	0.9601	1.0263
13	3617	Morgan Brewery	-	1.0001	0.9996
14	3790	North British Locomotive Co	0.9867	1.0201	1.0754
15	5665	Wilson Lovatt & Sons	0.9996	0.9510	0.9687
16	969	Bydand Ltd	0.9973	1.0256	0.9828
17	3576	Mitchell Construction	1.0029	1.0127	1.0442
18	4481+	St Martin Preserving Co	-	1.0875	1.0488
19	4765	Smiths Food Group	0.9956	1.0235	1.0166
20	5476	Wardle & Davenport	1.0233	1.0052	0.9698

* London Share Price Database

\+ Securities traded until the quotations were cancelled at least 10 months after failure announcement dates

++ Case excluded because of unreliable estimates ($\hat{\beta}$ = 0.297 and R^2 = 0.0119).

Table 7.5 Some Descriptive Statistics of the β Estimates

Periods	Mean	Standard Deviation	Extreme Values Minimum	Maximum	Skewness
1	0.997	0.015	0.962	1.023	-0.524
2	1.008	0.033	0.951	1.088	0.846
3	1.024	0.051	0.969	1.165	1.231

available data of 84 months (see the computing program in Appendix E3). As indicated in Chapter 3, the residuals of the market model measure the effect of an event specific to a company during a certain period of time. The purpose of analysing these residuals is to investigate the average effect of a specific event (impending failure) on the stock prices of a group of (failing) companies. It should be noted, however, that the market model "is certainly a grossly over-simplified model of price formation; general market conditions alone do not determine the returns on an individual security. ....The effects of these 'omitted variables' are impounded into the disturbance term u" (Fama, et al., 1969). In particular, the residuals of the securities of some failing companies during the long period of analysis, 84 months, may eventually reflect the effect a specific event other than that of failing condition, e.g. the announcements by a struggling failing company of good prospects as a result of a change in top management, cash infusion or a new contract. However, the residual analysis is concerned with the average behaviour of the residuals of a group of securities due to an event specific to that group.

Table 7.6 presents the average residuals (AR), cumulative average residuals (CAR), abnormal performance index (API) and the sample size for each of the 84 months prior to and including the month of failures' announcement. Most of the values of average residuals are negative, i.e. in the expected direction. The positive values of some average residuals may be due to a temporary event, as mentioned above, specific to some or even one company in our sample. Because of the saml1 size of the analysis sample - only 20 securities - a positive residual may absorb all other negative residuals and results in a positive average residual for a given month. However, the cumulative average residuals indicate that the negative average residuals started to dominate the series from month -66

Table 7.6 Residual Analysis for 84 Months

Month m	Sample Size n	AR	CAR	API
-83	17	-0.0260	-0.0260	0.9740
-82	18	-0.0159	-0.0419	0.9529
-81	18	0.0294	-0.0125	0.9803
-80	18	-0.0032	-0.0157	0.9793
-79	18	-0.0042	-0.0199	0.9666
-78	18	-0.0132	-0.0332	0.9521
-77	18	0.0128	-0.0203	0.9548
-76	19	-0.0005	-0.0208	0.9521
-75	19	0.0164	-0.0045	0.9677
-74	19	-0.0008	-0.0053	0.9686
-73	19	0.0129	0.0076	0.9794
-72	19	0.0233	0.0310	1.0056
-71	19	-0.0197	0.0113	1.0023
-70	19	0.0228	0.0341	1.0183
-69	18	-0.0100	0.0241	1.0289
-68	18	0.0048	0.0289	1.0232
-67	20	-0.0158	0.0130	1.0127
-66	20	-0.0197	-0.0067	0.9625
-65	20	-0.0109	-0.0176	0.9446
-64	20	0.0058	-0.0118	0.9515
-63	19	-0.0337	-0.0455	0.9302
-62	19	0.0084	-0.0371	0.9424
-61	20	-0.0377	-0.0748	0.8804
-60	20	-0.0128	-0.0877	0.8737
-59	20	-0.0241	-0.1118	0.8486
-58	20	-0.0079	-0.1197	0.8479
-57	20	0.0254	-0.0943	0.8662
-56	20	0.0076	-0.0867	0.8767
-55	20	-0.0007	-0.0875	0.8677
-54	20	-0.0079	-0.0954	0.8670
-53	20	0.0099	-0.0855	0.8548
-52	20	0.0234	-0.0621	0.8867
-51	20	0.0099	-0.0522	0.8886
-50	20	-0.0280	-0.0802	0.8720

Table 7.6 continued

Month m	Sample Size n	AR	CAR	API
-49	20	0.0099	-0.0703	0.8750
-48	20	0.0208	-0.0494	0.8898
-47	20	-0.0278	-0.0773	0.8562
-46	20	0.0171	-0.0602	0.8573
-45	20	-0.0085	-0.0687	0.8441
-44	20	0.0096	-0.0590	0.8460
-43	20	0.0327	-0.0263	0.8542
-42	20	-0.0416	-0.0679	0.8258
-41	20	-0.0110	-0.0789	0.8030
-40	20	0.0200	-0.0589	0.8237
-39	20	0.0007	-0.0582	0.8168
-38	20	0.0004	-0.0578	0.8089
-37	20	-0.0213	-0.0793	0.7789
-36	20	-0.0109	-0.0902	0.7594
-35	20	0.0137	-0.0765	0.7747
-34	20	0.0163	-0.0601	0.7835
-33	20	-0.0541	-0.1142	0.7621
-32	20	0.0277	-0.0865	0.7510
-31	20	-0.0215	-0.1079	0.7174
-30	20	0.0141	-0.0938	0.7179
-29	20	-0.0042	-0.0980	0.7157
-28	20	-0.0045	-0.1025	0.7206
-27	20	-0.0300	-0.1325	0.6818
-26	20	0.0434	-0.0891	0.6869
-25	20	0.0080	-0.0811	0.6805
-24	20	-0.0380	-0.1191	0.6607
-23	20	-0.0126	-0.1317	0.6546
-22	20	0.0031	-0.1286	0.6592
-21	20	-0.0178	-0.1464	0.6456
-20	20	-0.0465	-0.1929	0.6210

Table 7.6 continued

Month m	Sample Size n	AR	CAR	API
-19	20	-0.0096	-0.1833	0.6175
-18	20	-0.0195	-0.2028	0.6028
-17	20	-0.1015	-0.3043	0.5414
-16	20	0.0478	-0.2565	0.5408
-15	20	-0.0691	-0.3256	0.5274
-14	20	-0.0118	-0.3374	0.5023
-13	20	-0.0193	-0.3567	0.4873
-12	20	-0.0171	-0.3738	0.4867
-11	20	0.0033	-0.3705	0.4742
-10	20	0.0082	-0.3623	0.4651
- 9	20	-0.0359	-0.3982	0.4564
- 8	20	-0.0179	-0.4161	0.4429
- 7	20	-0.0421	-0.4582	0.4360
- 6	20	-0.0301	-0.4883	0.4272
- 5	20	-0.0699	-0.5582	0.4090
- 4	20	0.0431	-0.5151	0.4097
- 3	20	-0.0598	-0.5749	0.3911
- 2	20	-0.0297	-0.6047	0.3680
- 1	20	-0.0806	-0.6853	0.3334
0	19	-0.4683	-1.1536	0.1855

with values negatively large ($\simeq$ - 0.05) from month -61, except for month -43 with CAR of -0.0262. The values of CAR were never greater than -0.05 from month -42 and never greater than -0.1 from month -24 and reached their minimum value (maximum negative value) in month 0.

The values of the abnormal performance index (API) show a behaviour similar to that of the CAR's.

Therefore, the above results appear to indicate that the London Stock Exchange (LSE) began bidding down the prices of the securities of failing companies as far back as five years (62 months) before failure. Thus, it appears investors used all the publicly available accounting and non-accounting information to anticipate, correctly, companies' failures. As concernes accounting information, the investors' average behaviour seems to have been affected by the message conveyed by the financial statements five years before failure about the deteriorating conditions of failing companies, as indicated by the univariate comparison of Chapter 5. This finding is consistent with the efficient market hypothesis which holds that security prices (in an efficient capital market) will fully reflect all publicly available information concerning the securities traded. Accordingly, it adds to the accumulated evidence regarding the efficiency of the LSE in the pricing of equities in anticipation of public information about forthcoming events (failure). (See: Richards, 1979, for an extensive survey of UK studies in this point). Also, it seems to confirm the usefulness of accounting information, because of its content.

Finally, the above finding appears to be consistent with that of Westerfield in 1970. His study, relating to the US, also used the market model, and he too had to rely on a small sample of data, (see: Chapter 2).

7.5 Comparing the Results of the Market and Failure Prediction Models

The above finding, which seems to confirm the efficiency of the LSE, may be thought to imply that although failure prediction models are powerful predictors of corporate failure (see: chapter 6) they are only of doubtful use as they convey a message which has already been reflected in share prices. (See: Chapter 1 for a typical argument against the usefulness of accounting information). Consequently, no investor or share dealer can make a profit from using failure prediction models. This inference, however, does not appear to be justified by real world events. The proprietary nature of, for example, Taffler's models in the UK (see: Taffler, 1977a) and the ZETA model in the US (see: Altman, et al., 1977) indicates that some organizations (Laurence, Prust & Co in UK and Wood, Struthers and Winthrop in the US) regard these models as profitable (either by being first with 'inside' information (in a non-legal sense) or by attracting clients). Thus, further explanations are needed to resolve this argument.

As indicated above, the analysis of the residuals is ex post in nature and is concerned with the behaviour of monthly average residuals. The positive average residuals of some months (see: the third column of table 7.6) indicates that investors reacted to two types of information:, that, on the one hand, indicating a company's difficulties; and, on the other, suggesting an improvement in a company's situation (e.g. an announcement of a cash infusion or a new contract). Therefore, it appears that investors temporarily adjusted their decisions regarding the securities of failing companies as if these companies were having temporary difficulties. This reaction seems to reflect investors' uncertainty about the end-results of a company's difficulties (or about the seriousness of its situation).

Thus, although the market is efficient and anticipated (on average) companies' failures as far back as five years before they occurred, i.e. recognized the increasing risk of investing in the securities of failing companies, it cannot be concluded that the market identified these companies - from the beginning - as failing. One could say that the publicly available accounting and non-accounting information showed investors that the companies (at the time they started their down turn towards failure) were having temporary difficulties, but it did not decrease investors' uncertainty about the end-results of these difficulties. The cumulative effect of this information is, thus, that the market began bidding down the prices of the securities of failing companies as far back as five years (62 months) before failure. Therefore, investors need information which reduces their uncertainty about the end-results of a company's difficulties. The expected effect of such a piece of information would be to accelerate the process of bidding down the security prices of failing companies and, thus, advance their collapse - thus, presumably, ensuring a more 'optimal' allocation of national resources.

Failure prediction models, on the other hand, are developed to give an early warning of corporate failure. For a company classified as 'failing', they indicate that its financial characteristics resemble those of failed companies. Therefore, failure prediction models appear to be able to provide the piece of information which is needed by the investors - and, accordingly, they appear to be useful of them.

As shown in Chapter 6, the two failure prediction models of this study which incorporate accounting ratios and industry dummy-variables identified failing companies (at least ex post) with very high accuracy up to the fifth year before failure. This finding appears to indicate that these models do rather more than justify growing uncertainty on the part of investors about the seriousness of the failing companies' situations.

However, the expected ability of our fifth year's model (Model 1 - see Chapter 6) to correctly classify failing companies upon the basis of their data for some years prior to the fifth BF does not imply that this model can identify failing companies before the market can react to their difficulties. Table 7.6 shows that some average residuals were negative for some months earlier than month (-61) and the cumulative average residuals were negative for the first ten months (from month -83 to month -74). This indicates that the market reacted to the available information about the difficulties experienced by some of the companies in our small sample.

7.6 Conclusions

The findings of this chapter and their comparison with those of Chapter 6 support four conclusions and the rejection of hypothesis 6 of Chapter 1 which is represented in the introduction of this chapter. The four conclusions are concerned with the efficiency of the London Stock Exchange, the content of accounting information, the usefulness of failure prediction models and the usefulness of accounting information relative to share price information.

First, the efficiency of the LSE is supported by the findings that the market (on average) began bidding down the prices of the securities of failing companies as far back as five years before failure, i.e. by its recognition of the increasing risk of investing in those securities. It is also supported by the indication that the market bid down the security prices of some failing companies earlier than the fifth year before failure. These periods of anticipation appear to be long enough to conclude that the market is efficient. (This efficiency is not strictly concented with the speed at which the market impounds information).

Second, the content of accounting information is supported by the findings of the univariate analysis (see: Chapter 5) and the failure prediction models (see: Chapter 6) as compared with the above findings. The univariate analysis indicated that some accunting ratios pin-point the difference between failing and non-failing companies for at least five years before failure. Failure prediction models correctly classified failing and non-failing companies with considerable efficiency up to the fifth year before failure and there is an indication that the fifth year's model can correctly classify failing and non-failing companies for some years prior to the fifth before failure. The correspondence between the time dimension of the above and these findings indicates that the accounting information has had a positive content for the capital market. Therefore, accounting information appears to satisfy the previously defined two aspects of usefulness.

Third, the usefulness of failure prediction models is supported by the investors' need for the piece of information which can be provided by these models (see: section 7.5 above).

Fourth, the usefulness of accounting information relative to share price information is indicated by the comparison between the results of the market model and those of the failure prediction models (see: section 7.5 above). Share price information as used in the market model reflects investors' uncertainty about the end-results of the difficulties experienced by failing companies. On theother hand, accounting information as used in failure prediction models reflects resemblance between the financial characteristics of a classified failing or non-failing company and those of failed or healthy companies, respectively. Therefore, as concerns corporate failure, accounting information appears to be more indicative than share price information (despite the incompleteness and the other limitations of the former - see Chapter 4).

Fifth, the above conclusions and their supporting findings indicate that hypothesis 6 of Chapter 1 should be rejected.

CHAPTER VIII

CONCLUSIONS AND SUGGESTIONS FOR FUTURE WORK

CHAPTER 8

Conclusions and Suggestions for Future Work

8.1 Introduction

This study has been based upon the premise that the proper evaluation of the usefulness of accounting information is an empirical question and that this evaluation requires investigation of both the ability of models incorporating accounting numbers to predict an important business event (e.g. failure); and the content that accounting data may have for the stock market in connection with that event. The two investigations, presumably, provide evidence regarding the usefulness of accounting information and a comparison between them may reveal the relative usefulness of accounting and share price information. Therefore, this empirical evaluation is related to a specific event and the generality of its results is limited to this event.

However, according to the above premise, this study has been concerned with the development of failure prediction models and the application of the market model to test the content of accounting data. The former required the statistical preparation of the independent variables of failure prediction models. Nevertheless, throughout the study it was apparent that there is need for future work on various points related to the present study. Accordingly, a summary of the results of this study, its conclusions and the suggestions for future work are each considered in one of the following sections.

8.2 Summary of Results

The results of the above mentioned three aspects are summarized below:

8.2.1 Variables' Statistical Preparation

The results of preparing the independent variables of failure prediction models are:

(1) Of the 96 accounting ratios considered, 25 were excluded because of missing values. Of the remaining 71 ratios, 20 were normally distributed, 30 were transformed-normally distributed and 21 were neither normally nor transformed-normally distributed. Generally, the ratios of non-failed companies are more normally distributed than those of failed companies. Also, the distribution of failed companies' ratios departs increasingly from normality as the companies approach failure. However, in terms of this study, the selected distribution of each ratio is the closest one to normality for each group of companies for each of the five years before failure. Thus, it is not necessarily the best distribution for each group-year.

(2) The univariate analysis indicated that there is a difference between various ratios of failed and non-failed companies and that the ratios of failed companies deteriorate as the year of failure approaches.

(3) Principal components analysis (PCA) was performed for each year of data and for each group of companies separately and together. The results indicated:

a. The difference between the a priori and the empirical groupings of ratios. For example, the pay-out ratio (and its complement, the retention ratio) define a separate empirical group which is not recognized in the literature. Also, several a priori gearing ratios were empirically grouped, for most of the cases of PCA, as liquidity ratios (e.g. net worth/total liabilities, total liabilities/equity capital and total liabilities/total assets).

b. The instability of some groups of ratios for the different years and for the different groups of companies. For example, the ratios of growth loaded on profitability for all and for failed companies in both the second and first years before failure. For non-failed firms, this occurred only in the second year before failure while in the first year before failure only 2 out of the 4 growth-ratios loaded on the component of pay-out ratios.

c. The instability of several ratios for the different groups of companies and for the different years. For example, some funds flow ratios (e.g. funds flow/current liabilities and funds flow/ total liabilities) loaded on the component of profitability for all and for failed companies while they loaded on liquidity for non-failed companies. Also, the ratios of net working capital/total capital employed and net worth/fixed assets changed their groups in the first two years before failure.

(4) The results of cluster analysis indicated the possibility of regrouping the 19 industries, represented in this study, into a small number of groups. Therefore, they were regrouped a priori into manufacturing, construction and distribution industries. The validity of this broad classification was confirmed by three-groups discriminant analysis. The fitted two discriminant functions incorporated 5 industry-ratios and classified correctly 94 out of the 95 cases (19 industries x 5 years). Using Lachenbruch's hold-out test, 93 out of the 95 cases were correctly classified. Thus, a set of three dummy variables was used to represent the industry factor, one of them (manufacturing) was dropped for the purpose of the subsequent analysis.

(5) The selected economy-wide indicator was the standard deviation of the FTA (all share) index for the working days of each company's financial year.

8.2.2 Failure Prediction Models

Armed with the above results, two failure prediction models were developed using stepwise discriminant analysis and the data of the analysis samples. The first model (Model 1) is based upon the data of the fifth year before failure; and none of the previous studies has developed such a model. The second model (Model 2) is based upon the data of the first year before failure; as are the models of almost all previous studies. Each model incorporated three accounting ratios and the industry-dummy variables. Each model's discriminant function (the first function) performed well on six tests of applicability: (1) statistical overall significance; (2) the relative importance of each independent variable; (3) hold-out test; (4) inter-temporal validation test; (5) the expected performance on a random sample and the expected cost of using the function per unit of decision-making relative to the proportional chance criterion; and (6) the classification of the companies using their data of the four years subsequent to or prior to the year of the model. Model 1 performed consistently better than Model 2 for the five years before failure.

A second discriminant function was then fitted to each model using the data of the combined (both analysis and hold-out) samples. The two functions performed well on all the above tests; with Lachenbruch's test replacing the classifications of the companies in the hold-out sample. Again, Model 1 consistently performed better than Model 2. This is shown in table 8.1 which also shows the results of classifying the inter-temporal validation samples by the second function. Unfortunately, the inter-temporal validation sample is a small sample including 9 failed and 9 non-failed companies and only the failed companies are related to periods of time subsequent to those of both the analysis and hold-out samples.

Two regression functions corresponding to the discriminant functions were fitted to each model. Regression functions performed exactly the same as the corresponding discriminant functions.

Table 8.1 Comparison between the Second Functions of the Two Models

Year B.F.	5		4		3		2		1	
Efficiency measure	M1*	M2*	M1	M2	M1	M2	M1	M2	M1	M2
Combined Sample										
Total %	94	91	94	91	92	93	94	92	98	97
G1 correct classification %	88	81	91	82	91	86	91	84	95	93
Prediction Sample										
Total %	94	94	94	94	94	94	94	94	94	94
G1 correct classification %	89	89	89	89	89	89	89	89	89	89

*M1 and M2 stand for Model 1 and Model 2, respectively; and G1 = Group 1 (failed companies).

8.2.3 The Market Model

The market model was used to compute the systematic risk of each security for three periods prior to the 18 months before failure; and to test the ability of the London Stock Exchange (LSE) to anticipate corporate failure. The results of this model appear to show a changing $\hat{\beta}$ of individual failing companies and an increasing trend of their mean $\hat{\beta}$ (the mean systematic risk increased from 0.997 to 1.008 and then 1.024). The results of the cross-sectional analysis of the market model's residuals appear to indicate that, on average, the market began bidding down the security prices of failing companies as far back as five years (62 months) before failure.

However, not all the systematic risk indicators of failing companies exhibited the increasing trend, nor were all monthly average residuals negative for the whole period considered (84 months). Moreover, negative average residuals were observed for various months prior to month -61.

8.3 Conclusions

Upon the basis of the above results the following are the main conclusions of this study.

(1) Several accounting ratios are normally distributed and many are transformed-normally distributed. This conclusion appears to be dependent on a particular set of data; and thus each study has to perform tests of normality and consider a wide range of possible transformations (including various values of a constant term). However, generalization appears possible within the data of a particular group of companies.

(2) Since the difference between various ratios of failed and non-failed companies exists for at least five years before failure, there is no reason why failure prediction models should only be based on the data of the first year before failure. The deterioration of the ratios of failed companies as the year of failure approaches reflects the increasing severity of the symptoms of failure. However, this univariate finding confirms the validity of hypothesis 1 and hypothesis 2 of Chapter 1. It represents, in general, the basis of all failure prediction models and, in particular, the basis of hypothesis 4 and Model 1 of this study.

(3) Some accounting ratios are unstable measures of a firm's financial attributes, both for different periods of time and for different groups of

companies. Therefore, accounting-based models should be defined a priori by a set of financial attributes rather than a set of accounting ratios. For the same reason, the stepwise seletion of a model's ratios should be guided by the results of Factor Analysis rather than a researcher's a priori knowledge about the ratios considered.

(4) The difference between broad groups of industries should be accounted for in models based on cross-sectional sets of data. However, if a broad classification is a priori proposed, its validity has to be tested by discriminant analysis. The latter is the statistical technique concerned with testing the validity of an a priori classification.

(5) The inclusion of the industry dummy variables in the two failure prediction models indicates the importance of allowing for the industry effect. It may also explain the high efficiency of the two models; and, as indicated below, it may have accounted for the economy-wide effect. Therefore it confirms hypothesis 3 regarding the industry factor.

(6) The selected economy-wide indicator was not one of the constituting variables of the two models. This was explained by, possibly, the inadequacy of the selected indicator; the ability of the industry factor to pick up the economy-wide effect; or the less discriminating power (than that of the reported models) of a vector variable including the economy-wide indicator.

(7) Model 2, the first year's model, possesses very high efficiency relative to the models of previous studies, especially in terms of its performance for the years which are more remote from failure. For the purpose of a very specific comparison with a UK model, the Rolls Royce company was included in the analysis samples of Taffler's two models (1977a and 1977b) and was misclassified by both of them. In contrast, Rolls Royce

was included in our inter-temporal validation sample and was correctly classified by each of the two functions of Model 1 and of Model 2 upon the basis of its data for each of the five years before failure. Table 8.2 shows the z-scores of Rolls Royce using the different functions for the different years before failure.

