A COMBINATION OF A STATIONARY AND NON-STATIONARY MODEL TO PREDICT CORPORATE FAILURE IN SOUTH AFRICA

BY

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ABSTRACT

Business failure should be of concern in most industralised countries and the importance of accurately evaluating the phenomenon from a management and investment point of view is enormous. Were it possible to predict failure with a certain degree of confidence, steps could be taken to rectify the situation and the benefit would accrue to all of the stakeholders in the macroenvironment.

In essence, the profitability of a business is influenced by two sets of variables. In the first instance, it is influenced by a variety of internal (microeconomic) variables which are firm- specific and which management is generally able to control. A further distinction in this regard may be made between the financial and non-financial variables. In the second instance, it is generally accepted that profitability will be influenced by a number of external (macroeconomic) variables which are generally beyond the control of management. In the main, however, the profitability of the firm is generally determined by a combination of both sets of factors.

To date, a great deal of research has been undertaken in an attempt to establish a reliable model which may be used to predict failure. This has mainly been confined to the microeconomic variables which can be used to predict failure and attempts have been made to isolate either a single financial ratio or a number of financial and non-financial variables which can be used to model corporate failure. The research has met with a certain degree of success although this appears to be confined to the economic environment to which the models have been applied. The models are less successful when applied to other macroenvironments.

Limited research has been undertaken into the macroeconomic variables which contribute to business failure or to a combination of the two types of variables. It is appropriate therefore that further consideration be given to the establishment of a model incorporating ALL the variables which could contribute to corporate failure.

The purpose of this research is to undertake an investigation of micro- and macroeconomic variables that are freely available to reserachers and which may be used in a failure prediction model. The intention is to obtain a comprehensive, yet simple model which can be used as an overall predictor of PENDING failure.

TABLE OF CONTENTS

List of tables

List of figures

List of Appendices.

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CHAPTER ONE

INTRODUCTION

1.1. Introduction.

Corporate failure is today a sobering economic reality which is no longer confined to small businesses. As Altman, the foremost researcher on the subject maintains,

> it is no longer the exclusive province of the small undercapitalised business but occurs increasingly among the large industrial and financial firms.
>
> (Altman, 1983:1).

The importance of evaluating business failure from an investment and management point of view emerged after the collapse of Penn Central in the United States of America in 1970 and Rolls-Royce in the United Kingdom during 1971. Now, rather than accept failure as it occurred, businessmen and academics sought to enhance their knowledge of this phenomenon.

Since the work of Beaver (1966), the use of financial ratios as predictors of failure has become widely accepted. Altman (1968) extended the use of a single ratio in predicting failure (univariate approach) to a number of ratios from which a failure prediction score could be obtained (multivariate approach). These ratios were generally confined to the financial ratios which could be obtained from a set of financial statements (Annual Report) of a company.

During the seventies, the efficacy of the statistical techniques used in establishing failure prediction models was questioned. During the eighties, the research was extended into other areas of failure prediction. More specifically, the use of firm- specific, non-financial variables in a failure prediction model was examined. In addition, the extent to which economic variables influenced the business failure rate was acknowledged and attempts were made to integrate these variables in a failure prediction model.

As yet however no comprehensive model of failure prediction which is freely available, has been evolved. A possible reason for this is that the significant micro- and macroeconomic variables which could be used in the prediction of failure cannot easily be accommodated in a single model. The models which do cater for both types of variables can only be applied by those with access to specific information which is not available to the general body of practitioners.

This thesis investigates the possibility of developing a model which uses both micro- and macroeconomic predictor variables when establishing whether a company may fail in the future. The intention is that the model be easily applicable by those concerned with failure prediction. By achieving this, it is hoped that the prediction of failure will be a relatively simple matter, and that an accurate assessment of a possible future demise by practising analysts and management alike, would be financially beneficial as it would preclude unnecessary expenditure.

1.2. The nature of bankruptcy.

A variety of factors may cause a successful company to fail. Initially, businessmen paid little attention to corporate failure. The following were suggested by Sharma and Mahajan (1980) as reasons for this lack of interest:-

1. the term failure had negative connotations.
2. the reasons why each firm failed were different and did not lend themselves to scientific study.
3. published information relating to business failure was scarce.
4. the belief that business failure occurred suddenly rather than evolving over time.

In essence, the success or otherwise of any business is a result of the interaction of two sets of factors. (See Pearce and Robinson, 1988:100). Firstly, performance is influenced by a variety of internal (microeconomic) factors which are firm- specific and which management is generally able to control. As Sharma and Mahajan (1980:82) say

> through a continuous process of formulating strategic market plans and executing, monitoring and evaluating those plans, management attempts to keep performance of the enterprise consistent with its environment and its resources.