Table 8.2 The Rolls Royce z-scores *

Year B.F.	First Function		Second Function	
	M1	M2	M1	M2
-5	-0.636	-0.463	-0.540	-0.353
-4	-0.824	-0.761	-0.645	-0.605
-3	-0.708	-0.594	-0.571	-0.447
-2	-0.643	-0.465	-.0474	-0.329
-1	-1.270	-0.493	-1.017	-0.372

* The cut-off point is 0.0

Although, Taffler's (1977a) model has a total efficiency of 98.5% in the first year before failure, it only classified correctly 35% of the failed companies upon the basis of their data for the fourth year before failure, compared with 82% for our model (Model 2).

(8) Model 1 performs consistently better than Model 2 (see table 8.1) despite the high efficiency of the latter. This finding may appear strange but it is justifiable in terms of the argument of hypothesis 4 in Chapter 1.

(9) The results of applying the above two models appear to indicate that this study achieved the objective of improving our ability to predict corporate failure. Also, they indicate the usefulness of accounting data on its own. However, since even Model 2 can pinpoint a company's failure as early as five years before it occurs, it may well be that

Model 1 can pinpoint failure earlier than this. As mentioned below, there is an indication that the stock market also bid down the residual security prices of some failing companies earlier than 5 years before failure.

(10) The results of the market model appear to indicate the efficiency of the LSE in pricing securities in anticipation of a forthcoming failure. The negative average residuals of some months prior to month -61 appear to indicate that the market began bidding down the security prices of some failing companies earlier than five years before failure. However, the positive average residuals for some months subsequent to month -61 appear to indicate that the stock market reacted to two types of information; on the one hand, that indicating a compnay's difficulties; and, on the other, suggesting an improvement in a company's situation (e.g. an announcement of a cash infusion or a new contract). Therefore, one could say that the publicly available accounting and non-accounting information showed investors that the companies (at the time they started their down-turn towards failure) were having temporary difficulties, but it did not seem to decrease investors' uncertainty about the eventual outcome of these difficulties.

(11) The comparion between the results of failure prediction models and the market model appears to indicate the apparent content of accounting data, investors' need for failure prediction models and the usefulness of accounting data relative to share prices in the context of corporate failure. While share prices reflect investors' uncertainty about the eventual outcome of a company's difficulties, failure prediction models reflect a similarity between the financial characteristics of a classified failing company and those of failed companies.

8.4 Suggestions for Future Work

The following matters are suggested as requiring further research.

(1) Given an updated data-bank of company accounts, it would be possible and interesting to investigae the following:

a. The robustness of the two failure prediction models. This investigation may indicate (further) the predicitve ability of the models and the future period of time for which the models are viable. Despite the changing economic conditions and diversity of causes of failure, the financial symptoms of failure (and thus the financial characteristics of failing companies) appear to be reasonably stable over time. However, this can be tested by following up the models over a long period of time.

b. The ability of Model 1 to predict failure earlier than 5 years before it ocurs.

c. The relationship between various economy-wide indicators and the relationship between them and various industry indicators (see: Chapter 3, subsection 3.4.2.2). (It may also be possible to sample sufficient numbers of failed and non-failed companies at the turning points of the economic cycle to investigate, more clearly, the effect of the economy-wide indicators).

(2) The effect of failure prediction models on residual share prices of failing companies. As argued previously, the availability of a powerful model of failure prediction to investors may reduce their uncertainty about the eventual outcome of the problems facing a failing company and, thus, may accelerate its collapse. However, such an investigation might require a considerable time series span of data if it were to prove worthwhile,

viz. from the time of making the model available until the data concerning failed companies are published. Alternatively, such an investigation could be made in a behavioural context; e.g. by simulating investors, share prices and accounting data in a laboratory experiment or business game. The latter approach however, is less than ideal: it is abstracted from the real world, and there are also problems in finding suitable subejcts and avoiding bias on the part of the researcher.

(3) The possibility of altering a failure trend. Given a prediction of a company's failure, it is interesting to consider the possibility of altering a failure trend. Several possibilities exist, in fact: e.g. reversing a failure trend, merger, reorganization or liquidation. However, this question can be better answered by a computer simulation model; in which the outcomes relating to all key variables affecting a firm's financial position can be modelled. By including a failure prediction model as an element in a simulation model it might be possible to forewarn against failure under various simulated conditions and/or decisions. Such a model could also evaluate the alternative procedures that might alter a failure trend (e.g. cash infusion). This approach is intuitively appealing; especially as many British companies nowadays employ computer simulation models.

APPENDICES

APPENDIX A DATA

Table A1 The Comparative Layout of Accounting Data*

Variable No.	W/DTI No.	Description
		The Indicative Data
D1	K1	Duplicate Indicator
D2	K2	Industry No.
D3	K3	Company No.
D4	K4	Sub-group
D5	K5	Industry No.
D6	K6	Company No.
D7	K7	Sub-group
D8	K8	Year of Data
D9	K9	Accounting Date
D10	K10	Publication Date
D11	K11	Issue of Shares
D12	K12	Linking
D13	K13	Revaluation
D14	K14	Turnover
D15	K15	Year of Birth
D16	K16	Type of Birth
D17	K17	Type of Death
D18	K18	Number of Acquirer
D19	K19	Company Control Code
D20	K20	Acquisition Code
D21-29	K21-35	Company Name
D30	K36	Company Registration Number
D31	K37	Investiment Grant Indicator
D32	K38	Number of the taken-over Company
D33	K39	Net assets of the victim

Table A1 - continued

Variable No.	W/DTI No.	Description
		The Quantitative Data
R1	T1	Issued Capital: Ordinary
R2	T2	Issued Capital: Preference
R3	T3	Capital and Revenue Reserves
R4	T4	Provisions
R5	T5	Future Tax Reserves
R6	T6	Memorandum - contracts for capital expenditure
R7	T7	Interest of minority shareholders in subsidiaries
R8	T8	Long-term liabilities
R9	T9	Bank overdrafs and loans
R10	T10	Trade and other creditors
R11	T11	Dividends and interest liabilities
R12	T12	Current taxation liabilities
R13	T14	Fixed assets: tangible, net of depreciation
R14	T15	Fixed assets: intangible
R15	T16	Fixed assets: trade investments
R16	T17	Stock and Work in progress
R17	T18	Trade and other debtors
R18	T19	Marketable securities
R19	T20	Tax reserve certificates
R20	T21	Cash
R21	T23	Issue of shares: ordinary
R22	T24	Issue of shares: preference
R23	T27	Bank credit received
R24	T31	Increase in future tax reserves
R25	T32	Balance of Profit: depreciation provision
R26	T33	Balance of Profit: provision for amortisation
R27	T34	Balance of Profit: other provisions
R28	T35	Balance of Profit: retained in reserves
R29	T36	Other receipts
R30	T40	Increase in value of stacks and work in progress

Table A1 - continued

Variable No.	W/DTI No.	Description
R31	T41	Increase in credit given - trade and other debtors
R32	T43	Sundry expenditure
R33	T48	Change in tax reserve certificate
R34	T50	Operating profit (before depreciation)
R35	T51	Dividends and interest received (gross of income tax)
R36	T52	Other income
R37	T53	Interest paid on long-term liabilities, gross
R38	T54	Tax on current profit
R39	T55	Dividend, ordinary
R40	T56	Dividend, other
R41	T57	To minority interest in subsidiaries, net of taxation
R42	T58	Prior year adjustments - tax
R43	T49	Prior year adjustments - general
R44	T104	Investment Grants - Amount deducted from fixed assets
R45	T105	Investment Grants - other treatments
R46	T110	Pension Fund
R47	T113	Provisions
R48	T127	Sales
R49	T128	Exports
R50	T132	Change in fixed assets due to revaluation
R51	T134	Average number of employees
R52	T135	Employees remuneration
R53	T136	Total directorps pay
R54	T137	Chairman's pay
R55	T148	Schedule F payable
R56	T149	Transitional tax relief: ordinary dividends
R57	T150	Transitional tax relief: preference dividends

* The data are written in the following Fortran Format:

(I2, 7I4, 9I3, I7, 2I3,/9A4, I7, I6, 4I7, 5(/,11I7))

Table A2 - Standard Industrial Classification

S.I.C. Group	Industry Name and Sub-groups
	Mining and Quarrying
10	Mining and Quarrying
	Food
21	Grain millin - baking etc. - sugar - confectionery - fruit & vegetable products - vegetable & animal oils, fats & margarine - other food.
	Drink
23	Brewing & malting - soft drinks - other drink industries.
	Tobacco
++ 24	Tobacco
	Chemicals and Allied Industries
26	Paint & printing ink - pharmaceutical & toilet preparations - other chemicals - mineral oil refining, lubricating oils & greases.
	Metal Manufacture
31	Iron & steel - non-ferrous metals.
	Non-electrical Engineering
33	Textile machinery - metal working machine tools - pumps, valves & compressors - agricultural machinery (exc. tractors), construction, & earth-moving equipment - industrial engines - mechanical handling equipment - industrial (inc. process) plant & steel-work - other non-electrical engineering - instrument engineering (non-electrical).
	Electrical Engineering
36	Electrical machinery - wires & cables - telegraph, telephone, radio, and electronic apparatus - domestic & other electrical goods - electronic computer - instrument engineering (electrical).
	Shipbuilding and Marine
37	Shipbuilding & marine engineering

Table A2 - continued

S.I.C. Group	Industry Name and Sub-groups
	Vehicles
38	Motor vehicles, motor & pedal cycles - aircraft & airframes - aero-engines, hovercraft, parts & accessories for aerospace equipment - other vehicles
	Metal Goods N.E.S.
39	Metal goods n.e.s.
	Textiles
41	Woollen & worsted - hosiery & other knitted goods - carpets - textile finishing - jute - cotton, manmade fibres, and other textiles.
	Leather, Leather Goods and Fur
++ 43	Leather, leather goods, & fur.
	Clothing and Footwear
44	Clothing - footwear
	Bricks, Pottery, Glass, Cement, etc.
46	Pottery - glass - cement - building materials, etc.
	Timber, Furniture, etc.
47	Furniture & bedding - other timber industries.
	Paper, Printing and Publishing
48	Paper, etc. - newspapers & periodicals - other printing, etc.
	Other Manufacturing Industries
49	Rubber - other manufacturing.
	Construction
50	Construction.
	Transport and Communication
++70	Transport & communication (ex. Shipping) - storage.

Table A2 - continued

S.I.C. Group	Industry Name and Sub-groups
	Wholesale Distribution
81	Food wholesale - other wholesale.
	Retail Distribution
82	Food retail - other retail.
	Miscellaneous Services
++ 88	Cinemas - other entertainment & sport - catering, hotels, etc. - laundries - other services - motor repairers, distributors, garages & filling stations.

SOURCE: DABMUE, undated, section 2.d.1.

++ Industries not represented in this study.

Table A3 - Sampled Companies

S. No.	Comp. No.	Company Name	Last Published Accounts*
		1. The Analysis Sample	
		a. Failed Companies	
1	21071	Smiths Food Group+	3.68
2	23092	Morgans Brewery Co+	9.60
3	26101	English Oilfields	9.60
4	33003	Adlam George & Sons	3.61
5	33298	Hills West Bromwich	12.60**
6	36146	Dansette Products	12.68**
7	37286	Denny William & Brothers	12.62
8	38029	Handley Page+	12.67
9	38084	Associated Motor Cycles+	12.64**
10	39148	Rolls Razor+	12.63
11	41103	Wardle & Davenport+	2.68**
12	41409	Bee Hive Spinning Co+	3.66
13	41461	Ripponden Commercial Co	12.60
14	41545	Lord Cyril	6.67**
15	48017	Brown James & Co	3.66
16	48086	British Celilynd	5.68
17	49162	Thornton & Co	2.65
18	50005	Cozens & Sutcliffe	6.67
19	82132	Gorringes Department Stores	1.66
20	82148	Graves J G	3.66
21	50130	Howarth of Burnley	12.63
22	81058	Doves Routledge & Co+	
		b. Sound Companies	
1	23232	Macallan-Glenlivet	7.73
2	31090	Newmans Tubes	1.73
3	33347	Nu-Swift Industries	12.73
4	36011	Bulgin (AF) & Co	1.73
5	33516	Desoutter Brothers (Holdings)	12.73
6	36153	Scholes (George H) & Co	6.73
7	38160	Group Lotus Car Co's	1.73

Table A3 - continued

8	39021	Bruntons (Musselburgh)	12.73
9	36201	Crossland (R & A G)	12.73
10	39273	Walker Crosweller & Co	4.73**
11	44175	Gelfer (A & J)	3.73
12	44177	Miller (F) (Textiles)	2.73
13	47117	Wrighton (F) & Sons	3.73
14	33500	Jentique (Holdings)	6.73
15	47184	Gomme Holdings	7.73
16	49165	Kalamazoo	7.73
17	49274	Kelsey Industries	9.73
18	81381	Leboff (S) (FOBEL)	12.73
19	81382	Nurdin & Peacock	1.73
20	82210	Martin The Newsagent	9.73
21	82315	Frost & Reed (Holdings)	12.73
22	82355	Wallis (F J)	12.73

2. The Hold-Out Sample

a. Failed Companies

1	21068	St Martin Preserving Co+	3.61
2	21087	Whiteside (HS) & Co+	12.64
3	26067	Laws Chemical Co	9.68
4	33061	Crossley Bros	4.65
5	33204	Wood Edwards & Co	8.68
6	33316	Main A J & Co	12.66
7	33319	Robey & Co	12.67
8	37079	Fairfield Shipbuilding & Engineering	6.64
9	38041	North British Locomotive Co+	12.60
10	38076	Excelsior Motor Co	9.60
11	39219	Feaver John	12.67
12	41192	York Street Flax Spinning Co	6.60
13	41350	Reddihough John	12.68
14	41535	Lion Spinning Co	3.66
15	41562	White Job & Sons	3.68**
16	46051	Minton Hollins+	8.60
17	49093	Rubber Improvement	5.61
18	49147	Willesden Holdings	12.67

Table A3 - continued

19	50021	Ragusa	12.63
20	81295	Connell James N Holdings	2.67
21	82178	Camp Bird	2.61**
22	50073	Crawley Russell & Co+	3.60
		b. Sound Companies	
1	26163	Silkolene Lubricants	12.73
2	81396	Brown & Tawse	3.73
3	31180	Castings	3.73
4	39250	Whiley (George M)	12.73
5	36168	Newmark (Louis)	3.73
6	39237	Excaliber Jewellery	4.73
7	33534	Rotaprint	3.73
8	41578	Leeds & District Dyers & Finishers	9.73
9	44055	Sumrie Clothes	3.73**
10	46008	Atlas Stone Co	10.73
11	47050	Heal & Son Holding	1.73
12	49076	Mentmore Manufacturing Co	1.73**
13	33524	Benford Concrete Machinery	1.73
14	33523	Jeavons (EE) & Co	3.73
15	81262	Triefus & Co	12.73
16	82036	Curry's	1.73
17	82083	Marks & Spencer	3.73
18	82147	Grattan Warehouses	1.73
19	82228	Beattite (James)	1.73
20	81413	EMMS (Theodore)	9.73
21	82349	Morrison (WM) Supermarkets	1.73
22	82354	Wades Department Stores	4.73

3. The Inter-Temporal Validation Sample

a. Failed Companies

1	10022	Bydand+	12.71**
2	38018	Dennis Motor Holdings	9.71
3	38048	Rolls Royce+	12.69
4	41570	Tulketh Group	12.69
5	49069	Lines Bros+	12.69

Table A3 - continued

6	50035	Wilson Lovatt & Sons+	12.69
7	50105	Mitchell Construction Holdings+	12.71
8	81130	Metal Traders+	3.71
9	41499	Pickles (Robert)+	3.69
		b. Sound Companies	
1	23099	Oldham Brewery	1.73
2	33111	Jones (A A) & Shipman	12.73
3	38163	Turner Manufacturing Co	13.73
4	39076	Richards of Sheffield	3.73
5	46192	Beatson Clark & Co	12.73
6	48007	Benn Brothers	12.73
7	82062	Hinton (Amos) & Sons	3.73
8	82212	Empire Stores (Bradford)	1.73
9	82213	Turner (W & E)	12.73

* The year of data refers to the fiscal, e.g. year 65 refers to the fiscal year 6.4.65 to 5.4.66.

+ Companies included in the sample of the market model.

** Companies changed their accounting date

APPENDIX B RATIOS

Table B1 List of Accounting Ratios

NO.	NAME +
	I Profitability ++
1	EBIT/Adj TCE1
2	EBIT/NCE
3	PBT/TrA
**4	NE//qC
5	OD/NE
6	Rt/NE
7	EBIT/TCE
8	EBIT/Adj TCE2
**9	EBIT/NCE
10	PBT/NCE
11	PBT/PhA
12	ODG/EqC
*13	EBIT/S
*14	PBT/S
*15	NE/S
	II Liquidity
16	CA/CL
17	QA1/CL
18	QA2/CL
19	QA3/CL
20	NTCG/CL
21	Inv/CL
22	NWC/CL
**23	ΔNTCG/CL_{t-1}
**24	ΔInv/CL_{t-1}
**25	BCY/CL_{t-1}
*26	S/AvInv
*27	Days Inv
*28	S/AvDr
*29	Day Dr
*30	S/AvCr

Table B1 - continued

NO.	NAME +
*31	Days Cr
*32	S/Av NWC
*33	Days NWC
*34	FF/NWC
35	FF/CL
36	FF/TL
37	FF/QA1
38	FF/TCE
39	FF/NW
*40	FF/Int3
**41	TL/DFF
**42	FL/DFF
**43	QA1/DEOE
**44	(QA1-CL)/DEOE
**45	(QA1-Dr)/DEOE
*46	DFF/DEOE
*47	EBIT/Int3
	III Capital Gearing
48	Adj TL1/EqC
49	FL/NCE
50	FLBO/NCEBO
51	Adj TL2/EqC
52	TL/TA
53	TL/EQC
54	NW/TL
*55	NW/FL
56	NW/FA
**57	PC/NW
58	FL1/EqC
59	EqC/TCE
*60	Int2/(Int2 + ODG +Rr)
*61	Int1/(Int1 + NE)
*62	Int2/FL1
*63	Int1/FL

Table B1 - continued

NO.	NAME +
	IV Growth
64	$\Delta NCE/NCE_{t-1}$
65	$\Delta TCE/TCE_{t-1}$
66	$\Delta TrA/TrA_{t-1}$
67	S & W GNA
**68	W - ExtG
	V Prestige or importance of a Firm
69	VA/Adj TCE
*70	EX/S
	VI Size
71	TCE
72	NCE
73	TrA
**74	EqC
**75	S
**76	FF
77	FA
**78	Employees
**79	PBT
	VII Other Ratios
*80	S/FA
*81	S/TCE
*82	S/NW
*83	FF/S
84	FF/NCE
85	CA/TCE
86	QA1/TCE
87	NWC/TCE
**88	NWC/EqC
89	EqC/FA
90	(NCE-FTR)/FA
91	(Dep + Amo)/FA

Table B1 - continued

NO.	NAME +
	VIII Earning Variability Risk
**92	STD (1)
**93	STD (2)
94	STD (3)
**95	STD (4)
96	STD (5)

+ See Table B2 for the key to Ratios' Names.

++ An a priori grouping of ratios.

* Variables excluded because of missing values.

** Variables excluded because of non-normality.

Table B2 Key to Accounting Ratios

Item	Description*
Adj TCE1	(TCE - BO -Cr)
Adj TCE2	(TCE - BO)
Adj TL1	(TL - BO -Cr)
Adj TL2	(Adj TL1 - Minority Interest)
Amo	Amortisation (R26)
AV	Average
BCr	Bank Credit received (R23)
BO	Bank Overdrafts (R9)
CA	Current Assets (R16 + R17 + R18 + R19 + R20)
CL	Current Liabilities (R4 + R9 + R10 + R11 + R12)
Cr	Creditors (R10)
Dep	Depreciation (R25)
DEOE	Daily Estimated Operating Expenditures ((S-PBT + Dep.)/365)
DFF	Daily Funds Flow (FF/365)
Dr	Debtors (R17)
EBIT	Earnings Before Interest and Tax (PBT + R35 + R36 + R42)
EqC	Equity Capital (R1 + R3 + R5 - R14 - R50)
EX	Exports (R49)
FA	Fixed Assets (R13 + R15 - R50)
FF	Funds Flow (R34)
FL	Long-term debt (R2 + R7 + R8)
FL1	(FL - Minority interest (R7))
FLBO	(FL + BO)
FTR	Future Tax Reserves (R5)
Int 1	Net interest on F1 (R37 $(1-y)^{+}$+ R40 + R41)
Int 2	Gross interest on FL1
Int 3	Int 2 + minority interest's share of profit (R41)
Inv	Inventory (R16)
NCE	Net Capital Employed (EqC + FL)
NCEBO	(NCE + BO)
NE	Net Earnings (R39 + R28)

Table B2 continued

Item	Description*
NTCG	Net Trade Credit Given (Dr - Cr)
NW	Net Worth (EqC + R2)
NWC	Net Working Capital (CA - CL)
OD	Ordinary Dividends, net (R39)
ODG	Ordinary Dividends, gross (R39 $(\frac{1}{1-y})$)
PBT	Profit Before Tax (R34 - R25 - R26 - R27)
PC	Preference Capital (R2)
PhA	Physical Assets (R13 + R16 - R50)
QA1	Quick Assets = CA - Inv
QA2	(AQ1 - Dr)
QA3	(QA2 - BO)
Rt	Retention (R28)
S	Sales (R48)
S & WGNA	Singh' & Whitington's Measure of Net Assets Growth
STD (n)	Standard Deviation of ratio number n
TA	Total Assets (NCE + CA)
TCE	Total Capital Employed (TA)
TL	Total Liabilities (FL + CL)
TrA	Trading Assets (PhA + R16 + R20)
VA	Value Added (R52 + R53 + R54 + Int 1 + R39 + R38 + R25 + R26 + R27 + R28)
W-Ext G	Whittington's measure of External Growth
Δ	A change between two successive balance sheets