When considering the firm-specific factors which may be used in the evaluation of a firm's performance, a further distinction can be made between financial and non-financial variables. The relevant financial variables used are the accounting ratios which can be extracted from a company's financial statements, as these are the only financial reports to which external researchers to the company have access. The non-financial variables are the non- accounting variables, some of which could point to the financial well-being of a business. Some of these variables may also be extracted from the Annual Report of a company. It is these variables which form the basis of this investigation.

Secondly, performance is influenced by a number of external (macroeconomic) factors. These consist of such factors as economic growth activity (credit availability, money and capital market activity), business population characteristics (shifting preferences, attitudes and behaviour of consumers), price level changes (consumer price index, production price index), and many more. In most instances, these factors are not firm-specific and are beyond the control of management.

Although the main body of research has focused on the internal factors which contribute to business failure, it is universally accepted that macroeconomic factors also have an influence on business failure. As Altman (1980:83) says

> the importance of microeconomic issues and the attendant large number of analytical studies have obscured the relevance and influence of macroeconomic influences on the business failure phenomenon.

It is appropriate therefore that the data base on failure prediction be broadened to include the macroeconomic factors which contribute to corporate failure.

1.3 The definition of bankruptcy.

Failure is defined broadly in the Oxford Dictionary (1989) as "non-performance of something, lack of success". The Chambers English Dictionary (1988) defines failure more specifically as "falling short or cessation, lack of success, bankruptcy".

It is apparent from the definition that the term failure covers a broad spectrum of business activity and van Horne (1986:741) quite rightly finds the term confusing. As he points out "the word failure is vague, partly because there are varying degrees of failure". Beaver (1966:71) who was the first researcher of note to investigate the subject, defines failure "as the inability of a firm to pay its financial obligations as they mature". More specifically, he refers to operational failure as "when any of the following events have occurred: bankruptcy, bond default, an overdrawn bank account or non-payment of a preferred stock dividend". (Beaver, 1966:71).

Argenti (1976) on the other hand, contends that the most definitive words are "insolvent, liquidation, receivership and bankrupt." Companies become insolvent when they cannot pay their debts as they fall due or when their net asset values are negative. Should this be the case, the company will be placed in the hands of a Receiver who will decide whether the company should continue to trade or whether it should be placed in liquidation. Finally, Argenti (1976) contends that, in the United Kingdom, only individuals "go bankrupt".

Taffler and Tisshaw (1977:51), following Argenti, define failure as "entry into receivership, creditor's voluntary liquidation, compulsory winding up order, by order of the court or government action taken as an alternative".

In the South African context, de la Rey (1981:11) has defined corporate failure without referring to specific terminology but by using a very broad base. His definition is along the following lines. Any business:-

1. of which the equity became negative.
2. forced to discontinue operations because of the fact that it had committed an act of insolvency or was, as a result thereof, put under judicial management.
3. which could not show profit for two out of three years.

4. that was unable to pay its preference dividend on time.
5. that was unable to declare an ordinary dividend for that year.
6. that was unable to honour its loan commitments on time according to a contractual agreement.
7. that reduced the nominal value of its share capital to bring it into line with the assets it represents.

In general, the "varying degrees of failure" are classified in the literature as economic failure, technical insolvency, bankruptcy or financial failure. Platt (1985:7) defines economic failure rather vaguely as being "when the business is not sufficiently prosperous given the level of capital investment and human effort put into making it work". Altman (1983:6) states that economic failure occurs when "the realised rate of return on invested capital with allowances for risk considerations, is significantly and continually lower than prevailing rates on similar investments".

Economic failure is defined more specifically in the McGraw-Hill Dictionary of Economics (1973) as the "cessation of operations by a business concern because of its involvement in court procedures or voluntary actions which will result in the loss of its creditors".

When evaluating technical insolvency, Platt (1985:10) points to a situation in which a firm cannot meet its current obligations, signifying a lack of liquidity. This position may either be temporary or permanent. Once the position is permanent the firm may be regarded as being bankrupt. Under these circumstances the firm has two options, either to liquidate or to reorganise.

As regards bankruptcy, Weston and Copeland (1986: 952) contend that a firm is bankrupt when its total liabilities are greater than a fair value of its assets; in essence the net worth of the company is negative. The Oxford Dictionary (1989) on the other hand defines bankruptcy as the state in which either a person or a business is "unable to pay (their) debts in full and whose estate is administered and distributed for the benefit of the creditors".

Finally, van Horne (1986:741) maintains that financial failure covers the entire spectrum between technical insolvency and bankruptcy.

As this study investigates both the financial and economic causes of failure, it will be necessary to define both these concepts. In the first instance, when the microeconomic factors are investigated, a company which has failed financially is defined as one which was delisted from the Johannesburg Stock Exchange due solely to poor financial performance. In the second instance, an economically failed company is defined as either a private or public company which has been removed from the list of registered companies by the Registrar of Companies.

1.4. The aim of the study and the format of the thesis.

The aim of the research is to develop a practical model of failure prediction which can easily be applied by the general body of practitioners involved in the financial evaluation of companies. In order to achieve this, the thesis is in the following format:-

A discussion of the need for financial statements and their use in predicting failure is undertaken in Chapter Two. The prior literature on the firm-specific financial factors using multiple discriminant analysis in predicting failure is evaluated in Chapter Three. In Chapter Four, a review of the various statistical techniques used in the prediction of failure is undertaken and an attempt is made to identify the most appropriate technique within the South African context. An investigation into the firm specific non-financial factors which contribute to failure in South Africa is undertaken in Chapter Five and the firm-specific microeconomic factors are combined in a single failure prediction model. Chapter Six deals with the macroeconomic factors which contribute to failure. Finally, in Chapter Seven all of the significant variables are combined in a two-stage model of failure prediction. Chapter Eight concludes the study.

1.5 Conclusion

It was Argenti (1976:1) who said "Collapsed, failed, bankrupt, broke and bust. None of these are pleasant words and this is not a very pleasant subject". On the other hand, it is essential that forewarning of pending failure becomes available to those most intimately concerned with the management of a business. A great deal of research has been conducted in this area of finance and a large number of models have been developed which purport to predict failure. The only common thread in these models is the inconsistency in the choice of predictor variables as well as in the variation of the values of the coefficients of similarly chosen variables.

An attempt is made in this study to address this problem and to suggest a methodology whereby the factors which predict failure can be consistently determined. The intention is to present a model with practical applicability which can be used to indicate that failure may occur, *ceteris paribus.*

CHAPTER TWO.

FINANCIAL STATEMENTS AND RATIO ANALYSIS.

2.1 Introduction.

A business is an economic unit which contributes to the macro-environment through it's participation in the relevant product market. In a capitalistic society, where economic advancement can best be achieved through a strategic analysis of the environment, it is important that the data necessary for rational decision making be made available to those who need it. An essential element in this process is that the financial transactions of the economic unit are clearly documented and presented at specified intervals to the individuals most concerned with the well-being of the organisation. This task, which is known as financial reporting, is concerned with the quantitative expression of economic transactions.

A summary of these transactions is contained in the financial statements of the company which convey to those concerned the financial well-being of a business. These statements comprise the Balance Sheet, the Income Statement, and the Statement of Changes in Financial Position, the Directors' and Auditors' Report.

In this chapter the need for, and the shortcomings of financial statements are discussed. In addition a description is given of how these statements may be used to assess a company's financial well-being.

2.2 Financial statements.

Financial statements are presented for external use throughout the world. In South Africa, Act No.61 (1973), Section 286(3), requires that

> annual financial statements of a company shall, in conformity

> with generally accepted accounting practice, fairly present the state of affairs of the company...and the profit or loss of the company for that financial year.

Although the nature of the information disclosed in the financial statements of companies is similar, the format of these disclosures may differ from country to country. The three main sources for disclosure requirements in South Africa are: Schedule Four of the Companies Act, the standards of Generally Accepted Accounting Practice as approved by the Accounting Practices Board and Statements issued by the International Accounting Standards Committee. A detailed discussion on disclosure in South Africa is given by Everingham (1992).

2.2.1. Definition.

The United States of America has been the leader in setting accounting standards through the Statements of the Financial Accounting Standards Board. Where possible, these standards have been followed in the United Kingdom and in South Africa.

In 1941, the Committee on Terminology of the American Institute of Accountants, the forerunner of the American Institute of Certified Public Accountants defined accounting as

> the art of recording, classifying, and summarising in a significant manner and in terms of money, transactions and events which are in part at least of a financial character and interpreting the results thereof.
>
> (from Hendriksen and van Breda, 1992:13).

The American Accounting Association (1966:1) subsequently defined accounting as "the process of identifying measuring and communicating economic information to permit informed judgements and decisions by the users of information". On the other hand, economists provide economic information but are certainly not accountants and hence the Accounting Practices Board (1970; para 40) redefined accounting as a service activity whose function it is "to provide quantitative information, primarily financial in nature about economic entities, that is intended to be useful in making economic decisions".