*For the R-variables, see table A1

+ y stands for the standard rate of income tax

APPENDIX C UNIVARIATE ANALYSIS

Table C1 Unbounded Distribution for Year -5 (example)*

VARIABLES*		FAILED COMPANIES						HEALTHY COMPANIES					
NO	FORM	D	W	MN	STD	SKW	KUR	D	W	MN	STD	SKW	KUR
1	X	.2389	-.084	0.045	0.119	-1.681	6.391	.2701	-.024	0.243	0.071	1.053	0.531
2	X	.2416	-.058	0.051	0.129	-1.119	5.064	.2641	-.061	0.319	0.121	1.232	0.833
3	X	.2522	-.004	0.038	0.078	-0.120	3.197	.2750	0.022	0.184	0.073	0.808	0.439
5	X	.1755	-.340	0.474	1.955	-1.353	15.815	.2859	0.047	0.569	0.195	0.039	-0.819
6	X	.1753	-.341	0.479	1.955	1.423	15.946	.2859	0.047	0.431	0.195	-0.039	-0.819
7	X	.2528	-.021	0.038	0.074	-0.546	3.008	.2773	0.044	0.181	0.065	0.637	0.539
8	X	.2425	-.069	0.038	0.087	-1.410	5.844	.2756	0.038	0.186	0.062	0.763	0.798
10	X	.2437	-.048	0.047	0.128	-1.117	5.067	.2609	-.071	0.306	0.115	1.327	1.079
11	X	.2509	-.019	0.057	0.116	0.175	3.087	.2731	-.010	0.315	0.150	0.963	0.309
12	1/(X+.375)	.2672	-.016	2.429	0.192	-1.158	1.642	.2564	-.028	1.827	0.354	-1.458	4.514
16	1/(X+0.50)	.2854	0.040	0.393	0.183	-0.175	-0.771	.2640	-.015	0.472	0.148	1.407	3.059
17	1/(X+1.00)	.2836	0.030	0.489	0.205	-0.375	-0.597	.2665	-.001	0.507	0.140	1.114	1.352
18	1/(X+.375)	.2720	-.113	1.810	0.928	-0.584	-1.184	.2843	-.043	1.723	0.731	-0.006	-1.434
19	1/(X+1.00)	.2810	0.031	1.201	0.755	0.574	-0.292	.2725	0.008	0.888	0.338	0.986	0.956
20	1/(X+3.00)	.2716	0.010	0.306	0.055	-0.962	1.115	.2640	-.029	0.314	0.050	1.233	1.386
21	1/(X+2.25)	.2753	-.011	0.292	0.063	-0.878	0.015	.2844	0.053	0.343	0.033	-0.136	-0.563
22	1/(X+2.25)	.2811	0.019	0.291	0.115	-0.559	-0.494	.2758	0.038	0.343	0.075	0.795	0.888
35	LN(X+2.25)	.2596	0.003	0.902	0.145	-0.914	3.579	.2831	0.046	1.023	0.090	0.338	-0.452
36	1/(X+2.25)	.2713	0.049	0.418	0.035	0.144	1.095	.2847	0.039	0.368	0.033	-0.286	-0.695
37	X	.2633	0.019	0.217	0.303	0.562	1.766	.1301	-.592	0.700	1.124	5.758	33.165
38	X	.2682	0.038	0.056	0.076	0.179	1.102	.2795	0.059	0.200	0.060	0.361	0.167
39	X	.2676	0.041	0.092	0.138	-0.107	1.405	.1814	-.405	0.418	0.290	3.629	13.032
48	1/(X+0.50)	.2800	0.038	1.260	0.442	-0.480	-0.101	.2508	-.066	1.103	0.289	-1.632	3.198
49	1/(X+3.00)	.2699	-.023	0.313	0.018	-1.082	1.415	.2246	-.243	0.323	0.017	-2.278	5.286
50	1/(X+0.50)	.2818	0.018	1.323	0.355	0.457	-0.658	.2683	-.102	1.655	0.393	-0.858	-0.553
51	1/(X+.375)	.2821	0.041	1.576	0.614	-0.302	-0.499	.2588	-.026	1.297	0.370	-1.304	2.200
52	X	.2827	0.062	0.450	0.218	0.234	-0.315	.2758	0.012	0.474	0.167	0.835	0.298
53	1/(X+0.50)	.2801	0.050	0.820	0.431	0.504	0.009	.2835	0.044	0.745	0.292	-0.366	-0.538
54	1/(X+1.00)	.2847	0.049	0.414	0.191	0.053	-0.694	.2751	0.010	0.464	0.158	0.862	0.321
56	1/(X+1.00)	.2871	0.036	0.372	0.113	-0.045	-0.972	.2746	0.019	0.364	0.144	0.835	0.369
58	1/(X+.375)	.2836	-.000	1.549	0.765	0.108	-0.970	.2602	-.120	2.097	0.708	-1.112	0.425
59	X	.2827	0.062	0.550	0.218	-0.234	-0.315	.2758	0.012	0.523	0.167	-0.835	0.298
64	1/(X+3.00)	.2294	-.164	0.331	0.015	-1.680	3.358	.2039	-.254	0.328	0.011	3.035	16.096
65	1/(X+3.00)	.2303	-.124	0.328	0.022	-2.287	8.622	.2710	0.022	0.325	0.009	0.210	1.250
66	1/(X+3.00)	.2316	-.144	0.325	0.026	-2.091	5.601	.2588	-.007	0.324	0.012	-0.016	2.709
67	1/(X+2.25)	.2236	-.134	0.442	0.036	-1.150	5.074	.2604	-.077	0.431	0.012	-1.285	1.768
69	X	.2692	0.039	0.094	0.110	0.046	0.946	.2671	-.030	0.303	0.081	1.103	0.718
71	LN(X+1.00)	.2846	0.055	7.275	1.070	-0.086	-0.627	.2365	-.139	8.019	0.970	2.415	7.557
72	LN(X+1.00)	.2808	0.044	6.844	1.007	-0.048	-0.414	.2230	-.208	7.448	0.983	2.837	9.785
73	LN(X+1.00)	.2845	0.055	7.169	1.166	-0.245	-0.583	.2349	-.150	7.975	0.978	2.451	7.588
77	LN(X+1.00)	.2830	0.050	6.197	1.201	-0.028	-0.551	.2401	-.092	6.747	1.157	2.276	8.377
84	SQ(X+2.25)	.2607	0.020	1.526	0.042	-0.295	2.277	.2459	-.110	1.614	0.041	1.951	4.354
85	X	.2749	0.003	0.619	0.184	-0.833	0.150	.2706	0.011	0.688	0.147	-1.006	1.091
86	X	.2746	0.017	0.294	0.128	0.853	0.464	.2709	0.003	0.410	0.135	-0.889	0.370
87	X	.2826	0.042	0.301	0.207	0.344	-0.440	.2758	0.009	0.270	0.199	-0.847	0.621
89	SQ(X+2.25)	.2734	0.033	1.984	0.246	0.850	1.291	.2655	-.000	2.076	0.317	1.266	3.556
90	SQ(X+1.00)	.2740	-.014	1.732	0.286	0.941	0.295	.2668	-.002	1.798	0.364	1.245	2.478
91	1/(X+.375)	.2853	0.027	2.311	0.215	0.060	-0.834	.2791	0.053	2.146	0.202	-0.549	0.243

* The explanation of table 5.1a applies to tables C.1 to C2.5 (see: pp.174-175).

Table C2.1 Variables Distribution Year -5

VARIABLES*		FAILED COMPANIES						HEALTHY COMPANIES					
NO	FORM	D	W	MN	STD	SKW	KUR	D	W	MN	STD	SKW	KUR
1	X	.2620	-.002	0.051	0.097	-0.227	1.159	.2765	-.015	0.240	0.065	0.782	-0.257
2	X	.2605	-.005	0.056	0.106	0.060	1.221	.2713	-.047	0.314	0.109	0.953	-0.029
3	X	.2678	0.020	0.039	0.066	0.314	0.724	.2805	0.023	0.182	0.068	0.521	-0.379
5	X	.2313	-.086	0.520	1.023	-0.037	7.307	.2864	0.043	0.568	0.193	-0.009	-0.909
6	X	.2313	-.084	0.432	1.021	0.077	7.386	.2864	0.043	0.432	0.193	0.009	-0.909
7	X	.2649	-.001	0.041	0.065	0.347	0.695	.2834	0.045	0.180	0.061	0.281	-0.486
8	X	.2643	0.006	0.043	0.072	0.094	0.917	.2828	0.042	0.184	0.057	0.366	-0.429
10	X	.2635	0.007	0.052	0.105	0.035	1.151	.2685	-.063	0.302	0.104	1.034	0.060
11	X	.2679	0.026	0.056	0.095	0.199	0.916	.2784	-.012	0.311	0.141	0.711	-0.531
12	1/(X+.375)	.2778	-.002	2.436	0.173	-0.637	-0.264	.2705	0.026	1.837	0.317	-0.708	1.366
16	1/(X+0.50)	.2859	0.034	0.394	0.181	-0.125	-0.836	.2691	-.004	0.471	0.141	1.181	1.846
17	1/(X+1.00)	.2844	0.026	0.490	0.202	-0.316	-0.712	.2664	-.015	0.508	0.138	1.164	1.314
18	1/(X+.375)	.2721	-.116	1.813	0.923	-0.572	-1.214	.2840	-.051	1.727	0.724	0.020	-1.466
19	1/(X+1.00)	.2808	0.027	1.203	0.752	0.594	-0.291	.2721	0.000	0.889	0.336	1.013	0.987
20	1/(X+3.00)	.2796	0.019	0.308	0.051	-0.561	-0.189	.2711	-.010	0.312	0.046	0.959	0.449
21	1/(X+2.25)	.2791	-.016	0.293	0.059	-0.695	-0.499	.2853	0.043	0.344	0.032	-0.046	-0.711
22	1/(X+2.25)	.2824	0.015	0.293	0.112	-0.482	-0.651	.2784	0.035	0.343	0.072	0.702	0.367
35	LN(X+2.25)	.2777	0.045	0.906	0.122	-0.021	-0.032	.2847	0.038	1.022	0.088	0.223	-0.676
36	1/(X+2.25)	.2782	0.046	0.418	0.032	-0.050	0.001	.2861	0.029	0.368	0.032	-0.175	-0.921
37	X	.2754	0.044	0.211	0.262	0.328	0.242	.1999	-.302	0.590	0.458	3.516	14.297
38	X	.2751	0.034	0.056	0.069	0.380	0.157	.2836	0.055	0.199	0.057	0.090	-0.484
39	X	.2760	0.040	0.094	0.124	0.211	0.125	.2285	-.208	0.388	0.167	2.372	5.766
48	1/(X+0.50)	.2811	0.039	1.262	0.437	-0.419	-0.292	.2543	-.054	1.106	0.281	-1.474	2.440
49	1/(X+3.00)	.2810	-.009	0.314	0.016	-0.531	-0.576	.2444	-.194	0.324	0.013	-1.533	1.393
50	1/(X+0.50)	.2817	0.003	1.326	0.350	0.523	-0.704	.2700	-.115	1.661	0.379	-0.760	-0.852
51	1/(X+.375)	.2827	0.040	1.578	0.610	-0.263	-0.600	.2614	-.018	1.299	0.361	-1.163	1.699
52	X	.2845	0.054	0.448	0.212	0.123	-0.592	.2816	0.011	0.470	0.156	0.539	-0.653
53	1/(X+0.50)	.2802	0.047	0.821	0.430	0.523	-0.000	.2844	0.041	0.746	0.289	-0.310	-0.681
54	1/(X+1.00)	.2849	0.048	0.414	0.190	0.074	-0.731	.2747	0.003	0.464	0.157	0.886	0.336
56	1/(X+1.00)	.2876	0.022	0.373	0.111	0.041	-1.089	.2741	0.000	0.365	0.142	0.930	0.377
58	1/(X+.375)	.2837	-.002	1.550	0.763	0.120	-0.989	.2613	-.120	2.101	0.699	-1.059	0.210
59	X	.2845	0.054	0.552	0.212	-0.123	-0.592	.2816	0.011	0.530	0.156	-0.539	-0.653
64	1/(X+3.00)	.2440	-.097	0.332	0.012	-0.986	1.734	.2581	-.011	0.327	0.007	-0.121	2.573
65	1/(X+3.00)	.2603	0.004	0.329	0.017	-0.696	2.000	.2803	0.027	0.325	0.008	-0.303	-0.404
66	1/(X+3.00)	.2555	-.036	0.327	0.020	-1.072	2.073	.2749	0.015	0.324	0.010	-0.377	0.054
67	1/(X+2.25)	.2356	-.103	0.443	0.031	-0.054	2.726	.2746	-.023	0.432	0.010	-0.691	0.143
69	X	.2749	0.035	0.094	0.102	0.209	0.205	.2740	-.011	0.300	0.074	0.832	0.039
71	LN(X+1.00)	.2850	0.038	7.259	1.041	-0.197	-0.731	.2509	-.081	7.994	0.865	1.799	3.877
72	LN(X+1.00)	.2822	0.026	6.828	0.974	-0.220	-0.667	.2378	-.147	7.423	0.869	2.214	5.597
73	LN(X+1.00)	.2845	0.037	7.152	1.137	-0.353	-0.658	.2490	-.093	7.949	0.873	1.854	3.964
77	LN(X+1.00)	.2843	0.033	6.179	1.165	-0.176	-0.775	.2539	-.026	6.721	1.043	1.602	4.662
84	SQ(X+2.25)	.2725	0.035	1.527	0.037	0.108	0.520	.2652	-.058	1.612	0.034	1.175	0.630
85	X	.2802	0.010	0.624	0.172	-0.574	-0.543	.2798	0.030	0.693	0.133	-0.566	-0.176
86	X	.2806	0.017	0.291	0.120	0.541	-0.572	.2751	-.002	0.412	0.128	-0.670	-0.287
87	X	.2844	0.039	0.298	0.201	0.222	-0.688	.2838	0.013	0.276	0.183	-0.434	-0.779
89	SQ(X+2.25)	.2838	0.048	1.976	0.223	0.273	-0.622	.2853	0.057	2.061	0.270	0.177	-0.650
90	SQ(X+1.00)	.2806	-.011	1.723	0.263	0.630	-0.674	.2818	0.031	1.783	0.319	0.492	-0.503
91	1/(X+.375)	.2853	0.025	2.311	0.214	0.069	-0.845	.2844	0.048	2.150	0.190	-0.230	-0.614

Table C2.2 Variables Distribution Year -4

VARIABLES*		FAILED COMPANIES						HEALTHY COMPANIES					
NO	FORM	D	W	MN	STD	SKW	KUR	D	W	MN	STD	SKW	KUR
1	X	.2346	-.095	0.034	0.183	-0.913	5.366	.2818	0.009	0.233	0.058	0.542	-0.472
2	X	.2313	-.103	0.038	0.205	-0.799	5.992	.2796	-.007	0.298	0.091	0.654	-0.404
3	X	.2717	0.029	0.024	0.086	-0.563	0.657	.2817	0.030	0.175	0.065	0.499	-0.340
5	X	.2378	-.059	0.281	0.781	0.140	5.498	.2857	0.043	0.532	0.172	0.211	-0.722
6	X	.2378	-.059	0.719	0.781	-0.140	5.498	.2857	0.043	0.468	0.172	-0.211	-0.722
7	X	.2747	0.041	0.030	0.076	-0.481	0.493	.2855	0.044	0.172	0.059	0.194	-0.730
8	X	.2712	0.030	0.031	0.090	-0.563	0.811	.2854	0.035	0.177	0.056	0.233	-0.775
10	X	.2300	-.107	0.030	0.202	-0.797	6.186	.2817	0.005	0.287	0.083	0.562	-0.551
11	X	.2706	0.030	0.033	0.124	-0.563	0.790	.2600	0.001	0.296	0.127	0.641	-0.527
12	1/(X+.375)	.2803	-.021	2.433	0.201	-0.581	-0.579	.2574	-.027	1.850	0.339	-1.534	5.384
16	1/(X+0.50)	.2776	0.039	0.431	0.204	0.533	0.808	.2735	0.010	0.472	0.147	0.934	0.841
17	1/(X+1.00)	.2836	0.037	0.529	0.204	-0.257	-0.617	.2629	-.042	0.510	0.143	1.221	1.261
18	1/(X+.375)	.2648	-.141	1.931	0.867	-0.774	-0.883	.2832	-.063	1.804	0.733	-0.236	-1.422
19	1/(X+1.00)	.2710	0.016	1.272	0.739	0.953	1.484	.2810	0.025	0.892	0.297	0.500	-0.122
20	1/(X+3.00)	.2851	0.051	0.319	0.050	-0.073	-0.642	.2690	-.020	0.312	0.043	0.948	0.445
21	1/(X+2.25)	.2796	0.005	0.301	0.055	-0.652	-0.309	.2628	0.034	0.342	0.034	-0.409	-0.449
22	1/(X+2.25)	.2817	0.046	0.313	0.116	-0.156	-0.296	.2807	0.039	0.343	0.076	0.508	-0.063
35	LN(X+2.25)	.2800	0.056	0.894	0.118	-0.177	-0.019	.2844	0.020	1.020	0.095	0.361	-0.827
36	1/(X+2.25)	.2800	0.040	0.421	0.033	0.350	-0.027	.2855	0.022	0.369	0.032	-0.298	-0.912
37	X	.2260	-.150	0.156	0.481	-2.662	12.185	.2462	-.153	0.575	0.364	1.616	1.720
38	X	.2765	0.050	0.048	0.077	-0.265	0.278	.2845	0.052	0.192	0.053	-0.077	-0.603
39	X	.2281	-.107	0.073	0.224	-0.342	6.727	.2305	-.171	0.374	0.162	2.638	8.800
48	1/(X+0.50)	.2846	0.040	1.273	0.440	-0.162	-0.705	.2583	-.020	1.150	0.268	-1.509	4.212
49	1/(X+3.00)	.2810	-.010	0.313	0.016	-0.494	-0.547	.2552	-.152	0.325	0.011	-1.192	0.243
50	1/(X+0.50)	.2792	0.003	1.294	0.336	0.619	-0.375	.2744	-.100	1.657	0.362	-0.587	-1.163
51	1/(X+.375)	.2858	0.040	1.593	0.624	-0.056	-0.831	.2658	0.015	1.359	0.350	-1.094	2.583
52	X	.2838	0.050	0.473	0.214	0.114	-0.519	.2838	0.042	0.461	0.153	0.345	-0.575
53	1/(X+0.50)	.2780	0.036	0.776	0.424	0.624	0.264	.2834	0.065	0.763	0.295	-0.122	-0.360
54	1/(X+1.00)	.2832	0.047	0.441	0.201	0.200	-0.509	.2766	0.022	0.459	0.156	0.760	0.413
56	1/(X+1.00)	.2784	0.037	0.389	0.129	0.525	0.514	.2707	-.005	0.363	0.148	1.078	1.005
58	1/(X+.375)	.2833	-.010	1.532	0.759	0.182	-0.999	.2652	-.100	2.114	0.636	-0.960	0.378
59	X	.2838	0.050	0.527	0.214	-0.114	-0.519	.2838	0.042	0.539	0.153	-0.345	-0.575
64	1/(X+3.00)	.2628	0.003	0.334	0.013	0.238	1.062	.2560	-.012	0.324	0.007	-0.963	2.507
65	1/(X+3.00)	.2514	-.011	0.329	0.017	-0.861	3.768	.2684	0.015	0.323	0.009	0.006	0.547
66	1/(X+3.00)	.2543	-.003	0.329	0.017	-0.749	3.610	.2749	0.033	0.323	0.010	0.189	0.087
67	1/(X+2.25)	.2168	-.197	0.447	0.044	3.041	12.924	.2547	-.001	0.427	0.014	-0.152	2.662
69	X	.2453	-.044	0.089	0.168	-0.650	4.265	.2816	0.015	0.295	0.063	0.561	-0.547
71	LN(X+1.00)	.2847	0.035	7.264	1.050	-0.157	-0.744	.2519	-.081	8.069	0.877	1.754	3.592
72	LN(X+1.00)	.2818	0.031	6.756	1.033	-0.371	-0.481	.2356	-.160	7.500	0.854	2.251	5.680
73	LN(X+1.00)	.2844	0.036	7.163	1.141	-0.307	-0.671	.2519	-.086	8.025	0.889	1.755	3.484
77	LN(X+1.00)	.2833	0.034	6.176	1.188	-0.352	-0.565	.2549	-.018	6.797	1.058	1.447	4.031
84	SQ(X+2.25)	.2348	-.092	1.521	0.063	-1.127	5.443	.2790	0.003	1.608	0.028	0.699	-0.292
85	X	.2803	0.010	0.628	0.171	-0.617	-0.475	.2797	0.022	0.691	0.137	-0.564	-0.350
86	X	.2800	0.038	0.278	0.123	0.435	-0.141	.2765	-.013	0.409	0.134	-0.743	-0.406
87	X	.2821	0.057	0.272	0.214	0.138	-0.313	.2834	0.036	0.275	0.190	-0.364	-0.632
89	SQ(X+2.25)	.2802	0.040	1.961	0.225	0.454	-0.295	.2827	0.055	2.073	0.280	0.298	-0.278
90	SQ(X+1.00)	.2767	0.014	1.696	0.282	0.617	-0.211	.2826	0.039	1.782	0.315	0.447	-0.426
91	1/(X+.375)	.2842	0.041	2.280	0.202	-0.025	-0.628	.2851	0.047	2.155	0.187	-0.075	-0.652
94	X	.2724	-.036	0.024	0.022	0.984	0.224	.2772	-.016	0.009	0.007	0.777	-0.052
96	1/(X+0.50)	.2754	-.053	1.434	0.526	-0.800	-0.477	.2805	-.020	1.888	0.077	-0.604	-0.590