The Corporate Report of the Institute of Chartered Accountants in England and Wales (1975:9) has succinctly defined financial accounting as "the comprehensive package of information of all kinds which most completely describes an organisation's economic activity".

No formal definition of financial accounting in South Africa is documented. Faul, Everingham, Redlinghuys, and van Vuuren (1981:5) adopted the traditional American definition of financial accounting as "the art of recording transactions and funds of a financial nature in monetary terms". As this definition did not embody the claims of the stakeholders, however, they accordingly redefined accounting as

> a service activity ... (whose) function is to provide quantitative information primarily of a financial nature about economic entities. Such information must be usable in the process of economic decision making.
>
> (Faul *et al*, 1981:5)

Faul, van Wyk and Smith (1991:4) on the other hand, follow a microeconomic approach when defining accounting as

> the process of identifying, measuring and communicating financial information, so as to enable the users of that information to evaluate it and make decisions based on their

evaluation.

2.2.2. Objectives.

The objectives of financial statements according to Moonitz (1961), can be broadly summarised as follows:-

1. To measure the resources held by specific entities.
2. To reflect the claims against the interests in those entities.
3. To measure the changes in those resources, claims and interests.
4. To assign the changes to specifiable periods of time.
5. To express the foregoing in terms of money as a common denominator.

The Financial Accounting Standards Board (1978; para.34) abbreviated these objectives when stating that the basic objective for publishing financial statements is to

> provide information that is useful to present and potential investors and creditors and other users in making rational investment, credit, and similar decisions.

In the United Kingdom, Solomons (1989) following the lead of American Institute of Certified Public Accountants (1973), states that the purpose of financial accounting is to provide information that will be useful to a variety of users who have an interest in:

1. assessing the financial performance and position of the enterprise
2. assessing the performance of those responsible for its management
3. making decisions about investing in, lending or extending credit to, doing business with or being employed by the enterprise.

With due recognition of all the stakeholders in the company, the Corporate Report of the Institute of Chartered Accountants in England and Wales (1975:78) states that the objective of financial accounting in the United Kingdom is

> to communicate economic measurements of and information about the resources and performance of the reporting entity useful to those having reasonable rights to such information.

The South African Institute of Chartered Accountants through its representation on the Board of the International Accounting Standards Committee states in AC 000 (1990) that the objective of financial statements

> is to provide information about the financial position, performance and changes in the financial position of an enterprise that is useful to a wide range of users in making economic decisions.

Faul *et al.* (1991:513) adopt a similar stance when they maintain that financial statements summarise the results of activities of an undertaking for a specific period whose purpose is

> to provide financial information about the undertaking for use by interested parties such as management owners, creditors potential investors and certain government departments.

In order to meet these objectives, financial statements are prepared on the accrual basis of accounting whereby transactions and other events are recognised when they occur. This provides users with information about past transactions as well as future obligations to pay and receive cash. An additional underlying assumption of financial statements is that the enterprise is a going concern and will continue to trade in the foreseeable future on this premise.

2.2.3. Characteristics.

In order to make the information contained in financial statements meaningful to users, AC 000 (1990) has laid down four qualitative characteristics which statements should reflect if they are to be useful. These are understandability, comparability, relevance and reliability.

2.2.3.1 Understandability.

Financial statements are directed at those engaged in economic enterprises who are expected to have a reasonable knowledge of accounting and who will study the statements in reasonable depth. On the other hand, complex matters useful to the decision-making process should not be excluded on the grounds that they are difficult to grasp.

2.2.3.2 Relevance.

The information contained in the financial statements must be relevant to users' needs when making economic decisions regarding the company. This condition will be observed when information contained in the statements is helpful in evaluating past, present and future events or in confirming previous evaluations.

2.2.3.3 Reliability.

Financial statements are used mainly for an evaluation of the firm's past performance and future prospects and their intention is to provide a reliable source of data. To be useful, data must also be reliable and must faithfully represent the transactions of the company. They must be neutral and free from material error and bias and must be prudently drawn up and complete within the bounds of cost.

They must also faithfully represent the transactions and other events they are intended to reflect. If this condition is adhered to they will need to be presented in accordance with their substance and economic reality.

2.2.3.4 Comparability.

To be useful, users must be able to compare the progress of the company through time in order to establish trends in the company's financial position and performance. In addition, users must also be able to compare the company to similar companies so that comparisons can be made with competitors. To be able to do this, accounting policies need to be disclosed in the notes to the financial statements in order that users may reconcile the various differences over time or between companies.