Table C2.3 Variables Distribution Year -3

VARIABLES'		FAILED COMPANIES						HEALTHY COMPANIES					
NO	FORM	D	W	MN	STD	SKW	KUR	D	W	MN	STD	SKW	KUR
1	X	.2629	-.027	0.002	0.172	-0.612	0.683	.2700	-.004	0.245	0.059	0.809	0.426
2	X	.2632	-.020	0.004	0.184	-0.542	0.733	.2672	-.036	0.310	0.094	0.992	0.318
3	X	.2769	0.023	0.007	0.091	-0.545	-0.142	.2747	0.024	0.189	0.062	0.661	0.337
5	X	.2075	-.214	0.311	1.250	0.901	6.355	.2794	0.029	0.504	0.191	0.426	-0.449
6	X	.2075	-.214	0.689	1.250	-0.901	6.355	.2794	0.029	0.496	0.191	-0.426	-0.449
7	X	.2744	0.020	0.009	0.087	-0.592	0.145	.2810	0.052	0.183	0.053	0.140	-0.211
8	X	.2671	-.017	0.003	0.113	-0.839	0.488	.2829	0.041	0.187	0.048	0.364	-0.435
10	X	.2653	-.012	0.000	0.182	-0.508	0.624	.2685	-.034	0.301	0.087	1.016	0.440
11	X	.2783	0.035	0.015	0.142	-0.367	-0.172	.2733	0.008	0.326	0.128	0.721	0.231
12	1/(X+.375)	.2719	-.064	2.448	0.222	-0.859	-0.154	.2771	0.041	1.852	0.304	-0.520	0.149
16	1/(X+0.50)	.2776	0.046	0.458	0.215	0.288	0.401	.2646	-.032	0.463	0.164	1.351	2.051
17	1/(X+1.00)	.2806	0.002	0.534	0.206	-0.609	-0.436	.2578	-.061	0.495	0.154	1.440	2.103
18	1/(X+.375)	.2603	-.151	1.971	0.848	-0.930	-0.467	.2866	-.028	1.635	0.728	0.040	-1.393
19	1/(X+1.00)	.2411	-.114	1.569	1.219	2.386	8.556	.2676	-.012	0.851	0.336	1.226	2.274
20	1/(X+3.00)	.2813	0.037	0.311	0.048	-0.288	-0.488	.2719	-.007	0.313	0.042	0.866	0.370
21	1/(X+2.25)	.2712	0.034	0.314	0.068	-0.105	0.668	.2854	0.033	0.343	0.035	-0.266	-0.738
22	1/(X+2.25)	.2777	0.034	0.326	0.122	-0.432	-0.025	.2763	0.018	0.336	0.083	0.841	0.462
35	LN(X+2.25)	.2659	0.033	0.858	0.162	-0.500	1.998	.2844	0.028	1.037	0.089	0.230	-0.795
36	1/(X+2.25)	.2734	0.044	0.432	0.043	0.501	0.715	.2847	0.030	0.362	0.031	-0.256	-0.802
37	X	.2715	0.030	0.113	0.395	-0.267	0.507	.1868	-.390	0.699	0.748	3.094	9.156
38	X	.2769	0.028	0.028	0.088	-0.440	-0.098	.2839	0.053	0.206	0.050	0.006	-0.545
39	X	.2620	-.010	0.044	0.214	-0.040	0.959	.2331	-.182	0.383	0.153	2.350	6.147
48	1/(X+0.50)	.2836	0.031	1.244	0.472	-0.071	-0.663	.2710	0.012	1.189	0.239	-1.065	1.643
49	1/(X+3.00)	.2820	-.007	0.312	0.017	-0.367	-0.692	.2554	-.155	0.325	0.010	-1.169	0.117
50	1/(X+0.50)	.2710	-.030	1.232	0.341	0.929	0.169	.2677	-.138	1.693	0.354	-0.719	-1.099
51	1/(X+.375)	.2846	0.034	1.566	0.659	0.041	-0.766	.2751	0.029	1.410	0.321	-0.839	0.864
52	X	.2853	0.053	0.507	0.218	-0.131	-0.651	.2828	0.024	0.442	0.145	0.422	-0.606
53	1/(X+0.50)	.2738	0.008	0.720	0.435	0.935	0.625	.2847	0.046	0.799	0.279	-0.157	-0.710
54	1/(X+1.00)	.2848	0.046	0.468	0.202	-0.232	-0.658	.2758	0.011	0.440	0.149	0.791	0.383
56	1/(X+1.00)	.2852	0.028	0.398	0.134	-0.028	-0.854	.2722	-.010	0.352	0.146	0.983	0.399
58	1/(X+.375)	.2830	-.016	1.485	0.779	0.295	-1.053	.2674	-.101	2.158	0.580	-0.825	-0.268
57	X	.2853	0.053	0.493	0.218	0.131	-0.651	.2828	0.024	0.559	0.145	-0.422	-0.606
64	1/(X+3.00)	.1942	-.314	0.329	0.043	-3.078	10.313	.2773	0.045	0.321	0.006	-0.357	0.112
65	1/(X+3.00)	.2042	-.235	0.327	0.036	-1.859	7.421	.2840	0.048	0.324	0.007	0.107	-0.548
66	1/(X+3.00)	.2010	-.248	0.326	0.036	-1.856	7.643	.2841	0.037	0.326	0.007	0.030	-0.741
67	1/(X+2.25)	.2019	-.272	0.436	0.070	-2.911	10.103	.2776	0.028	0.419	0.014	-0.547	-0.083
69	X	.2670	-.002	0.055	0.167	-0.496	0.636	.2706	-.008	0.305	0.062	0.911	0.405
71	LN(X+1.00)	.2847	0.045	7.334	1.025	-0.137	-0.585	.2523	-.083	8.149	0.878	1.743	3.474
72	LN(X+1.00)	.2849	0.035	6.802	0.928	-0.102	-0.860	.2378	-.151	7.611	0.851	2.191	5.381
73	LN(X+1.00)	.2831	0.041	7.236	1.117	-0.396	-0.360	.2539	-.079	8.093	0.900	1.692	3.220
77	LN(X+1.00)	.2840	0.037	6.234	1.175	-0.320	-0.594	.2580	-.007	6.864	1.097	1.311	3.415
84	SQ(X+2.25)	.2654	-.006	1.511	0.061	-0.511	0.682	.2687	-.036	1.612	0.028	1.086	0.720
85	X	.2787	0.003	0.626	0.182	-0.638	-0.289	.2785	0.020	0.692	0.143	-0.625	-0.225
86	X	.2780	-.000	0.298	0.145	0.678	-0.183	.2771	-.005	0.424	0.141	-0.740	-0.309
87	X	.2826	0.054	0.244	0.224	0.078	-0.326	.2812	0.020	0.293	0.196	-0.561	-0.530
89	SQ(X+2.25)	.2766	0.004	1.948	0.246	0.700	-0.340	.2818	0.054	2.102	0.296	0.395	-0.039
90	SQ(X+1.00)	.2757	-.024	1.699	0.309	0.753	-0.492	.2796	0.042	1.811	0.343	0.589	0.083
91	1/(X+.375)	.2795	0.037	2.302	0.209	0.053	-0.295	.2830	0.039	2.139	0.195	-0.182	-0.518
94	X	.2713	-.065	0.046	0.041	0.935	-0.273	.2714	-.035	0.017	0.010	0.934	0.245
96	1/(X+0.50)	.2830	-.003	1.257	0.533	-0.472	-0.796	.2794	-.006	1.820	0.106	-0.613	-0.677

Table C2.4 Variables Distribution Year -2

VARIABLES*		FAILED COMPANIES						HEALTHY COMPANIES					
NO	FORM	D	W	MN	STD	SKW	KUR	D	W	MN	STD	SKW	KUR
1	X	.2525	-.080	-0.053	0.251	-1.132	1.342	.2777	0.029	0.270	0.060	0.670	0.332
2	X	.2525	-.069	-0.049	0.262	-0.950	1.401	.2687	-.022	0.339	0.098	1.065	0.838
3	X	.2715	0.014	-0.015	0.119	-0.436	0.251	.2775	0.042	0.207	0.063	0.307	0.217
5	X	.2449	-.210	0.277	0.401	1.377	0.840	.2832	0.041	0.383	0.171	0.377	-0.460
6	X	.2548	-.169	0.672	0.435	-1.150	0.135	.2832	0.041	0.617	0.171	-0.377	-0.460
7	X	.2690	0.004	-0.013	0.115	-0.490	0.395	.2816	0.044	0.204	0.056	-0.085	-0.370
8	X	.2667	-.016	-0.024	0.139	-0.808	0.507	.2846	0.049	0.210	0.052	0.173	-0.593
10	X	.2530	-.065	-0.056	0.261	-0.939	1.408	.2681	-.026	0.328	0.093	1.112	0.916
11	X	.2685	0.009	-0.024	0.184	-0.580	0.436	.2786	0.037	0.362	0.132	0.303	-0.053
12	1/(X+.375)	.2640	-.138	2.514	0.181	-0.707	-0.775	.2731	0.031	1.911	0.318	-0.769	0.941
16	1/(X+0.50)	.2716	0.031	0.478	0.265	0.406	0.855	.2739	-.006	0.450	0.151	0.940	0.466
17	1/(X+1.00)	.2789	-.005	0.524	0.238	-0.707	-0.385	.2646	-.034	0.481	0.134	1.268	1.578
18	1/(X+.375)	.2522	-.195	1.969	0.937	-1.079	-0.396	.2825	-.056	1.572	0.744	0.308	-1.383
19	1/(X+1.00)	.2691	0.008	1.399	0.893	0.898	2.601	.2701	-.033	0.856	0.363	1.022	0.251
20	1/(X+3.00)	.2424	-.084	0.307	0.080	-2.162	7.852	.2683	-.037	0.310	0.038	1.009	0.584
21	1/(X+2.25)	.2680	0.002	0.324	0.063	-0.641	0.687	.2829	0.026	0.341	0.037	-0.399	-0.543
22	1/(X+2.25)	.2720	0.018	0.331	0.149	-0.563	0.156	.2812	0.022	0.330	0.080	0.587	-0.329
35	LN(X+2.25)	.2599	-.007	0.861	0.204	1.281	2.992	.2853	0.040	1.054	0.088	-0.008	-0.742
36	1/(X+2.25)	.2544	0.000	0.433	0.066	-0.796	3.291	.2857	0.039	0.355	0.030	0.080	-0.772
37	X	.2714	0.026	-0.001	0.115	-0.495	0.495	.1998	-.331	0.639	0.488	2.926	8.309
38	X	.2736	0.036	0.006	0.105	-0.224	0.323	.2830	0.057	0.222	0.051	-0.208	-0.386
39	X	.2616	0.001	0.030	0.284	-0.017	1.230	.2096	-.276	0.405	0.181	3.156	10.984
48	1/(X+0.50)	.2636	-.009	1.226	0.664	-1.062	3.304	.2603	-.017	1.240	0.236	-1.492	4.058
49	1/(X+3.00)	.2536	-.091	0.309	0.024	-1.777	5.138	.2479	-.167	0.327	0.008	-1.478	1.468
50	1/(X+0.50)	.2686	-.031	1.204	0.390	0.810	0.171	.2690	-.129	1.699	0.342	-0.576	-1.125
51	1/(X+.375)	.2734	0.041	1.576	0.870	-0.257	1.010	.2669	0.015	1.479	0.317	-1.130	2.609
52	X	.2784	0.046	0.529	0.264	-0.147	0.060	.2837	0.014	0.426	0.136	0.364	-0.778
53	1/(X+0.50)	.2644	-.012	0.691	0.544	0.691	0.914	.2837	0.029	0.826	0.274	-0.249	-0.688
54	1/(X+1.00)	.2797	0.050	0.493	0.249	-0.106	-0.062	.2746	0.006	0.425	0.146	0.857	0.937
56	1/(X+1.00)	.2442	-.103	0.435	0.208	2.306	8.294	.2716	0.010	0.338	0.145	1.031	1.247
58	1/(X+.375)	.2789	-.021	1.454	0.892	-0.013	-0.657	.2579	-.123	2.244	0.523	-1.253	1.446
52	X	.2784	0.046	0.471	0.254	0.147	0.060	.2837	0.014	0.574	0.136	-0.364	-0.778
64	1/(X+3.00)	.2352	-.088	0.339	0.029	0.868	4.448	.2707	0.026	0.314	0.012	-0.667	0.815
65	1/(X+3.00)	.2744	0.042	0.333	0.018	0.519	0.442	.2776	0.032	0.315	0.009	-0.551	-0.047
66	1/(X+3.00)	.2743	0.042	0.334	0.019	0.514	0.565	.2788	0.032	0.314	0.010	-0.437	-0.269
67	1/(X+2.25)	.2256	-.138	0.451	0.048	1.563	5.197	.2667	-.013	0.405	0.023	-0.923	0.882
69	X	.2592	-.030	0.014	0.222	-0.846	1.200	.2747	0.024	0.327	0.066	0.810	0.603
71	LN(X+1.00)	.2851	0.041	7.328	1.075	-0.211	-0.666	.2532	-.076	8.316	0.884	1.696	3.364
72	LN(X+1.00)	.2825	0.045	6.745	1.033	-0.254	-0.401	.2412	-.133	7.787	0.862	2.078	4.851
73	LN(X+1.00)	.2833	0.031	7.225	1.191	-0.411	-0.539	.2545	-.072	8.266	0.906	1.655	3.144
77	LN(X+1.00)	.2853	0.042	6.249	1.234	-0.227	-0.699	.2623	0.012	6.985	1.122	1.134	2.818
84	SQ(X+2.25)	.2578	-.037	1.494	0.081	-0.893	1.319	.2627	-.053	1.619	0.030	1.319	1.538
85	X	.2782	-.002	0.617	0.187	-0.688	-0.328	.2809	0.029	0.701	0.141	-0.496	-0.313
86	X	.2797	0.011	0.320	0.162	0.596	-0.441	.2798	0.014	0.431	0.128	-0.544	-0.416
87	X	.2787	0.046	0.223	0.244	0.143	-0.062	.2829	0.026	0.306	0.198	-0.468	-0.571
89	SQ(X+2.25)	.2743	0.043	1.911	0.259	0.100	0.694	.2786	0.041	2.146	0.333	0.650	0.169
90	SQ(X+1.00)	.2760	0.009	1.663	0.284	0.676	-0.168	.2752	0.016	1.849	0.392	0.833	0.347
91	1/(X+.375)	.2707	0.014	2.276	0.240	-0.864	1.155	.2851	0.033	2.134	0.213	-0.180	-0.736
94	X	.2738	-.053	0.059	0.051	0.871	-0.378	.2797	-.002	0.023	0.014	0.645	-0.592
96	1/(X+0.50)	.2816	0.010	1.226	0.497	-0.415	-0.613	.2834	0.022	1.722	0.115	-0.389	-0.607

Table C2.5 Variables Distribution Year -1

VARIABLES'		FAILED COMPANIES						HEALTHY COMPANIES					
NO	FORM	D	W	MN	STD	SKW	KUR	D	W	MN	STD	SKW	KUR
1	X	.2173	-.199	-0.205	0.547	-2.621	9.284	.2724	-.023	0.279	0.051	0.935	0.093
2	X	.2322	-.144	-0.207	0.533	-1.799	3.868	.2623	-.082	0.351	0.090	1.264	0.821
3	X	.2703	0.009	-0.041	0.125	-0.465	0.383	.2812	0.041	0.204	0.056	0.554	-0.166
5	X	.2375	-.253	0.273	0.455	1.227	-0.077	.2788	-.023	0.276	0.135	0.586	-0.939
6	X	.2375	-.253	0.727	0.455	-1.227	-0.077	.2788	-.023	0.724	0.135	-0.586	-0.939
7	X	.2690	-.004	-0.040	0.119	-0.564	0.349	.2844	0.044	0.207	0.054	0.289	-0.598
8	X	.2639	-.027	-0.069	0.170	-0.792	0.600	.2835	0.028	0.214	0.048	0.422	-0.607
10	X	.2298	-.157	-0.208	0.540	-1.831	3.835	.2600	-.091	0.334	0.083	1.375	1.286
11	X	.2706	0.015	-0.058	0.187	-0.301	0.422	.2704	-.010	0.354	0.131	0.949	0.483
12	1/(X+.375)	.2278	-.268	2.517	0.248	-1.827	2.370	.2807	0.022	2.140	0.231	-0.526	-0.368
16	1/(X+0.50)	.2608	0.023	0.514	0.329	0.072	2.742	.2762	0.011	0.454	0.138	0.851	0.377
17	1/(X+1.00)	.2524	-.086	0.553	0.394	-1.850	4.765	.2653	-.030	0.501	0.138	1.215	1.354
18	1/(X+.375)	.2209	-.264	1.950	1.182	-2.429	7.045	.2862	-.036	1.699	0.715	0.053	-1.453
19	1/(X+1.00)	.2784	0.029	1.614	0.959	0.481	0.048	.2666	-.027	0.898	0.356	1.214	1.292
20	1/(X+3.00)	.2532	-.043	0.340	0.065	1.261	3.418	.2697	-.016	0.314	0.042	0.903	0.504
21	1/(X+2.25)	.2708	0.021	0.334	0.058	-0.492	0.688	.2813	0.019	0.336	0.036	-0.481	-0.463
22	1/(X+2.25)	.2226	-.181	0.334	0.233	-3.047	13.568	.2823	0.035	0.333	0.074	0.509	-0.319
35	LN(X+2.25)	.2830	0.059	0.828	0.123	0.158	-0.371	.2864	0.034	1.047	0.086	0.216	-0.913
36	1/(X+2.25)	.2750	0.057	0.443	0.044	0.451	0.834	.2871	0.027	0.357	0.029	-0.110	-1.078
37	X	.2745	0.040	-0.065	0.475	-0.032	0.359	.1970	-.365	0.696	0.593	2.736	6.452
38	X	.2704	0.019	-0.011	0.113	-0.092	0.538	.2838	0.051	0.222	0.046	0.041	-0.485
39	X	.1922	-.341	-0.243	0.871	-3.240	10.928	.2387	-.153	0.397	0.117	2.133	4.850
48	1/(X+0.50)	.2568	-.003	1.200	0.947	0.505	2.963	.2687	0.021	1.254	0.203	-0.803	1.123
49	1/(X+3.00)	.2497	-.127	0.303	0.033	-1.799	4.049	.2537	-.155	0.328	0.007	-1.253	0.491
50	1/(X+0.50)	.2697	-.043	1.141	0.438	0.797	-0.250	.2726	-.114	1.704	0.321	-0.579	-1.193
51	1/(X+.375)	.2218	-.183	1.662	1.704	2.806	11.277	.2716	0.035	1.496	0.280	-0.587	0.766
52	X	.2757	0.047	0.595	0.335	-0.098	0.276	.2838	0.024	0.432	0.127	0.398	-0.703
53	1/(X+0.50)	.2528	-.046	0.634	0.698	1.437	3.886	.2862	0.037	0.813	0.245	-0.134	-0.899
54	1/(X+1.00)	.2779	0.060	0.555	0.318	-0.150	0.163	.2787	0.022	0.431	0.131	0.697	0.139
56	1/(X+1.00)	.1324	-.570	0.343	0.965	-5.753	33.996	.2788	0.039	0.328	0.138	0.668	0.165
58	1/(X+.375)	.2774	-.045	1.342	0.988	0.083	-0.960	.2657	-.111	2.294	0.436	-0.840	-0.325
59	X	.2757	0.047	0.405	0.335	0.098	0.276	.2838	0.024	0.568	0.127	-0.398	-0.703
64	1/(X+3.00)	.2577	-.036	0.350	0.036	1.102	1.458	.2771	0.027	0.315	0.008	-0.387	-0.037
65	1/(X+3.00)	.2642	0.020	0.334	0.025	0.035	1.470	.2851	0.049	0.313	0.009	0.093	-0.647
66	1/(X+3.00)	.2659	0.027	0.334	0.025	0.019	1.323	.2831	0.049	0.312	0.010	-0.222	-0.403
67	1/(X+2.25)	.2570	-.012	0.464	0.062	0.705	2.078	.2748	-.006	0.402	0.018	-0.774	0.038
69	X	.2198	-.149	-0.063	0.481	-1.768	8.628	.2784	0.014	0.333	0.054	0.701	-0.136
71	LN(X+1.00)	.2836	0.035	7.309	1.060	-0.057	-0.621	.2564	-.062	8.493	0.886	1.570	2.848
72	LN(X+1.00)	.2832	0.041	6.549	1.129	-0.079	-0.552	.2436	-.121	7.950	0.863	1.996	4.492
73	LN(X+1.00)	.2831	0.033	7.209	1.167	-0.263	-0.547	.2564	-.065	8.456	0.899	1.586	2.798
77	LN(X+1.00)	.2811	0.045	6.245	1.216	-0.439	-0.057	.2651	0.027	7.104	1.172	0.945	2.463
84	SQ(X+2.25)	.2209	-.163	1.458	0.194	-1.957	6.197	.2558	-.090	1.621	0.026	1.477	1.746
85	X	.2777	-.006	0.610	0.196	-0.696	-0.414	.2835	0.043	0.714	0.139	-0.374	-0.507
86	X	.2757	-.015	0.291	0.164	0.820	-0.034	.2795	0.041	0.415	0.139	-0.352	-0.114
87	X	.2805	0.050	0.164	0.294	0.094	-0.172	.2837	0.038	0.308	0.187	-0.377	-0.628
89	SQ(X+2.25)	.2657	0.009	1.843	0.313	-0.193	1.240	.2686	-.001	2.181	0.378	1.150	1.537
90	SQ(X+1.00)	.2779	0.019	1.598	0.317	0.674	-0.075	.2690	-.006	1.882	0.442	1.130	1.245
91	1/(X+.375)	.2467	-.084	2.263	0.317	-1.979	6.653	.2841	0.045	2.125	0.203	-0.205	-0.594
94	X	.2752	-.034	0.074	0.059	0.842	-0.285	.2764	-.032	0.026	0.014	0.780	-0.372
96	1/(X+0.50)	.2772	0.015	1.180	0.455	-0.285	-0.271	.2775	0.027	1.624	0.100	-0.221	-0.123

Table C3 W Statistic for Untransformed Ratios *

W	Failed Companies					Non-Failed Companies				
	Y-5	Y-4	Y-3	Y-2	Y-1	Y-5	Y-4	Y-3	Y-2	Y-1
1	-.002	-.095	-.027	-.080	-.199	-.015	0.009	-.004	0.029	-.023
2	-.005	-.103	-.021	-.069	-.144	-.047	-.007	-.036	-.022	-.082
3	0.020	0.029	0.022	0.014	0.009	0.023	.030	0.024	0.042	0.041
5	-.086	-.059	-.183	-.210	-.253	0.043	0.043	0.029	0.041	-.023
6	-.084	-.059	-.183	-.169	-.253	0.043	0.043	0.029	0.041	-.023
7	-.001	0.041	0.020	0.004	-.004	0.045	.044	0.052	0.044	0.044
8	0.006	0.030	-.017	-.016	-.027	0.042	.035	0.041	0.049	0.028
10	0.007	-.107	-.013	-.065	-.157	-.063	.005	-.034	-.026	-.091
11	0.026	.030	0.034	0.009	0.015	-.012	.001	0.008	0.037	-.010
12	-.029	-.044	-.095	-.138	-.318	-.193	-.546	-.067	-.145	-.023
16	-.270	-.233	-.365	-.366	-.306	0.052	0.030	0.050	0.035	0.037
17	-.335	-.323	-.443	-.417	-.362	0.053	0.043	0.042	0.051	0.047
18	-.442	-.493	-.552	-.433	-.500	-.102	-.142	-.098	-.054	-.068
19	-.359	-.389	-.476	-.390	-.458	0.016	-.020	0.008	0.030	0.038
20	-.080	0.013	-.020	-.596	0.011	0.047	.037	0.041	0.015	0.035
21	-.124	-.102	-.124	-.173	-.120	0.030	-.003	0.008	-.011	-.026
22	-.270	-.233	-.365	-.366	-.306	.052	.030	o.050	0.035	0.037
35	0.038	.056	0.038	-.126	0.046	.030	.009	0.019	0.041	0.028
36	0.029	.048	0.054	-.238	0.063	.016	.002	0.010	0.035	0.017
37	0.044	-.150	0.030	0.025	0.040	-.302	-.153	-.390	-.331	-.365
38	0.034	0.050	0.028	0.036	0.019	.055	0.052	0.053	0.057	0.051
39	0.040	-.107	-.010	0.001	-.314	-.208	-.171	-.182	-.276	-.153
48	-.552	-.232	-.471	-.078	-.164	-.505	-.700	-.356	-.503	-.145
49	-.020	-.021	-.014	-.209	-.271	-.213	-.160	-.162	-.176	-.161
50	0.026	0.027	0.035	-.098	-.078	-.172	-.129	-.163	-.150	-.134
51	-.559	-.246	-.485	-.108	-.187	-.504	-.700	-.357	-.503	-.145
52	0.054	0.050	0.053	0.046	0.047	+.011	0.042	0.024	0.014	0.024
53	-.469	-.400	-.291	-.029	-.224	-.383	-.640	-.221	-.368	-.082
54	-.529	-.467	-.556	-.455	-.459	.030	0.013	0.017	0.007	0.025
56	-.034	-.041	-.082	-.004	0.013	0.040	0.036	0.029	0.000	-.062
58	-.616	-.282	-.517	-.058	-.091	-.508	-.701	-.373	-.509	-.183
59	0.054	0.050	0.053	0.046	0.047	0.011	0.042	0.024	0.014	0.025

Table C3 - continued

W	Failed Companies Y-5	Y-4	Y-3	Y-2	Y-1	Non-Failed Companies Y-5	Y-4	Y-3	Y-2	Y-1
64	-.125	0.004	0.506	-.087	-.014	0.015	-.028	-.039	0.004	0.018
65	-.033	-.061	-.385	0.056	-.003	0.022	0.014	0.049	0.019	0.050
66	-.094	-.052	-.393	0.056	0.006	0.007	0.035	0.037	0.022	0.044
67	-.128	-.055	-.562	-.090	-.018	-.031	-.008	0.014	-.053	-.029
69	0.032	-.042	-.770	-.030	-.092	-.017	0.007	0.005	-.003	-.005
71	-.098	-.115	-.124	-.122	-.164	-.559	-.549	-.540	-.536	-.514
72	-.078	-.069	-.077	-.112	-.185	-.615	-.608	-.599	-.587	-.577
73	-.087	-.106	-.102	-.112	-.155	-.561	-.546	-.536	-.534	-.514
77	-.103	-.088	-.089	-.125	-.135	-.680	-.668	-.660	-.653	-.659
84	0.033	-.075	0.000	-.022	-.096	-.065	0.000	-.041	-.060	-.096
85	0.010	0.010	0.003	-.002	-.006	0.030	0.022	0.020	0.029	0.043
86	0.017	0.038	0.000	0.011	-.015	-.002	-.013	-.005	o.014	0.041
87	0.039	0.057	0.054	0.046	0.050	0.013	0.036	0.020	0.026	0.038
89	0.035	0.019	-.023	0.028	0.001	0.047	0.038	0.032	0.006	-.064
90	-.035	-.025	-.062	-.033	-.026	0.000	0.012	0.000	-.041	-.087
91	0.024	0.030	0.029	-.078	0.414	0.026	0.036	0.019	0.012	0.021
94	-	-.036	-.064	-.053	-.033	-	-.016	-.035	-.002	-.032
96	-	-.330	-.322	-.316	-.312	-	-.031	-.027	0.001	0.009

* See the comment of table 5.1a pp.174-175.

Table C4 - t-test, the 2-tail Probability associated with t value ++

V. No.	Y - 5	Y - 4	Y - 3	Y - 2	Y - 1
1	0.000	*0.000	*0.000	*0.000	*0.000
2	0.000	*0.000	*0.000	*0.000	*0.000
3	0.000	0.000	0.000	*0.000	*0.000
5	*0.763	*0.042	*0.316	*0.114	*0.964
6	*0.998	*0.042	*0.316	*0.438	*0.964
7	0.000	0.000	*0.000	*0.000	*0.000
8	0.000	*0.000	*0.000	*0.000	*0.000
10	0.000	*0.000	*0.000	*0.000	*0.000
11	0.000	0.000	0.000	0.000	0.000
12	*0.000	*0.000	0.000	*0.000	0.000
16	0.030	0.287	0.902	*0.552	*0.271
17	0.634	0.607	0.312	*0.303	*0.311
18	0.635	0.458	0.049	0.031	*0.232
19	0.015	*0.002	*0.000	*0.000	*0.000
20	0.690	0.459	0.856	*0.810	*0.029
21	*0.000	*0.000	*0.013	*0.131	*0.795
22	*0.017	*0.161	0.668	*0.972	*0.976
35	0.000	0.000	*0.000	*0.000	0.000
36	0.000	0.000	0.000	*0.000	*0.000
37	*0.000	0.000	*0.000	0.000	0.000
38	0.000	0.000	*0.000	*0.000	*0.000
39	0.000	0.000	0.000	*0.000	*0.000
48	*0.053	*0.117	*0.489	*0.890	*0.713
49	0.002	0.000	*0.000	*0.000	*0.000
50	0.000	0.000	0.000	0.000	0.000
51	*0.012	*0.033	*0.159	*0.488	*0.527
52	0.582	0.768	*0.103	*0.024	*0.004
53	0.346	0.865	*0.313	*0.147	*0.113
54	0.188	0.646	0.45=	*0.121	*0.20
56	0.758	0.396	0.127	0.013	*0.917
58	0.001	0.000	0.000	*0.00	*0.000
59	0.582	0.029	*0.103	*0.024	*0.004

Table C4 - continued

V. No.	Y - 5	Y - 4	Y - 3	Y - 2	Y - 1
64	*0.026	*0.000	*0.208	*0.000	*0.000
65	*0.184	*0.036	*0.686	*0.000	*0.000
66	*0.432	*0.051	*0.936	*0.000	*0.000
67	*0.025	+0.005	*0.138	*0.000	*0.000
69	0.000	*0.000	*0.000	*0.000	*0.000
71	0.001	0.000	0.000	0.000	0.000
72	0.004	0.000	0.000	0.000	0.000
73	0.000	0.000	0.000	0.000	0.000
77	0.026	0.011	0.011	0.004	0.001
84	0.000	*0.000	*0.000	*0.000	*0.000
85	0.041	0.060	0.062	0.020	0.005
86	0.000	0.000	0.000	0.001	0.000
87	0.600	0.942	0.285	0.083	*0.008
89	0.112	0.042	0.009	0.000	0.000
90	0.341	0.180	0.109	0.013	0.001
91	0.000	0.003	0.000	0.004	*0.018
94	-	*0.000	*0.000	*0.000	*0.000
96	-	*0.000	*0.000	*0.000	*0.000

++ If any of the above probabilities is less than a selected value of α, .05, the null hypothesis, $H_0: \mu_1=\mu_2$, is rejected, i.e., the difference between the two population means is significant at the 5% level.

* The asterisk indicates that t is based upon separate variance estimate, otherwise it is based upon pooled-variance estimate.

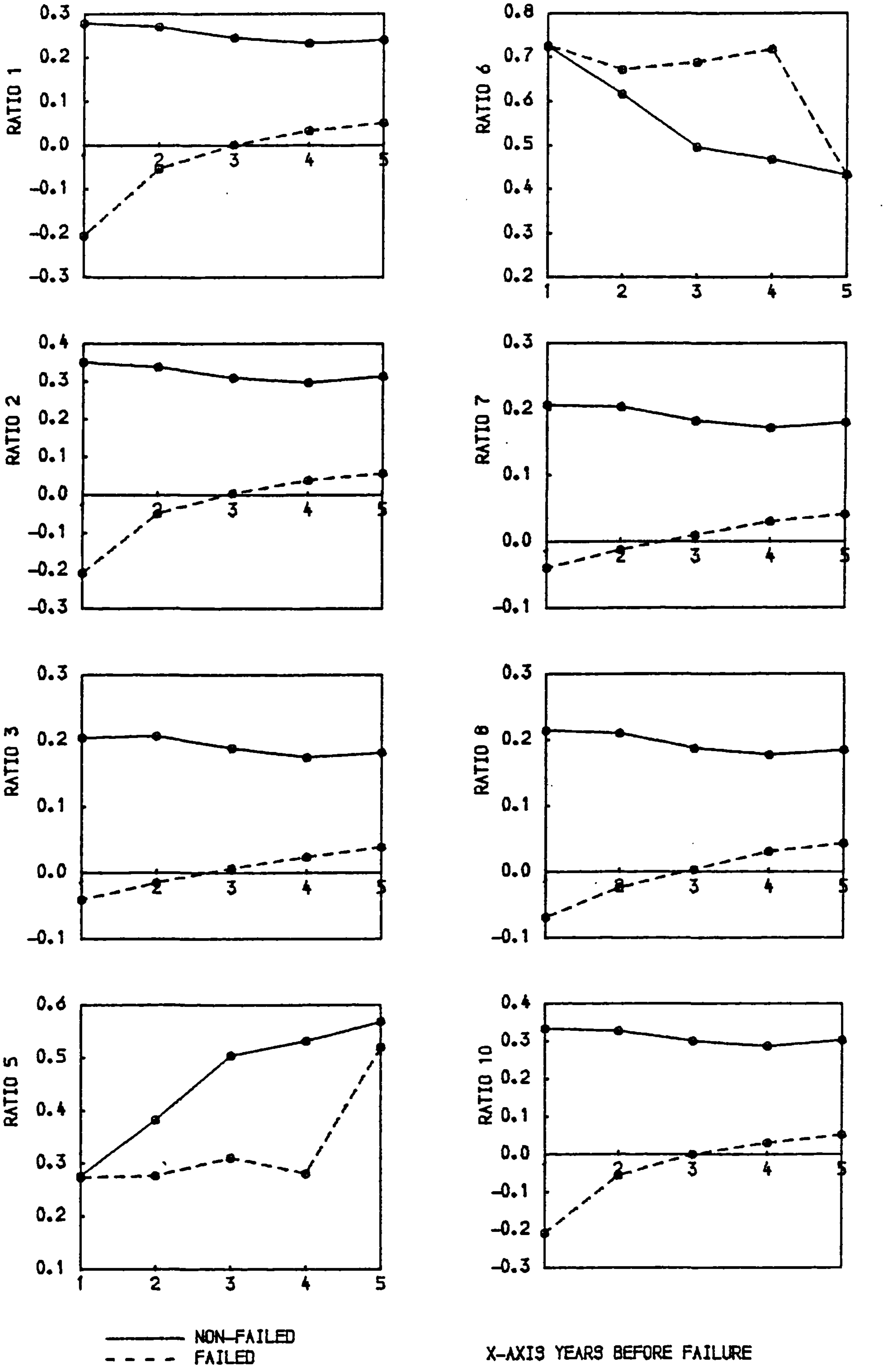


Figure C1 - Profile Analysis, Comparison of Mean Values.

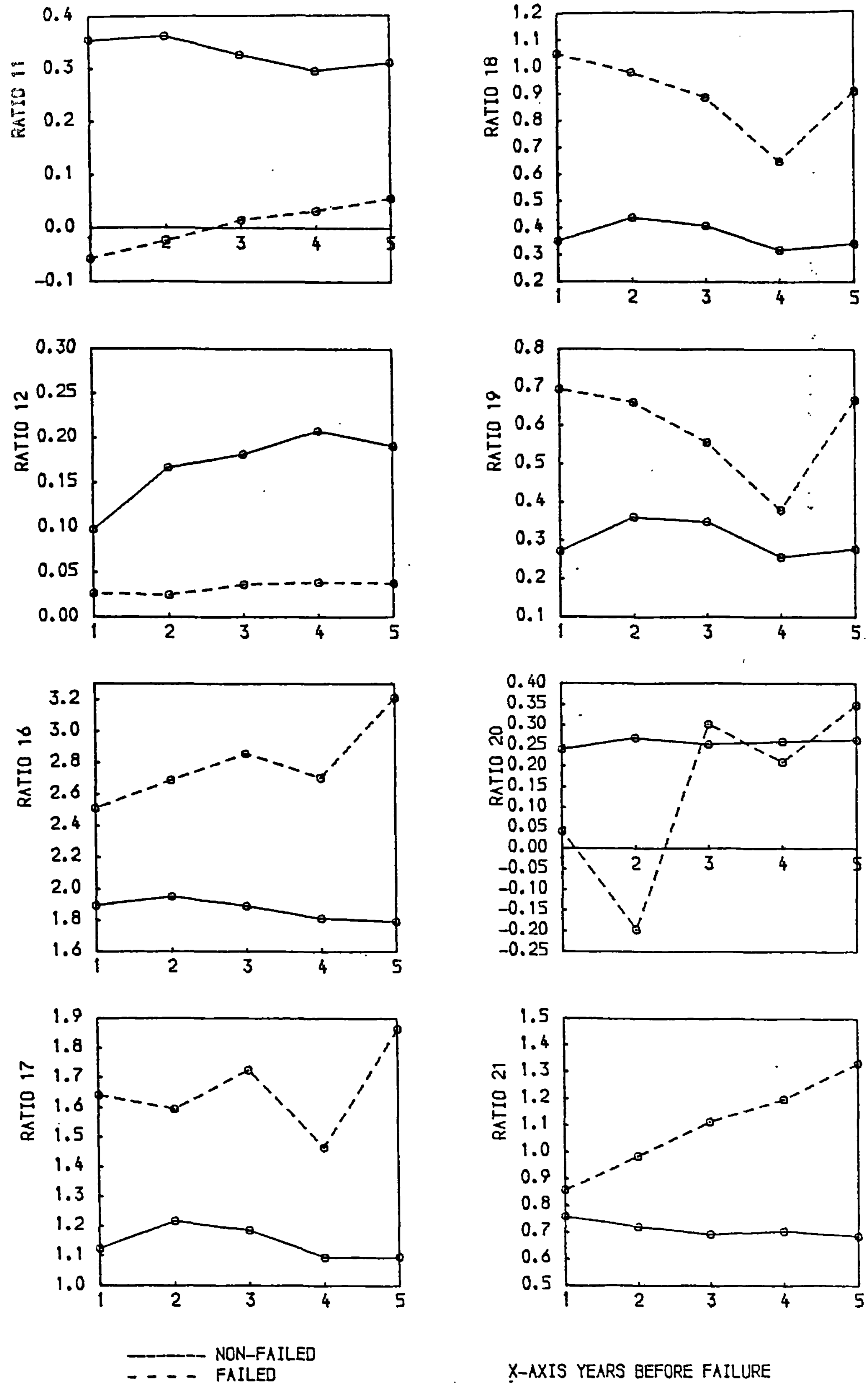


Figure C1 - continued

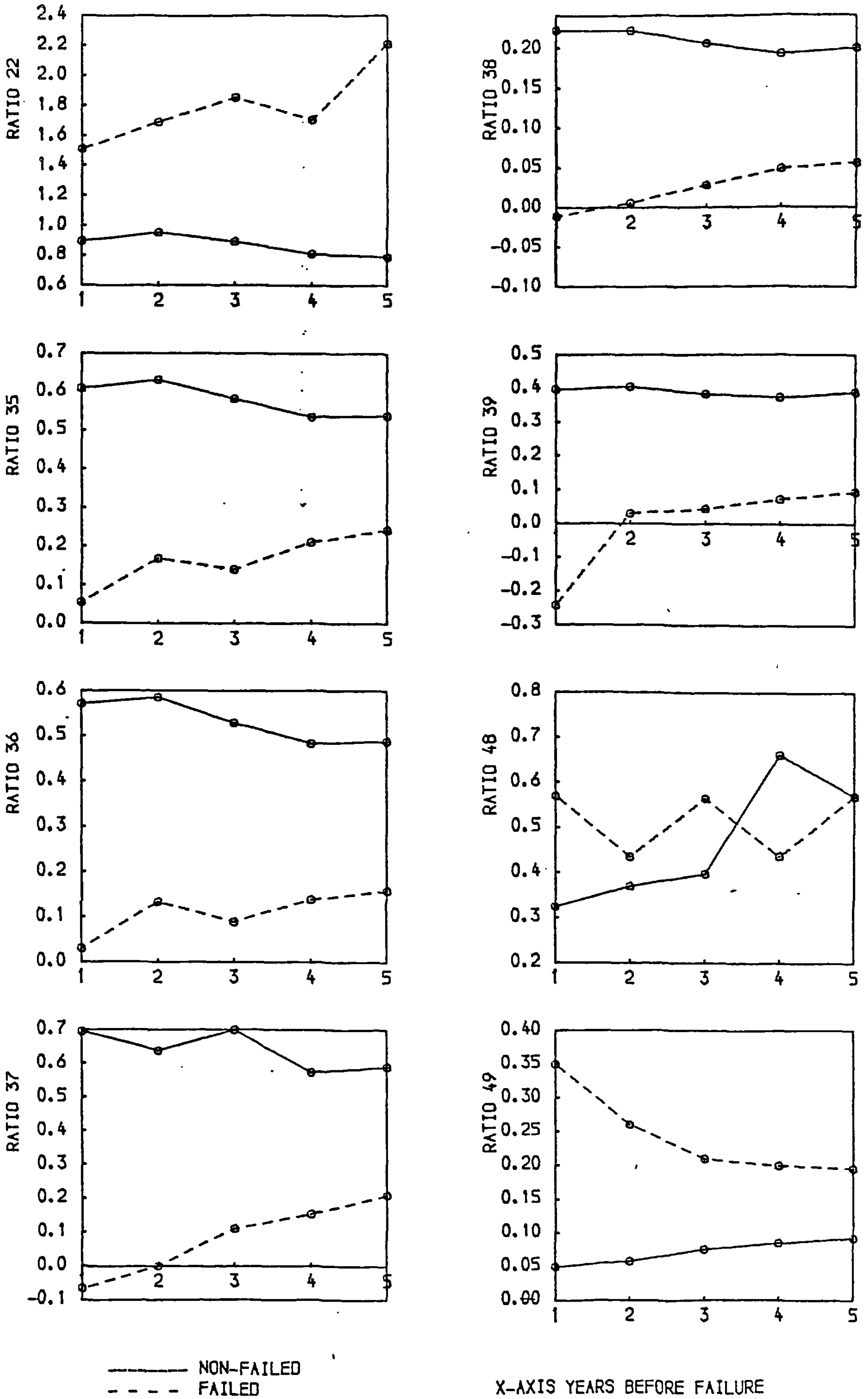


Figure C1 - continued

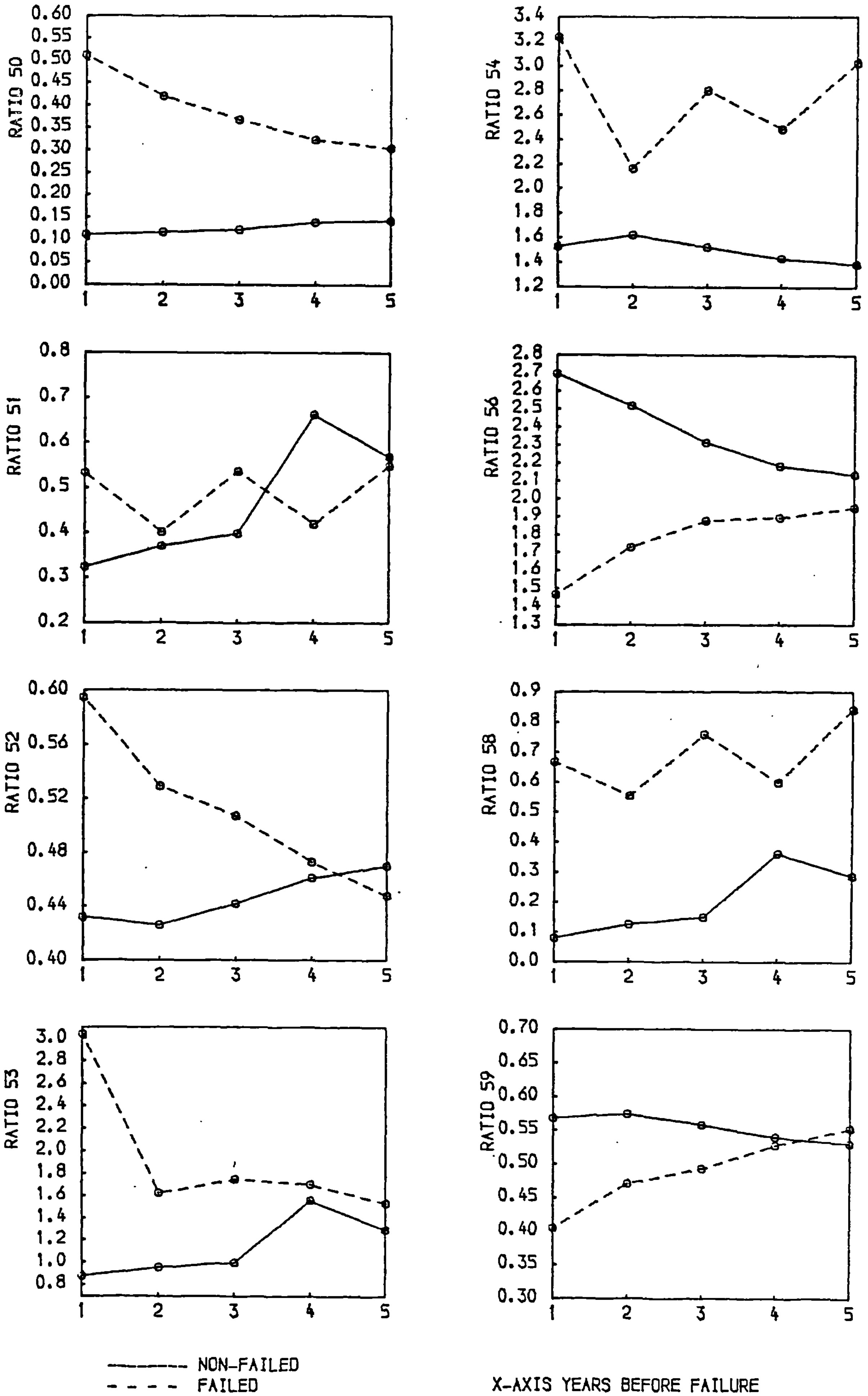


Figure C1 - continued

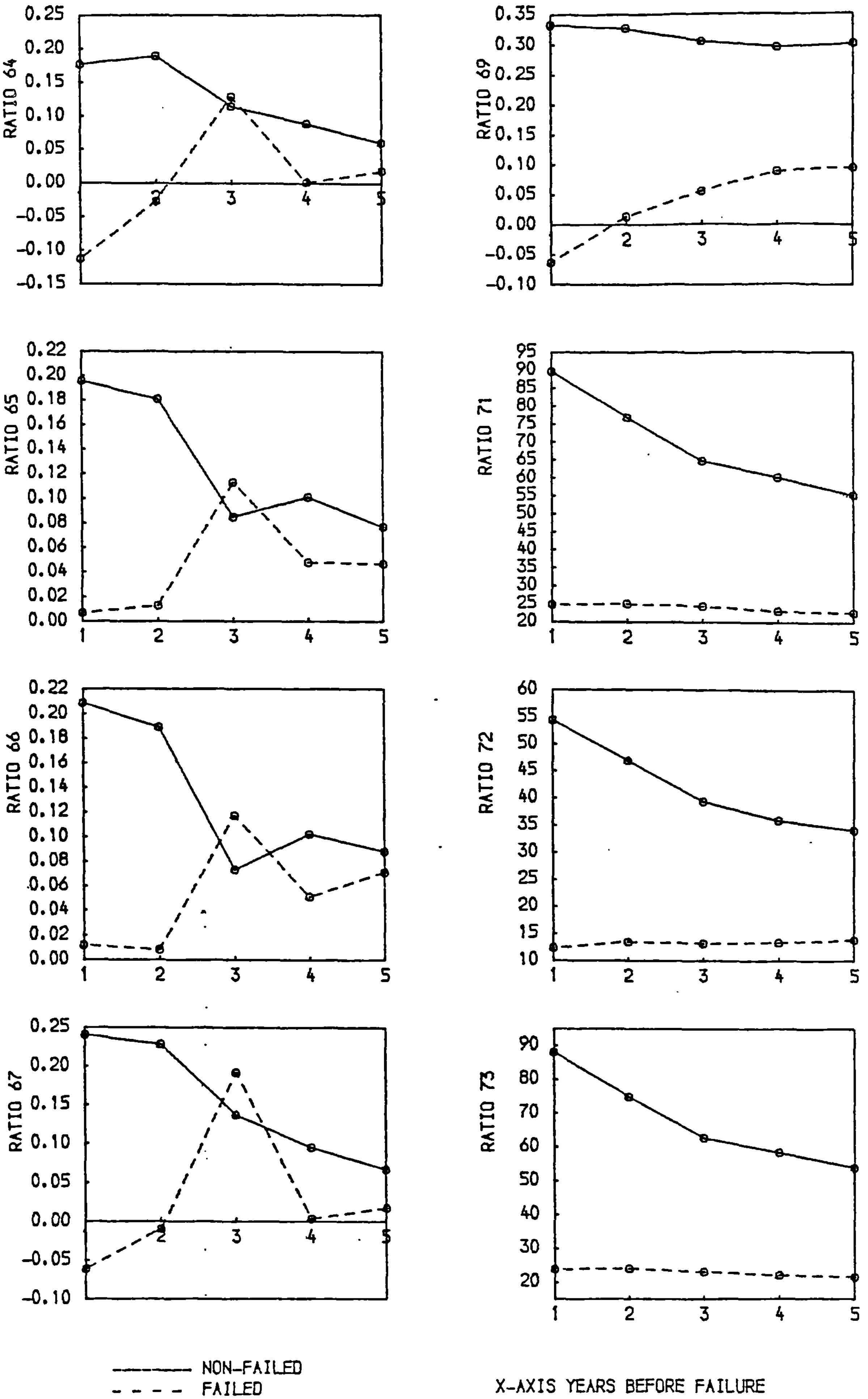


Figure C1 - continued

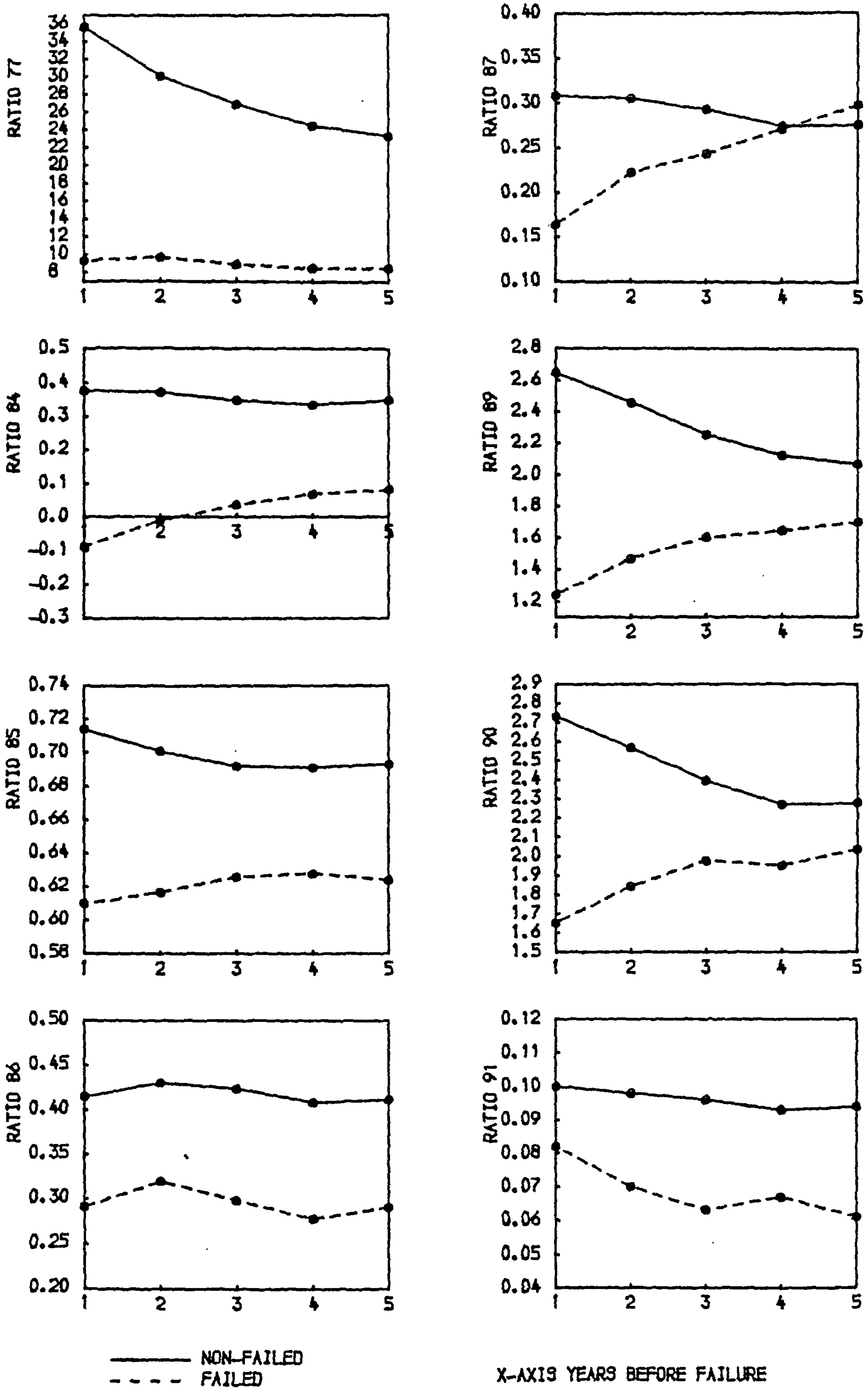


Figure C1 - continued

```
      APPENDIX  D  TESTS ØF NØRMALITY - CØMPUTER PRØGRAM
C     -----------  ------------------------------------
C
C
C
C        ***  APRØGRAM TØ CØMPUTE BØTH "W" AND "D" VALUES ***
C             ++++++++++++++++++++++++++++++++++++++++++
C
C     FRY =ARRAY ØF ACCOUNTING RATIØS(INPUT DATA)
C     X(N)= "    FØR EACH DISTRIBUTIØN A RATIØ
C     A   = "    STØRING THE TABULATED VALUES ØF THA CØNSTANT A
C     WT  = "       "    "     "      "    "  W
C     M01AJF IS A SUBRØUTINE FRØM THE NAG
C
      PRØGRAM(WTST1)
      INPUT 5=CR0
      INPUT 3=CR1
      INPUT 1=CR3
      ØUTPUT 6=LP0
      ØUTPUT 8=LP1
      ØUTPUT 4=LP2
      TRACE 2
      END
      MASTER TNØRM
      INTEGER N,N1,NW,IND(44),INDW(10),IFAIL
      REAL FRY(100,44),X1(44),X2(44),X3(44),X4(44),X5(44),X6(44)
      REAL X7(44),X8(44),X9(44),W(10),A(22,25),WT(25)
      KK=44
      KK1=KK-19
      DØ 150 J=1,25
150   READ(3,102)(A(I,J),I=1,22)
      DØ 160 J1=1,44
160   READ(5,101)(FRY(I1,J1),I1=1,100)
      READ(1,103)(WT(K2),K2=1,25)
      NV=0
      II=4
200   IFAIL=0
      N=KK
      NW=10
      II=II+1
      NV=NV+1
      DØ 5 J2=1,N
      IF(J2.GT.10) GØTØ 2
      INDW(J2)=0
      W(J2)=0.0
 2    IND(J2)=0
      X1(J2)=0.0
      X2(J2)=0.0
```

```
      X3(J2)=0.0
      X4(J2)=0.0
      X5(J2)=0.0
      X6(J2)=0.0
      X7(J2)=0.0
      X8(J2)=0.0
      X9(J2)=0.0
  5   CONTINUE
      N1=0
      N2=0
      N3=0
      N4=0
      N5=0
      DO 6 J3=1,N
      IF(FRY(II,J3).EQ.9.999) GOTO 6
      N1=N1+1
      X1(N1)=FRY(II,J3)
      X8(N1)=FRY(II,J3)+4.0
      X9(N1)=FRY(II,J3)+3.0
      IF(X8(N1).EQ.0.0) GOTO 1
      N2=N2+1
      X2(N2)=1.0/X8(N1)
  1   CONTINUE
      IF(X9(N1).EQ.0.0) GOTO 3
      N3=N3+1
      X3(N3)=1.0/X9(N1)
  3   CONTINUE
      IF(X8(N1).LE.0.0)GOTO 4
      N4=N4+1
      X4(N4)=ALOG(X8(N1))
      X5(N4)=SQRT(X8(N1))
  4   CONTINUE
      IF(X9(N1).LE.0.0) GOTO 6
      N5=N5+1
      X6(N5)=ALOG(X9(N1))
      X7(N5)=SQRT(X9(N1))
  6   CONTINUE
      IF(N1.LT.20) GOTO 500
      IF(N2.LT.20) GOTO 500
      IF(N3.LT.20) GOTO 500
      IF(N4.LT.20) GOTO 500
      IF(N5.LT.20) GOTO 500
C ** M01AJF SORST A VECTOR OF REAL NUMBERS INTO ASCENDING ORDER**
      CALL M01AJF(X1,W,IND,INDW,N1,NW,IFAIL)
      DO 7 M1=1,N
      IF(M1.GT.10)GOTO 7
      INDW(M1)=0
      W(M1)=0.0
  7   IND(M1)=0
      CALL M01AJF(X2,W,IND,INDW,N2,NW,IFAIL)
```

```
      DØ 8 M2=1,N
      IF(M2.GT.10) GØTØ 8
      INDW(M2)=0
      W(M2)=0.0
 8    IND(M2)=0
      CALL M01AJF(X3,W,IND,INDW,N3,NW,IFAIL)
      DØ 9 M3=1,N
      IF(M3.GT.10) GØTØ 9
      INDW(M3)=0
      W(M3)=0.0
 9    IND(M3)=0
      CALL M01AJF(X4,W,IND,INDW,N4,NW,IFAIL)
      DØ 14 M4=1,N
      IF(M4.GT.10) GØTØ 14
      INDW(M4)=0
      W(M4)=0.0
 14   IND(M4)=0
      CALL M01AJF(X5,W,IND,INDW,N4,NW,IFAIL)
      DØ 17 M5=1,N
      IF(M5.GT.10) GØTØ 17
      INDW(M5)=0
      W(M5)=0.0
 17   IND(M5)=0
      CALL M01AJF(X6,W,IND,INDW,N5,NW,IFAIL)
      DØ 18 M6=1,N
      IF(M6.GT.10) GØTØ 18
      INDW(M6)=0
      W(M6)=0.0
 18   IND(M6)=0
      CALL M01AJF(X7,W,IND,INDW,N5,NW,IFAIL)
      K1=N1/2
      K2=N2/2
      K3=N3/2
      K4=N4/2
      K5=N5/2
      SUM1=0.0
      SUM2=0.0
      SUM3=0.0
      SUM4=0.0
      SUM5=0.0
      SUM6=0.0
      SUM7=0.0
      SUMSQ1=0.0
      SUMSQ2=0.0
      SUMSQ3=0.0
      SUMSQ4=0.0
      SUMSQ5=0.0
      SUMSQ6=0.0
0
      SUMSQ7=0.0
```

```
B1=0.0
B2=0.0
B3=0.0
B4=0.0
B5=0.0
B6=0.0
B7=0.0
BS1=0.0
BS2=0.0
BS3=0.0
BS4=0.0
BS5=0.0
BS6=0.0
BS7=0.0
SS1=0.0
SS2=0.0
SS3=0.0
SS4=0.0
SS5=0.0
SS6=0.0
SS7=0.0
T1=0.0
T2=0.0
T3=0.0
T4=0.0
T5=0.0
T6=0.0
T7=0.0
D1=0.0
D2=0.0
D3=0.0
D4=0.0
D5=0.0
D6=0.0
D7=0.0
CW1=0.0
CW2=0.0
CW3=0.0
CW4=0.0
CW5=0.0
CW6=0.0
CW7=0.0
SG1=0.0
SG2=0.0
SG3=0.0
SG4=0.0
SG5=0.0
SG6=0.0
SG7=0.0
DO 10 J5=1,N1
```

```
      SUM1=SUM1+X1(J5)
      SUMSQ1=SUMSQ1+(X1(J5)*X1(J5))
      T1=T1+(FLOAT(J5)-((FLOAT(N1)+1.0)/2.0))*X1(J5)
      IF(J5.GT.N2) GOTO 10
      SUM2=SUM2+X2(J5)
      SUMSQ2=SUMSQ2+(X2(J5)*X2(J5))
      T2=T2+(FLOAT(J5)-((FLOAT(N2)+1.0)/2.0))*X2(J5)
      IF(J5.GT.N3) GOTO 10
      SUM3=SUM3+X3(J5)
      SUMSQ3=SUMSQ3+(X3(J5)*X3(J5))
      T3=T3+(FLOAT(J5)-((FLOAT(N3)+1.0)/2.0))*X3(J5)
      IF(J5.GT.N4) GOTO 10
      SUM4=SUM4+X4(J5)
      SUMSQ4=SUMSQ4+(X4(J5)*X4(J5))
      T4=T4+(FLOAT(J5)-((FLOAT(N4)+1.0)/2.0))*X4(J5)
      SUM5=SUM5+X5(J5)
      SUMSQ5=SUMSQ5+(X5(J5)*X5(J5))
      T5=T5+(FLOAT(J5)-((FLOAT(N4)+1.0)/2.0))*X5(J5)
      IF(J5.GT.N5) GOTO 10
      SUM6=SUM6+X6(J5)
      SUMSQ6=SUMSQ6+(X6(J5)*X6(J5))
      T6=T6+(FLOAT(J5)-((FLOAT(N5)+1.0)/2.0))*X6(J5)
      SUM7=SUM7+X7(J5)
      SUMSQ7=SUMSQ7+(X7(J5)*X7(J5))
      T7=T7+(FLOAT(J5)-((FLOAT(N5)+1.0)/2.0))*X7(J5)
10    CONTINUE
      IF(SUMSQ1.EQ.0.0) GOTO 600
      SS1=SUMSQ1-((SUM1*SUM1)/FLOAT(N1))
      SS2=SUMSQ2-((SUM2*SUM2)/FLOAT(N2))
      SS3=SUMSQ3-((SUM3*SUM3)/FLOAT(N3))
      SS4=SUMSQ4-((SUM4*SUM4)/FLOAT(N4))
      SS5=SUMSQ5-((SUM5*SUM5)/FLOAT(N4))
      SS6=SUMSQ6-((SUM6*SUM6)/FLOAT(N5))
      SS7=SUMSQ7-((SUM7*SUM7)/FLOAT(N5))
      AN1=0.0
      AN2=0.0
      AN3=0.0
      AN4=0.0
      AN5=0.0
      AN6=0.0
      AN7=0.0
      AN1=SS1*(FLOAT(N1)**3)
      AN2=SS2*(FLOAT(N2)**3)
      AN3=SS3*(FLOAT(N3)**3)
      AN4=SS4*(FLOAT(N4)**3)
      AN5=SS5*(FLOAT(N4)**3)
      AN6=SS6*(FLOAT(N5)**3)
      AN7=SS7*(FLOAT(N5)**3)
      D1=T1/(SQRT(AN1))
      D2=T2/(SQRT(AN2))
```

```
      D3=T3/(SQRT(AN3))
      D4=T4/(SQRT(AN4))
      D5=T5/(SQRT(AN5))
      D6=T6/(SQRT(AN6))
      D7=T7/(SQRT(AN7))
      L1=0
      L2=0
      L3=0
      L4=0
      L5=0
      IA=N1-19
      IB=N2-19
      IC=N3-19
      ID=N4-19
      IE=N5-19
      DO 12 L=1,K1
      L1=N1-L+1
      L2=N2-L+1
      L3=N3-L+1
      L4=N4-L+1
      L5=N5-L+1
      B1=B1+(A(L,IA)*(X1(L1)-X1(L)))
      IF(L.GT.K2) GOTO 12
      B2=B2+(A(L,IB)*(X2(L2)-X2(L)))
      IF(L.GT.K3) GOTO 12
      B3=B3+(A(L,IC)*(X3(L3)-X3(L)))
      IF(L.GT.K4) GOTO 12
      B4=B4+(A(L,ID)*(X4(L4)-X4(L)))
      B5=B5+(A(L,ID)*(X5(L4)-X5(L)))
      IF(L.GT.K5) GOTO 12
      B6=B6+(A(L,IE)*(X6(L5)-X6(L)))
      B7=B7+(A(L,IE)*(Y7(L5)-X7(L)))
12    CONTINUE
      BS1=B1*B1
      BS2=B2*B2
      BS3=B3*B3
      BS4=B4*B4
      BS5=B5*B5
      BS6=B6*B6
      BS7=B7*B7
      CW1=BS1/SS1
      CW2=BS2/SS2
      CW3=BS3/SS3
      CW4=BS4/SS4
      CW5=BS5/SS5
      CW6=BS6/SS6
      CW7=BS7/SS7
      SG1=CW1-WT(IA)
      SG2=CW2-WT(IB)
      SG3=CW3-WT(IC)
```

```
      SG4=CW4-WT(ID)
      SG5=CW5-WT(ID)
      SG6=CW6-WT(IE)
      SG7=CW7-WT(IE)
      GOTØ 550
500   CW1=.999
      CW2=.999
      CW3=.999
      CW4=.999
      CW5=.999
      CW6=.999
      CW7=.999
      SG1=.999
      SG2=.999
      SG3=.999
      SG4=.999
      SG5=.999
      SG6=.999
      SG7=.999
      D1=.999
      D2=.999
      D3=.999
      D4=.999
      D5=.999
      D6=.999
      D7=.999
 550  WRITE(6,306) T1,T2,T3,T4,T5,T6,T7
      WRITE(4,206)NV,N1,D1,N2,D2,N3,D3,N4,D4,N4,D5,N5,D6,N5,D7
      WRITE(8,106)NV,N1,CW1,SG1,N2,CW2,SG2,N3,CW3,SG3,N4,CW4,SG4,
     &N4,CW5,SG5,N5,CW6,SG6,N5,CW7,SG7
      GOTØ 560
600   WRITE(4,601)
      WRITE(8,501)
560   IF(II.LT.100) GØTØ 200
      STØP
101   FØRMAT(F5.0,F8.0,2F5.0/5(8F10.5/),5F10.2,3F10.5/6F10.5,F10.4,
     1F10.5/8F10.5/6F10.5,2F10.1/7F10.1,F10.5,/2(8F10.5/))
102   FØRMAT(11F7.4,/11F7.4)
103   FØRMAT(5F6.3)
105   FØRMAT(3X,6F6.3)
106   FØRMAT(I3,7(I3,1X,F4.3,1X,F5.3,2X))
206   FØRMAT(I3,7(I4,2X,F7.4))
108   FØRMAT(1X,8F12.5)
207   FØRMAT(/)
306   FØRMAT(1X,7F12.6)
601   FØRMAT(1X,11H SUMSQ1=0.0)
      END
      FINISH
EJ
****
```

****

APPENDX E   RESDIUAL ANALYSIS - COMPYTER PROGRAMS

```
C              ***  PROGRAM E1 : PRICE RELATIVES  ****
C
C
C        *****   A PROGRAM TO COMPUTE PRICE AND MARKET RELATIVES  *****
C
C       THE AGE OF EACH PRICE IS COMPUTED,EXCLUDING WEEKENDS AND HOLIDAYS,
C                  TO ACCOUNT FOR NONTRADING(FISHER) EFFECT
C                 +++++++++++++++++++++++++++++++++++++++++
C
C        MIN   =    -1 AND INDICATES A BEGNING OF A NEW COMPANY'S DATA
C        DESC  =    ARRAY FOR DESCRIPTIVE DATA
C        CAP   =      "    "  CAP. CHANGES
C        DIV   =      "    "  DIVIDENDS
C        PV    =      "    "  PAR VALUES
C        PRI   =      "    "  PRICES
C        SHCP  =      "    "  SHARE CAP
C        EPS   =      "    "  EARNINGS PER SHARE
C        NDESC= NO. OF DESCRIPTIVE SUB RECORDS
C        NCAP =    "   CAP. CHANGES "    "
C        NDIV =    "   DIVIDEND     "    "
C        NPV  =    "   PAR VALUE    "    "
C        NPRI =    "   PRICES       "    "
C        NSHCP=    "   SHARE CAP. - "    "
C        NEPS =    "   EARN. PER SH "    "
C       ----------------------------------------
C
C        RIT   = ARRAY FOR OUTPUT DATA ( PRICE RELATIVES)
C        FTA   =    "     "  DAILY MARKET INDEX
C        CD    =    "     ".  FAILURE ANNOUNCEMENT DATES
C
C        ********************************************
C
      PROGRAM(SAMEH)
      INPUT 5=CR0
      INPUT 3=CR1
      INPUT 1=CR2
      OUTPUT 6=LP0
      OUTPUT 2=LP1
      OUTPUT 4=LP2
      TRACE 2
      END
      MASTER TEST
      INTEGER DESC(61),PV(3,5),SHCP(2,20),EPS(4,20)
      REAL CAP(14,16),DIV(11,71),PRI(10,240),RIT(9,240),FTA(2,7305)
```

```
      REAL CD(2,21)
      READ(1,101)((CD(I,J),I=1,2),J=1,21)
      READ(3,303)((FTA(I,J),I=1,2),J=1,7305)
100   READ(5,901) MIN,NDESC,NCAP,NDIV,NPV,NPRI,NSHCP,NEPS
303   FORMAT(F6.0,F7.2)
      IF (NDESC.LT.1) GOTO 90
      READ(5,902) (DESC(J),J=1,61)
      IF(NCAP.GT.0) READ(5,903)((CAP(I,J),I=1,14),J=1,NCAP)
      IF (NDIV.GT.0) READ(5,904)((DIV(I,J),I=1,11),J=1,NDIV)
      IF (NPV.GT.0) READ(5,905)((PV(I,J),I=1,3),J=1,NPV)
      IF (NPRI.GT.0) READ(5,906)((PRI(I,J),I=1,10),J=1,NPRI)
      IF (NSHCP.GT.0) READ(5,907)((SHCP(I,J),I=1,2),J=1,NSHCP)
      IF (NEPS.GT.0) READ(5,908)((EPS(I,J),I=1,4),J=1,NEPS)
101   FORMAT(2F5.0)
      IF(NPRI.LT.70) GOTO 100
      DLQ=0.0
      DO 445 I=1,21
      IF(DESC(1).EQ.CD(1,I)) GOTO 444
      GOTO 445
444   DLQ=CD(2,I)
      GOTO 448
445   CONTINUE
448   IF(DLQ.EQ.0.0) GOTO 100
      NCASES=0
      NC=NPRI-1
      KK=1
      IF((PRI(3,1)-55.0).GT.0.0) KK=(PRI(3,1)-55.0)*350.0
      LL=KK+600
      DO 2 J=1,NPRI
      PRID=PRI(2,J)*100.0+PRI(3,J)
      IF(PRID.EQ.DLQ) GOTO 447
      NCASES=NCASES+1
      PRIM=PRI(3,J)*10000.0+PRI(2,J)*100.0+PRI(1,J)
      PRIM1=PRIM
      IF(PRI(7,J).GT.0.0) PRIM1=PRI(9,J)*10000.0+PRI(8,J)*100.0+PRI(7,J)
      RIT(1,J)=PRIM1
      D=1.0
      N=0
      DO 3 I=KK,LL
      II=I
      IF(FTA(2,I).LT.0.0) GOTO 3
      IF(RIT(1,J).EQ.FTA(1,I)) GOTO 40
      GOTO 3
40    RIT(3,J)=FTA(2,I)
      IF(PRIM.NE.PRIM1) GOTO 50
      GOTO 333
50    M=II+449
      DO 4 K=II,M
      IF(FTA(2,K).LT.0.0) GOTO 4
      N=N+1
```

```
      IF(FTA(1,K).EQ.PRIM) GOTO 14
      GOTO 4
 14   D=FLOAT(N)-1.0
      GOTO 51
 4    CONTINUE
 51   RIT(4,J)=D
 333  KK=II
      LL=KK+499
      GOTO 222
 3    CONTINUE
 222  WRITE(2,3003) KK
      RIT(2,J)=PRI(6,J)
      RIT(9,J)=RIT(3,J)
 2    CONTINUE
 447  NPRI=NCASES
      WRITE(2,444)(RIT(3,I),I=1,NPRI)
      IF(NDIV.GT.0) GOTO 110
      GOTO 125
 110  DO 5 J=1,NDIV
      DIVM=DIV(2,J)*100.0+DIV(3,J)
      DO 6 I=1,NPRI
      PRIMT=PRI(2,I)*100.0+PRI(3,I)
      IF(DIVM.EQ.PRIMT) RIT(2,I)=RIT(2,I)+(DIV(5,J)*DIV(6,J)/10000.0)
 6    CONTINUE
 5    CONTINUE
 125  IF(NCAP.GT.0) GOTO 150
      DO 7 I=2,NPRI
      IF(PRI(6,I-1).EQ.0.0) GOTO 33
      IF(RIT(2,I).EQ.0.0) GOTO 33
      RIT(5,I)=RIT(2,I)/PRI(6,I-1)
      GOTO 7
 33   RIT(5,I)=999.999
7     CONTINUE
      GOTO 200
 150  DO 15 J=2,NCAP
      CM=CAP(2,J-1)*100.0+CAP(3,J-1)
      IF(NCAP.EQ.1) GOTO 160
      IF(CAP(5,J).GT.50.0) GOTO 77
      GOTO 160
 77   CAP(4,J-1)=(CAP(4,J-1)*CAP(4,J))/10000.0
      CM=1.0
 160  DO 30 I=2,NPRI
      PRIMS=PRI(2,I-1)*100.0+PRI(3,I-1)
      IF(PRI(6,I-1).EQ.0.0) GOTO 36
      IF(CM.EQ.PRIMS) PRI(6,I-1)=(PRI(6,I-1)*CAP(4,J-1))/1000.0
      IF(RIT(2,I).EQ.0.0) GOTO 36
      RIT(5,I)=RIT(2,I)/PRI(6,I-1)
      GOTO 30
 36   RIT(5,I)=999.999
 30   CONTINUE
```

```
  15   CONTINUE
 200   DØ 500 I=2,NPRI
       IF(RIT(5,I).EQ.999.999) GØTØ 55
       IF(RIT(4,I).EQ.0.0) GOTO 55
       RIT(6,I)=RIT(5,I)/RIT(4,I)
       GØTØ 56
  55   RIT(6,I)=RIT(5,I)
  56   RIT(9,I)=RIT(9,I)/RIT(3,I-1)
       IF(RIT(4,I).EQ.0.0) GOTO 57
       RIT(7,I)=RIT(9,I)/RIT(4,I)
       RIT(8,I)=RIT(3,I)/RIT(4,I)
       GØTØ 500
  57   RIT(7,I)=RIT(9,I)
       RIT(8,I)=RIT(3,I)
 500   CONTINUE
       WRITE(6,3003) NCASES
       WRITE(6,5002)((RIT(I,J),I=1,8),J=2,NPRI)
       WRITE(4,5002)((RIT(I,J),I=1,8),J=2,NPRI)
       WRITE(2,5005) DESC(1),NCASES
       DØ 80 J=1,10
       DØ 85 I=1,NPRI
       IF(J.GT.7) GØTØ 88
  85   RIT(I,J)=0.0
  88   PRI(I,J)=0.0
  80   CONTINUE
       GØTØ 100
  90   WRITE(6,1011)
       STØP
 901   FØRMAT(I2,7I4)
 902   FØRMAT(I4,3I3,2I2,I4,I2,I4,I2,2I5,2I6/,I6,2I2,
      F3I4,2I6,I7,I4,I6,I2/,I4,I3,4I5,I3,6A4/,12A4,I4/,9I6)
 1011 FØRMAT(///)
 444   FØRMAT(1X,10F8.4)
903    FØRMAT(3F2.0,F6.0,2F2.0,F1.0,F6.0,6F5.0)
904    FØRMAT(3F2.0,3F6.0,4F2.0,F6.0)
905    FØRMAT(I6,I2,I6)
906    FØRMAT(3F2.0,3F6.0,4F2.0)
907    FØRMAT(I2,I8)
908    FØRMAT(I2,3I4)
3003   FØRMAT(I6)
5002   FØRMAT(1X,F8.0,7F10.4)
5005   FØRMAT(I7,5X,I7)
912    FØRMAT(2X,6H CØMNØ,5X,7H NCASES)
916    FØRMAT(2X,4F10.3)
       END
       FINISH
EJ
****
```

`*********************************************************************************************`

```
C                         ***      PRØGRAM E2      ****
C
C
C        *****   A PRØGRAM TØ EXCLUDE PRICE RELATIVES ØF ANY MONTH
C                     WITH OUTLIER RESIDUALS                            ******
C                  +++++++++++++++++++++++++++++
C
C        RIT   = INPUT  ARRAY ØF PRICE RELATIVES
C        RIT1 = ØUTPUT   "    "     "          "   EXCLUDING ØUTLIERS
C        CØEF = INPUT     "    "  ESTIMATED CØEFFICIENTS  USING ALL DATA
C        RES  = ARRAY ØF  CØMPUTED RESIDUALS
C        RESSQ=    "    "  SQUARE       "
C
C        *********************************************
C
      PRØGRAM(FADI2)
      INPUT 5=CR0
      INPUT 3=CR1
      OUTPUT 6=LP0
      ØUTPUT 8=LP1
      ØUTPUT 4=LP2
      TRACE 2
      END
      MASTER RSDEX
      DIMENSION RIT(3,239),RIT1(3,239),CØEF(2),RES(239),RESSQ(239)
  100 READ(5,101)NNN
      N=NNN-1
      IF(NNN.EQ.0) GOTØ 50
      READ(5,102)((RIT(I,J),I=1,3),J=1,N)
      READ(3,103)(COEF(I),I=1,2)
      L=0
C
      DØ 6 I=1,N
      IF(RIT(2,I).EQ.999.999) GOTØ 5
      L=L+1
      RES(I)=ALOG(RIT(2,I))-(CØEF(1)+CØEF(2)*ALØG(RIT(3,I)))
C
      RESSQ(I)=RES(I)*RES(I)
      GØTØ 6
    5 RES(I)=999.999
    6 CØNTINUE
      SUM=0.0
      SUMQ=0.0
      DØ 200 I=1,N
      IF(RES(I).EQ.999.999) GØTØ 200
      SUM=SUM+RES(I)
      SUMQ=SUMQ+RESSQ(I)
  200 CØNTINUE
      AMEAN=SUM/FLØAT(L)
      BMEAN=SUMQ/FLØAT(L)
```

```
      VAR=BMEAN-(AMEAN*AMEAN)
      STD=SQRT(VAR)
      WRITE(6,108)L,STD,VAR
      D=-2.0
      K= 0
      DO 300 I=1,N
      IF(RES(I).EQ.999.999) GOTO 333
      IF(RES(I).GT.(STD*2.0)) GOTO 300
      IF(RES(I).LT.(STD)*D) GOTO 300
  333 RIT1(1,I)=RIT(1,I)
      RIT1(2,I)=RIT(2,I)
      RIT1(3,I)=RIT(3,I)
      K=K+1
  300 CONTINUE
      WRITE(4,104)K
      WRITE(4,106)((RIT1(I,J),I=1,3),J=1,N)
      WRITE(8,106)((RIT1(I,J),I=1,3),J=1,N)
      WRITE(6,107)K,STD
C
      DO 500 I=1,3
      DO 550 J=1,N
550   RIT1(I,J)=0.0
500   CONTINUE
      GOTO 100
C
 50   STOP
 101  FORMAT(I5)
 102  FORMAT(F8.0,40X,2F10.4)
 103  FORMAT(2F8.5)
 104  FORMAT(I6)
 106  FORMAT(1X,F8.0,2F10.4)
 107  FORMAT(I6,F10.6)
 108  FORMAT(I6,2F10.6)
      END
      FINISH
EJ
****
```

****

```
C                        ***      PROGRAM E3      ****
C
C
C       ***   A PROGRAM TO COMPUTE AR,CAR,API FOR RESIDUAL ANALYSIS ***
C                  ++++++++++++++++++++++++++++++
C
C         RIT  = INPUT  ARRAY OF PRICE RELATIVES
C         COEF = INPUT     "    "  ESTIMATED COEFFICIENTS,EXCLUDING 18 MONTHS
C         RES  = ARRAY OF  COMPUTED 84 RESIDUALS FOR EACH OF THE SECURITIES
C         CAR  =    "    "  CAR
C         KK   =    "    "  NOMBER OF OBSERVATIONS FOR EACH AVERAGE RESIDUAL
C         KK1  =    "    "  THE NUMBER OF EACH OF THE 84 MONTHS RELATIVE TO MONT
C         AMEAN =    "    "  AVEARGE RESIDUALS
C         DD   = ASTORING ARRAY FOR THE COMPUTATION OF API
C         API  = ARRAY OF API
C       ++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
C
      PROGRAM(FADI2)
      INPUT 5=CR0
      INPUT 3=CR1
      INPUT 7=CR3
      OUTPUT 6=LP0
      OUTPUT 2=LP1
      OUTPUT 8=LP3
      TRACE 2
      END
      MASTER PSDAN
      DIMENSION RIT(2,239),COEF(2),RES(84,21),AM(84),CAR(84),KK(84)
      DIMENSION DD(20),API(84),KK1(84),ST(84),SK(84)
      M=0
 100  N=0
      READ(7,101)NNN
      N=NNN-1
      IF(NNN.EQ.0) GOTO 50
      READ(5,102)((RIT(I,J),I=1,2),J=1,N)
      M=M+1
      L=N-84
      IF(N.LE.84) L=0
      READ(3,103)(COEF(I),I=1,2)
C
      LL=84
      WRITE(6,101)N
      DO 5 J=M,M
      DO 6 I=1,LL
      IF(I.LE.(LL-N)) GOTO 7
      L=L+1
      IF(RIT(1,L).EQ.999.999) GOTO 7
      RES(I,J)=ALOG(RIT(1,L))-(COEF(1)+COEF(2)*ALOG(RIT(2,L)))
      GOTO 6
    7 RES(I,J)=999.999
```

```
    6  CØNTINUE
    5  CONTINUE
       WRITE(2,303)(CØEF(I),I=1,2)
C
       DØ 400 J=1,N
       DØ 401 I=1,2
  401  RIT(I,J)=0.0
  400  CØNTINUE
C
       GØTØ 100
   50  CØNTINUE
       DØ 200 I=1,LL
       K=0
       SUM=0.0
       SUM2=0.0
       SUM3=0.0
       DØ 300 J=1,20
       IF(RES(I,J).EQ.999.999) GØTØ 300
       SUM=SUM+RES(I,J)
       SUM2=SUM2+(RES(I,J)*RES(I,J))
       K=K+1
  300  CØNTINUE
       AM(I)=SUM/FLØAT(K)
       KK(I)=K
       ST(I)=SQRT((SUM2-(AM(I)*AM(I)*FLØAT(K)))/FLØAT(K-1))
       DØ 350 J1=1,20
       SUM3=SUM3+((RES(I,J1)-AM(I))/ST(I))*((RES(I,J1)-AM(I))/ST)**2.0
  350  CØNTINUE
  200  CØNTINUE
       CC=0.0
       DØ 700 I=1,LL
       CC=CC+AMEAN(I)
  700  CAR(I)=CC
C
C
       K5=-LL
       DØ 1 J=1,20
    1  DD(J)=1.0
       DØ 2 I=1,LL
       K1=0
       CC=0.0
       K5=K5+1
       KK1(I)=K5
       DØ 3 J=1,20
C
C
       IF(RES(I,J).EQ.999.999) GØTØ 3
       DD(J)=DD(J)*(1.0+RES(I,J))
       CC=CC+DD(J)
       K1=K1+1
```

```
    3 CONTINUE
      API(I)=CC/FLOAT(K1)
    2 CONTINUE
C
      N1=1
      N2=7
      N3=M
      WRITE(6,101)M
   51 WRITE(6,106)((RES(I,J),I=N1,N2),J=1,N3)
      WRITE(6,111)
  111 FORMAT(/,4H AR.)
C
      WRITE(6,106)(AM(I),I=N1,N2)
      WRITE(6,107)
      N1=N1+7
      N2=N2+7
      IF(N2.GT.LL) GOTO 55
      GOTO 51
   55 WRITE(6,110)
      WRITE(6,109)(KK1(I),AM(I),CAR(I),API(I),KK(I),I=1,LL)
      WRITE(2,109)(KK1(I),AM(I),CAR(I),API(I),KK(I),I=1,LL)
      WRITE(8,105)(KK1(I),AM(I),CAR(I),KK(I),ST(I),SK(I),I=1,LL)
      STOP
  101 FORMAT(I5)
  102 FORMAT(48X,2F10.4)
  103 FORMAT(2F8.5)
  303 FORMAT(2X,2F8.5)
  106 FORMAT(1X,7F11.5)
  107 FORMAT(//)
  109 FORMAT(5X,I7,3F12.5,I7)
  105 FORMAT(5X,I7,3F12.5,I7,2F12.5)
  110 FORMAT(/,7X,6H MONTH,5X,4H AR.,8X,4H CAR,8X,4H API,4X,5H SECS,/)
      END
      FINISH
EJ
****
```

```
*******************************************************************************************
```

BIBLIOGRAPHY

Abramowitz, Milton and Stegun, Irene A. (eds.) (1972), Handbook of Mathematical Functions, Ninth Printing (New York: Dover Publishing, Inc.).

Accounting Standard Steering Committee (ASSC) (1975), The Corporate Report, A discussion paper by the Comittee, ICAEW, London (October).

Altman, Edward I. (1968), "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy", Journal of Finance, Vol.23, No.4 (September), pp.589-609.

Altman, Edward I. (1970), "A Reply", Journal of Finance, Vol.25, No.5, (December), pp.1169-72.

Altman, Edward I. (1971) Corporate Bankruptcy in America, (Lexington, Mass.: Heath Lexington Books).

Altman, Edward I. (1973), "Predicting Railroad Bankruptcy in America", Bell Journal of Economics and Management Science, Vol.4, part 1, (Spring), pp.184-211.

Altman, Edward I. (1977), "The z-score Bankruptcy Model: Past, Present, and Future", in Altman, E.I. and Sametz, A.W. (Eds.), Financial Crises, (New York: John Wiley & Sons), pp.89-108.

Altman, Edward I. (1977a), "Predicting Performance in the Savings and Loan Association Industry", Journal of Monetary Economics, Vol.3 (July), pp.443-466.

Altman, E.I. and Brenner, M. (1976), "Information Effects and Stock Market Response to Signs of Firm Deterioration", Salomon Brothers Center for the Study of Financial Institutions, Working Paper, No.75, May.

Altman, E.I. and Loris, B. (1976), "A Financial Early Warning System for Over-the-Counter Broker-Dealers", Journal of Finance, Vol.31, No.4 (September), pp.1201-17.

Altman, E., Haldeman, P., and Narayaman, P. (1977), "ZETA Analysis: A new model to identify bankruptcy risk of corporations", Journal of Banking and Finance, Vol.1, pp.29-54.

Altman, E., Margaine, Schlosser, and Vernimmen, P. (1974), "Financial and Statistical Analysis for Commercial Loan Evaluation: A French Experience," Journal of Financial and Quantitative Analysis, Vol.9, part 2, pp.195-211.

Altman, E. and McGough, T. (1974), "Evaluation of a Company as a Going Concern, Journal of Accountancy,Vol. 138, No.6 (December), pp.50-57.

American Accounting Association (AAA) (1966), A Statement of Basic Accounting Theory, by the Committee to Prepare a Statement of Basic Accounting Theory (N.Y.: AAA).

American Institute of Certified Public Accountants (AICPA) (1973), Objectives of Financial Statement, Report of the Trueblood Study Group, (N.Y.: AICPA, October).

Archibald, T.R. (1972), "Stock Market Reaction to the Depreciation Switch-Back", The Accounting Review, Vol.47, No.1 (January), pp.22-30.

Argenti, John (1976), Corporate Collapse - the Causes and Symptoms, (London: McGraw-Hill Book Co).

Ball, R. and Brown, P. (1968), "An Empirical Evaluation of Accounting Income Numbers", Journal of Accounting Research, Vol.6, (Autumn), pp.300-323.

Baran, A., Lakonishak, J. and Ofer, A.R. (1980), "The Information Content of General Price Level Adjusted Earnings: Some Empirical Evidence", The Accounting Review, Vol.55, No.1, (January), pp.22-35.

Barna, Tibor (1962), Investment and Growth Policies in British Industrial Firms, (Cambridge: Cambridge University Press).

Baskin, E.F. (1972), "The Communicative Effectiveness of Consistency Exceptions", The Accounting Review, Vol.47, No.1, (January), pp.38-51.

Basu, S. (1977), Inflation Accounting, Capital Market Efficiency and Security Prices, The Society of Management Accountants of Canada, (Hamilton, Ont.: SMA, September).

Baxter, William T. (1975), Accounting Values and Inflation, (London: McGraw-Hill).

Baxter, W.T. (1979), "The Sandilands Report", in Wanless, P.T. and Forrester, D.A.R., Readings in Inflation Accounting, (N.Y.: John Wiley & Sons) 1979, pp.409-420.

Bazley, John D. (1976), "An Examination of the Ability of Alternative Accounting Measurement Models to Predict Failure", Review of Business and Economic Research, Vol.12 (Fall), pp.32-46.

Beaver, William H. (1966), "Financial Ratios as Predictors of Failure", Empirical Research in Accounting: Selected Studies Supplement to Vol.4, Journal of Accounting Research, pp.71-111.

Beaver, William H. (1968), "Market Prices, Financial Ratios, and the Prediction of Failure", Journal of Accounting Research, Vol.6, No.2 (Autumn), pp.179-192.

Beaver, William H. (1968a), "The information Content of Annual Earnings Announcements", Empirical Research in Accounting: Selected Studies, Supplement to Vol.6, Journal of Accounting Research, pp.67-92.

Beaver, William H. (1968b), "Alternative Accounting Measures As Predictors of Failure", The Accounting Review, Vol.43, No.1, (January), pp.113-122).

Beaver, W., Kennelly, J. and Voss, W. (1968), "Predictive Ability as a Criteria for the Evaluation of Accounting Data", The Accounting Review, Vol.43, No.4, (October), pp.675-683.

Beaver, W., Ketteler, P. and Scholes, M. (1970), "The Association Between Market Determined and Accounting Determined Risk Measures", The Accounting Review, Vol.45, No.4 (October), pp.654-682.

Bedford, Norton M. (1973), Extensions in Accounting Disclosure, (New Jersey: Prentice-Hall).

Benishay, Haskel (1971), "Economic Information in Financial Ratio Analysis, A Note", Accounting and Business Research, Vol.1, No.2 (Spring), pp.174-179.

Benishay, Haskel (1973), "Discussion of A Prediction of Business Failure Using Accounting Data ", Empirical Research in Accounting: Selection Studies Supplement to Vol.11, Journal of Accounting Research, pp.180-2.

Benston, George J. (1976), Corporate Financial Disclosure in the UK and the USA, (London: Saxon House).

Bildersee, John S. (1975), "The Association Between a Market-Determined Measure of Risk and Alternative Measures of Risk". The Accounting Review, Vol.50, No.1 (January), pp.81-98.

Bird, Peter (1973), Accountability: Standards in Financial Reporting, (London: Accountancy Age Books, Haymarket Publishing Ltd).

Bird, R.G. nad McHugh, A.J. (1977), "Financial Ratios - An Empirical Study", Journal of Business Finance and Accounting, Vol.4, No.1 (Spring), pp.29-45.

Blum, Marc (1974), "Failing Company Discriminant Analysis", Journal of Accounting Research, Vol.12, No.1 (Spring), pp.1-25.

Brenner, Menachem (1977), "The Effect of Model Mis-specification on Tests of the Efficient Market Hypothesis", Journal of Finance, Vol.32, No.1, (March), pp.57-66.

Briggs, Douglas H. (1975), "Information Requirements of Users of Published Corporate Reports - Unit Trusts", Accounting and Business Research, Vol.5, (Winter), pp.18-20.

Brown, Philip and Ball, Ray (1967), "Some Preliminary Findings on the Association between the Earnings of a Firm, Its Industry, and the Economy", Empirical Research in Accounting: Selected Studies, Supplement to Vol.5, Journal of Accounting Research, pp.55-77.

Brown, Robert M. (1980), "Short-Range Market Reaction to Changes to LIFO Accounting Using Preliminary Earnings Announcement Dates", Journal of Accounting Research, Vol.18, No.1, (Spring), pp.38-63.

Buckmaster, D.A., Copeland, R.M. and Dascher, P.E. (1977), "The Relative Predictive Ability of Three Accounting Income Models", Accounting and Business Research, Vol.7, (Spring), pp.177-186.

Burton, J.C. (ed.) (1969), Corporate Financial Reporting: Conflicts and Challenges, (N.Y.: AICPA).

Carsberg, B., Hope, A. and Scapens, R.W. (1974), "The Objectives of Published Accounting Reports", Accounting and Business Research, Vol.4, (Summer), pp.162-173.

Casey, Cornelius J. (1980), "Variation in Accounting Information Load: The Effect on Loan Officers' Prediction of Bankruptcy", The Accounting Review, Vol55, No.1, (January), pp.36-49.

Chambers, R.J. (1976), "Accounting for Inflation Part or Whole?", The Accountant's Magazine, (March), pp.86-89.

Chiswick, Barry R. and Chiswick, Stephen J. (1975), Statistics and Econometrics, (London: University Park Press).

Comiskey, Eugene E. (1971), "Market Response to Changes in Depreciation Accounting", The Accounting Review, Vol.46, No.2, (April), pp.279-285.

Cooley, William W. and Lohnes, Paul R. (1971), Multivariate Data Analysis, (London: John Wiley and Sons).

Cunningham, S.W. (1973), "The Predictability of British Stock Market Prices", Applied Statistics, Vol.22, No.3, pp.315-331.

D'Agostino, R.B. (1971), "An Omnibus Test of Normality for Moderate and Large Size Samples", Biometrika, Vol.58, pp.341-8.

Dake, J.L. (1972), "Comment: An Empirical Test of Financial Ratio Analysis", Journal of Financial and Quantitative Analysis, Vol.7, No.2, (March), pp.1495-7.

Danill, Tory E. (1968), "Discriminant Analysis for the Prediction of Business Failures", University of Alabama, Ph.D. Thesis.

Deakin, Edward B. (1972),"A Discriminant Analysis of Predictors of Business Failure", Journal of Accounting Research, Vol.10, No.1, (Spring), pp.167-179.

Deakin, Edward B. (1976), "Distribution of Financial Accounting Ratios: Some Empirical Evidence", The Accounting Review, Vol.51, No.1, (January), pp.90-6.

Deakin, Edward B. (1977), "Business Failure Prediction: An Empirical Analysis" in Altman, E.I. and Sametz, A.W. (eds.) Financial Crises, (New York: John Wiley & Sons), pp.72-88.

Department of Accounting and Business Method, University of Edinburgh, (DABMUE) "Computer File of U.K. Quoted Companies" Accounts: 1948-1971, without date.

Department of Industry (1978), "Company Finance", Business Monitor M3, Business Statistics Office, HMSO, (Ninth Issue).

Derstine, Robert P. and Huefner, Ronald J. (1974), "LIFO-FIFO, Accounting Ratios and Market Risk", Journal of Accounting Research, Vol.12, No.2, (Autumn), pp.216-233 .

Dittman, D.A., Juris, H.A. and Revsine, L. (1976), "On the Existence of Unrecorded Human Assets: An Economic Perspective", Journal of Accounting Research, Vol.14, No.1, (Spring), pp.49-65.

Dittman, D.A. Juris, H.A. and Revsine, L. (1980), "Unrecorded Human Assets: A Survey of Accounting Firms' Training Programs", The Accounting Review, Vol.55, No.4, (October), pp.640-648.

Edmister, Robert O. (1972), "An Empirical Test of Financial Ratio Analysis for Small Business Failure Prediction", Journal of Financial and Quantitative Analysis, Vol.7, No.2, (March), pp.1477-1493.

Edwards, Edgar O. and Bell, Philip W. (1961), The Theory and Measurement of Business Income, (Berkeley: University of California Press, 7th printing, 1973).

Egginton, D.A. and Morris, R.C. (1973), "Borrowing Costs, Price Level Changes, and ED8", The Accountant, (October, 11th), pp.463-66.

Eggleton, I.R.C., Penman, S.H. and Twombly, J.R. (1976), "Accounting Changes and Stock Prices: An Examination of Selected Uncontrolled Variables", Journal of Accounting Research, Vol.14, No.1, (Spring), pp.66-88.

Eisenbeis, Robert A. (1977), "Pitfalls in the Application of Discriminant Analysis in Business, Finance and Economics, Journal of Finance, Vol.32, No.3, (June), pp.875-900.

Fadel, Hisham A. (1977), "Predictive Power of Financial Ratios in Selected British Firms within Three Industries", University of Bradford, Ph.D. Thesis.

Falk, Haim and Heintz, James A. (1975), "Assessing Industry Risk by Ratio Analysis", The Accounting Review, Vol.50, No.4, (October), pp.758-779.

Falk, Haim and Heintz, James A. (1977), "The Predictability of Relative Risk Over Time", Journal of Business Finance and Accounting, Vol.4, No.1, (Spring), pp.5-28.

Fama, Eugene F. (1970), "Efficient Capital Markets: A Review of Theory and Empirical Work", Journal of Finance, Vol.25, No.2, (May), pp.383-417.

Fama, Eugene F. (1976), Foundations of Finance, (Oxford: Basil Blackwell).

Fama, E.F., Fisher, L., Jensen, M.C. and Roll, R. (1969), "The Adjustment of Stock Prices to New Information", International Economic Review, Vol.10, No.1, (February), pp.1-21.

Farrar, Donald E. and Glauber, Robert R. (1967), "Multicollinearity in Regression Analysis: The Problem Revisited", The Review of Economics and Statistics, Vol.49, (February), pp.92-107.

Firth, Michael (1976), Share Prices and Mergers, (London: Saxon House).

Firth, Michael (1977), The Valuation of Shares and the Efficient Markets Theory, (London: The MacMillan Press Ltd).

Flamholtz, Eric (1972), "Toward a Theory of Human Resource Value in Formal Organizations", The Accounting Review, Vol.47, No.4 (October), pp.666-678.

Foster, George (1978), Financial Statement Analysis, (New Jersey: Prentice-Hall, Inc.).

Frank, Charles R. (1971), Statistics and Econometrics, (New York: Holt, Rinehart and Winston, Inc.).

Frank, Ronald E., Massy, W.F. and Morrison,D.G. (1965), "Bias in Multiple Discriminant Analysis", Journal of Marketing Research, Vol.11, (August), pp.250-258.

Frank, W. (1969), "A Study of the Predictive Significance of Two Income Measures", Journal of Accounting Research, Vol.7, (Spring), pp.123-136.

Franks, J.R., Broyles, J.E. and Hecht, M.J. (1977), "An Industry Study of the Profitability of Mergers in the United Kingdom", Journal of Finance, Vol.32, No.5, (December), pp.1513-1525.

Gnanadesikan, R. (1977), Methods for Statistical Data Analysis of Multivariate Observations, (New York: John Wiley and Sons).

Goldberger, A.S. (1964), Econometric Theory, (New York: John Wiley and Sons).

Gonedes, Nicholas J. (1969), "The Significance of Selected Accounting Procedures: A Statistical Test", Emprical Research in Accounting: Selected Studies, Supplement to Vol.7, Journal of Accounting Research, pp.90-113.

Gonedes, Nicholas J. (1973), "Evidence on the Information Content of Accounting Numbers: Accounting-based and Market-based Estimates of Systematic Risk", Journal of Financial and Quantitative Analysis, Vol.8, (June) pp.407-43.

Gooi, H. (1974), "Share Prices and Financial Ratios - Prediction of Bankruptcy", The City University Business School (London), Master dissertation (November).

Gorsuch, Richard L. (1974), Factor Analysis, (London: W.B. Saunders Company).

Grady, Paul (1965), Inventory of Generally Accepted Accounting Principles for Business Enterprises, Accounting Research Study, No.7, AICPA.

Green, Donald (1978), "To Predict Failure", Management Accounting, (U.S.), (July), pp.39-45.

Greenball, M.N. (1971), "The Predictive-Ability Criterion: Its Relevance in Evaluating Accounting Data", ABACUS, Vol.7, (June), pp.1-7.

Gupta, Manak C. (1969), "The Effect of Size, Growth and Industry on the Financial Structure of Manufacturing Companies", Journal of Finance, Vol.24, No.3, (June), pp.517-529.

Gynther, Reg S. (1974), "Why Use General Purchasing Power?", Accounting and Business Research, Vol.4, (Spring), pp.141-157.

Hendricks, James A. (1976), "The Impact of Human Resource Accounting Information on Stock Investment Decisions: An Empirical Study", The Accounting Review, Vol.51, No.2, (April), pp.299-305.

Henfrey, A.W., Albrecht, B. and Richards, P. (1977), "The U.K. Stock Market and the Efficient Market Model: A Review", The Investment Analyst, No.48, (September), pp.5-24.

Hicks, J.R. (1946), "Income" in Parker, R.H. and Harcourt, G.C., "Readings in the Concept and Measurement of Income", (Cambridge: Cambridge University Press, 1969), pp.74-82.

Hillison, William A. (1979), "Empirical Investigation of General Purchasing Power Adjustments on Earnings per Share and the Movement of Security Prices", Journal of Accounting Research, Vol.17, No.1, (Spring), pp.60-73.

Holdren, G.C. (1964), "LIFO and Ratio Analysis", The Accounting Review, Vol.39, No.1, (January), pp.70-85.

Horrigan, James O. (1965), "Some Empirical Bases of Financial Ratio Analysis", The Accounting Review, Vol.40, No.3, (July), pp.558-568.

Horrigan, James O. (1966), "The Determination of Long-Term Credit Standing with Financial Ratios", Empirical Research in Accounting: Selected Studies, Supplement to Vol.4, Journal of Accounting Research, pp.44-63.

Horrigan, James O. (1967), "An Evaluation of Financial Ratio Analysis, University of Chicago, Ph.D. Dissertation.

Ijiri, Yuji (1979), "Oil and Gas Accounting - Turbulence in Financial Reporting", Financial Executive, (August), pp.18-26.

Institute of Chartered Accountants in England and Wales (1973), "Survey of Published Accounts: 1972-1973, (London: ICAEW).

Jacquemin, A. and Cardon, M. (1973), "Size Structure, Stability and Performance of Largest British and EEC Firms", European Economic Review, No.4, pp.393-408.

Johnson, Bruce W. (1979), "The Cross-Sectional Stability of Financial Ratio Patterns", Journal of Financial and Quantitative Analysis, Vol.14, No.5, (December), pp.1035-1048.

Johnston, J. (1972), Econometric Methods, (London: McGraw-Hill Kogakusha, Ltd.), 2nd Edition.

Joy, Maurice O. and Tollefson, John O. (1975), "On the Financial Application of Discriminant Analysis", Journal of Financial and Quantitative Analysis, Vol.10, No.5, (December), pp.723-739.

Keller, Thomas F. (1965), "Unformity Versus Flexibility: A Review of the Rhetoric", Law and Contemporary Problems, Vol.30, No.4, (Autumn), pp.637-651.

Kendall, Maurice (1975), Multivariate Analysis, (London: Charles Griffin and Company Ltd.).

Kennedy, Henry A. (1975), "A Behavioural Study of the Usefulness of Four Financial Ratios", Journal of Accounting Research, Vol.13, No.1, (Spring), pp.97-116.

King, Benjamin F. (1966), "Market and Industry Factors in Stock Price Behaviour", The Journal of Business, Vol.39, No.1, Part II, (January), pp.139-170.

Kinney, William R. (1973), "Discussion of A Prediction of Business Failure Using Accounting Data", Empirical Research in Accounting: Selected Studies, Supplement to Vol.11, Journal of Accounting Research, pp.183-187.

Kirkman, Patrick R.A. (1974), Accounting Under Inflationary Conditions, (London: George Allan and Unwin Ltd.).

Kshirsagar, Anant M. (1972), Multivariate Analysis, (New York: Marcel Dekker, Inc.).

Kuh, Edwin and Meyer, John R. (1955), "Correlation and Regression Estimates when the Data are Ratios", Econometrica, Vol.23, (October), pp.400-416.

Lachenbruch, Peter A. (1975), Discriminant Analysis, (New York: Hafner Press).

Lachenbruch, Peter A. and Mickey, M. Ray (1968), "Estimation of Error Rates in Discriminant Analysis", Technometrics, Vol.10, No.1, (February), pp.1-11.

Lachenbruch, Peter A., Sneeringer, Cheryl and Revo, Lawrence T. (1973), "Robustness of the Linear and Quadratic Discriminant Function to Certain Types of Non-Normality", Communications in Statistics, 1(1), pp.39-56.

Ladd, George W. (1966), "Linear Probability Functions and Discriminant Functions", Econometrica, Vol.34, No.4, (October), pp.873-885.

Lee, T.A. (1971), "Utility and Relevance - the search for reliable financial accounting information", Accounting and Business Research, Vol.1, (Summer), pp.242-249.

Lee, T.A. (1974), Income and Value Measurement, (London: Nelson).

Lee, T.A. (1976), Company Financial Reporting, (London: Nelson).

Lev, Baruch (1969), "Industry Averages as Targets for Financial Ratios", Journal of Accounting Research, Vol.7, (Autumn), pp.290-9.

Lev, Baruch (1969a), Accounting and Information Theory, (Chicago: American Accounting Association, Studies in Accounting Research # 2).

Lev, Baruch (1971), "Financial Failure and Information Decomposition Measures", in R. R. Sterling and W.F. Bentz (eds.), Accounting in Perspective: Contribution to Accounting thoughts by other Disciplines, (Cincinnati: South-Western Publishing Co.), pp.102-111.

Lev, Baruch (1974), Financial Statement Analysis: A New Approach, (New Jersey: Prentice-Hall, Inc.).

Lev, Baruch (1974a), "On the Association Between Operating Leverage and Risk", Journal of Financial and Quantitative Analysis, Vol.9, (September), pp.627-41.

Lev, Baruch and Schwartz Aba (1971), "On the Use of the Economic Concept of Human Capital in Financial Statements", The Accounting Review, Vol.46, No.1, (January), pp.103-112.

Libby, Robert (1975), "The Use of Simulated Decision Makers in Information Evaluation", The Accounting Review, Vol.50, No.3, (July), pp.475-489.

Likert, Rensis and Pyle, William C. (1971), "A Human Organizational Approach", Financial Analysts Journal, Vol.27, No.1, (January-February), pp.75-84.

Livingston, Miles (1977), "Industry Movements of Common Stocks", Journal of Finance, Vol.37, No.3, (June), pp.861-874.

London Business School (1977), London Share Price Database, (London: London Business School, February).

Mahon, James J. (1965), "Some Observations on World Accounting", The Journal of Accountancy, (January), pp.33-37.

Malkovich, J.F. and Afifi, A.A. (1973), "On Tests for Multivariate Normality", Journal of the American Statistical Association, Vol.68, No.341, (March), pp.176-179.

Marais, D.A.J. (1979), "A method of quantifying companies' relative financial strength", Bank of England: Discussion Paper No.4.

Marris, Robin L. (1967), "Profitability and growth in the individual firm", Business Ratios, (Spring), pp.3-12.

Martin, Alvin (1971), "An Empirical Test of the Relevance of Accounting Information for Investment Decisions", Empirical Research in Accounting: Selected Studies, Supplement to Vol.9, Journal of Accounting Research, pp.1-31.

Mayers, David and Rice, Edward M. (1979), "Measuring Portfolio Performance and the Empirical Conent of Asset Pricing Models", Journal of Financial Economics, Vol.7, pp.3-28.

Mears, Preston K. (1966), "Discussion of Financial Ratios as Predictors of Failure", Empirical Research in Accounting: Selected Studies, Supplement to Vol.4, Journal of Accounting Research, pp.119-122.

Mecimore, Charles D. (1968), "Some Empirical Distributions of Financial Ratios", Management Accounting (N.Y.), (September), pp.13-16.

Meyer, Paul A. and Pifer, Howard W. (1970), "Prediction of Bank Failure", Journal of Finance, Vol.25, No.4, (September), pp.853-68.

Meyers, Stephen L. (1973), "A Re-examination of Market and Industry Factors in Stock Price Behaviour", Journal of Finance, Vol.28, No.3, (June), pp.695-705.

Morris, R.C. (1975), "Evidence of the Impact of Inflation Accounting on Share Prices", Accounting and Business Research, Vol.5, (Spring), pp.82-90.

Morrison, Donald G. (1969), "On the Interpretation of Discriminant Analysis", Journal of Marketing Research, Vol.6, (May), pp.156-63.

Mosteller, Frederick and Wallace, David L. (1963), "Inference in an Authorship Problem", Journal of the American Statistical Association, Vol.58, No.302, (June), pp.275-309.

Myer, John N. (1969), Financial Statement Analysis, (New Jersey: Prentice-Hall, Inc.).

Neter, John (1966), "Discussion of Financial Ratios as Predictors of Failure", Empirical Research in Accounting: Selected Studies, Supplement to Vol.4, Journal of Accounting Research, pp.112-118.

Nguyen, D.T. (1975), "A Library of Computer Programs for the Application of Econometric Techniques", Obtainable from the author, University of Lancaster, Department of Economics.

Nie, N.H., Hull, C.H., Jenkins, J.G., Steinbrenner, K. and Bent, D.H., (1975), (SPSS) Statistical Package for the Social Science", (New York: McGraw-Hill Book Company), Second Edition.

Norton, Curtis L. and Smith, Ralph E. (1979), "A Comparison of General Price Level and Historical Cost Financial Statements in the Prediction of Bankruptcy", The Accounting Review, Vol.54, No.1, (January), pp.72-87.

Ohlson, James A. (1980), "Financial Ratios and the Probabilistic Prediction of Bankruptcy", Journal of Accounting Research, Vol.18, No.1, (Spring), pp.109-131.

Parker, C. Reed (1975), "The Trueblood Report - An Analyst's View", Financial Analysts Journal, (January-February), pp.32-41.

Parker, R.H. and Harcourt, G.C. (1969), Readings in the Concept and Measurement of Income, (Cambridge: Cambridge University Press).

Pearson, E.S. and Hartley, H.O. (1976), Biometrika Tables for Statisticians, Vol.1, (Cambridge: Cambridge University Press).

Peasnell, K.V. (1973), "The Usefulness of Accounting Information to Investors", ICRA, Occasional Paper No.1, (University of Lancaster, International Centre for Research in Accounting).

Peasnell, K.V. and Skerratt, L.C.L. (1977), "Income-Group Inflation Rates and General Purchasing Power Adjustments - An Empirical Test of the Heterogeneity Hypothesis", Paper presented to the Annual Conference of AUTA, at University of Liverpool, (September).

Peasnell, K.V. and Skerratt, L.C.L. (1979a), "How Well Does a Single Index Represent the Nineteen Sandilands Plant and Machinery Indices?", Journal of Accounting Research, Vol.15, No.1, (Spring), pp.108-119.

Pinches, G.E., Eubank, A.A., Mingo, K.A., and Caruthers, J.K. (1975), "The Hierarchical Classification of Financial Ratios", Journal of Business Research, Vol.3, No.4, (October), pp.295-310.

Pinches, George E. and Mingo, Kent A. (1973), "A Multivariate Analysis of Industrial Bond Ratings", Journal of Finance, Vol.28, No.1, (March), pp.1-18.

Pinches, G.E., Mingo, K.A. and Caruthers, J.K. (1973), "The Stability of Financial Patterns in Industrial Organizations", Journal of Finance, Vol.28, (May), pp.389-396.

Prais, S.J. (1976), The Evaluation of Giant Firms in Britain, (London: Cambridge University Press).

Richards, Paul H. (ed.) (1979), UK & European Share Price Behaviour: The Evidence, (London: Kogan Page).

Roll, Richard (1977), "A Critique of the Asset Pricing Theory's Tests", Journal of Financial Economics, Vol.4, pp.129-176.

Roll, Richard (1978), "Ambiguity when Performance is Measured by the Securities Market Line", Journal of Finance, Vol.33, No.4, (September), pp.1051-1069.

Roll, Richard (1979), "A Reply to Mayers and Rice (1979)", Journal of Financial Economics, Vol.7, pp.391-400.

Rozebroom, William W. (1966), Foundations of the Theory of Prediction, (Homewood, Ill.: Dorsey Press).

Rutherford, B.A. (1977), "Value Added as a Focus of Attention for Financial Reporting: Some Conceptual Problems", Accounting and Business Research, Vol.7, (Summer), pp.215-220.

Sandilands, Report of the Inflation Accounting Committee (1975), Inflation Accounting, (London: HMSO).

Schwartz, Robert A. and Whitcomb, David K. (1977), "Evidence on the Presence and Causes of Serial Correlation in Market Model Residuals", Journal of Financial and Quantitative Analysis, Vol.12, (June), pp.291-313.

Shapiro, S.S. and Wilk, M.B. (1965), "An Analysis of Variance Test for Noramlity (complete sample)", Biometrika, Vol.52, No.3 and 4, pp.591-610.

Simmons, John K. and Gray, J. (1969), "An Investigation of the Effect of Differing Accounting Frameworks on the Prediction of Net Income", The Accounting Review, Vol.44, No.4, (October), pp.757-776.

Singh, A. and Whittington, G. (1968), Growth Profitability and Valuation, (Cambridge: Cambridge University Press).

Snavely, Howard J. (1967), "Accounting Information Criteria", The Accounting Review, Vol.42, No.2, (April), pp.223-232.

Spellman, Kevin (1978), "Predicting the failure of a construction company", Accountancy, Vol.89, No.1020, (August), pp.54-6.

Taffler, Richard J. (1977a), "Finding thos Firms in Danger Using Discriminant Analysis and Financial Ratio Data: A Comparative UK-Based Study", Working Paper No.3, The City University Business School, (September).

Taffler, Richard J. (1977b), "The Correct Way to Use Published Financial Statement Data: The Assessment of Financial Viability Example", Paper presented to the Annual Conference of AUTA, at University of Liverpool, (September).

Taffler, Richard and Tisshaw, Howard (1977), "Going, going, gone - four factors which predict", Accountancy, Vol.88, (March), pp.50-54.

Tamari, Meir (1966), "Financial Ratios as a Means of Forecasting Bankruptcy", Management International Review, Vol.4, pp.15-21.

Tamari, M. (1978), Financial Ratios, Analysis and Prediction, (London: Paul Elek Ltd).

Tew, Brian and Henderson, R.F. (eds.) (1959), Studies in Company Finance, (Cambridge: Cambridge University Press).

Theil, Henri (1969), "On the Use of Information Theory Concepts in the Analysis of Financial Statements", Management Science, Vol.15, No.9, (May), pp.459-480.

Thomas, J.J. (1973), An Introduction to Statistical Analysis for Economists, (London: Weidenfeld and Nicolson).

Trasi, Atma D. (1978), Cluster Analysis Package - clustan IA, The Computer Laboratory, University of Bradford, (March).

Weaver, D. (1971), Investment Analysis, (London: Longman in association with The Society of Investment Analysis).

West, Richard R. (1975), "On the Difference between Internal and External Market Efficiency", Financial Analysts Journal, Vol.31, No.6, (November-December), pp.30-34.

Whittington, Geoffrey (1971), The Prediction of Profitability, (Cambridge: Cambridge University Press).

Wilcox, Jarrod W. (1971), "A Gambler's Ruin Prediction of Business Failure Using Accounting Data", Sloan Management Review, Vol.12, No.3, (Spring), pp.1-10.

Wilcox, Jarrod W. (1973), "A Prediction of Business Failure Using Accounting Data", Empirical Research in Accounting: Selected Studies, Supplement to Vol.11, Journal of Accounting Research, pp.163-190.

Zar, Jerrold H. (1974), Biostatistical Analysis, (New Jersey: Prentice-Hall, Inc.,).