2.2.4. Users.

Financial statements report on the company's past and present financial position and the results of its operations; and as such can be used to obtain information about the company. This information was originally directed at the owners/shareholders of the business. On the other hand, a wide body of readers has need for this information. AC 000 (1990; para.9) has isolated seven categories of users of financial statements:-

1. investors;
2. employees;
3. lenders;
4. suppliers and other trade creditors;

5. customers;
6. government and their agencies; and
7. the general public.

These groups will require different information from the financial statements. Management require a daily flow of meaningful information if they are to operate the company on an efficient and effective basis. Investors are not so much concerned with the daily operations of the company, as with the profitability and cash flow of the company and the riskiness of their investments. They must be convinced that management is maximising their wealth.

A creditor's main concern is the risk involved in extending or increasing credit to a company and they are accordingly interested in the company's ability to pay its obligations, both long- and short-term, as they fall due. Customers must be convinced that the company will continue to operate and supply additional goods after the initial purchase has been made. Government needs to be in a position where the tax liability of the company can be determined. Finally, the general public will be interested in the continued well-being of the company in so far as it influences the wider environment.

2.2.5. Shortcomings.

Although financial statements are prepared according to Generally Accepted Accounting Practice, there are nevertheless a number of factors which impair their usefulness. These may be classified as follows:-

2.2.5.1 Ethical considerations.

The main concern is whether management, due to a conflict of interests, will report impartially on the performance of the company or whether an auditor is needed to verify the validity of the statements. It is also questioned whether auditors should assume responsibility for the accuracy of the statements as well as their conformity to generally accepted accounting practice.

2.2.5.2 Comparability

The different formats of financial statements and the variability of the information contained therein may impair their comparability. This problem is further compounded when comparing the financial statements of multinational companies where legal requirements in the presentation of statements may differ from country to country. On the other hand, exposure draft E32 of the International Accounting Standards Board as discussed by Accountancy SA (1989), recognised this problem and sets out to harmonise accounting across international boundaries. Nevertheless, when one compares the financial statements of a number of companies, it is essential to ensure that the same accounting policies and methods are used.

For this reason it is important that the notes to financial statements be studied closely so that financial policies may be correctly applied.

2.2.5.3 The desire for further information.

Investors are also interested in the financial aspects of the company's performance which are not included in the financial statements. These aspects may impair or even nullify the existing information. The Rank Hovis McDougall capitalisation of in-house brands is an excellent example of such an aspect. (See Wilson, 1989). It for this reason that additional information is required about intangibles, contingent liabilities and the special claims of other companies or the tax authorities.

2.2.5.4 Current value versus historical cost accounting.

A pressing debate is whether the assets of a company be valued at historical cost or current cost. Rising inflation has led to the demand that changes in a company's asset and liability structure be shown in the company's financial statements at current cost. It is argued that by adjusting for inflation, the earnings of the company and the value of assets and liabilities will be reflected more reliably and hence be of greater relevance to users.

Unfortunately the problem is largely philosophical and consensus on inflation accounting has not been universally achieved. Although South Africa suffers from a relatively high rate of inflation no standard has yet been reached on how the problem needs to be handled. During the late seventies, AC 201 (1978) was issued which recommended the preparation of a supplementary current cost income statement. In 1986, Exposure Draft 66 was issued which recommended that certain disclosures providing information as to the impact of inflation on the results of the operations of companies and its financial position, should be supplied. (See Accountancy SA (1986)). This was superseded by Exposure Draft 77 (1989) which was a much more comprehensive document on inflation adjusted accounting.

2.2.5.5 Budgets.

Due to the on-going nature of any business, it is necessary that information about the company's future projects and financial budgets be made available to the interested parties. The investor will require net cash flow figures, growth rates in earnings per share and return on investment for existing and proposed projects.

2.3 Ratio analysis.

When analysing the financial statements of a company, the value of each component in the Balance Sheet or Income Statement is of limited use as it is measured in absolute value. Although the statements should conform to the characteristics mentioned earlier, an evaluation of financial statements must be preceded by careful identification of the kind of information required. Bernstein (1978:3) defines financial statement analysis as

> the judgemental process which aims to evaluate the current and past financial positions and the results of operations of an enterprise, with the primary objective of determining the best possible estimates and predictions about future conditions and performance.

The most common "judgemental process" of financial statements is that of ratio analysis which is used to evaluate the overall well-being of the business. It must be remembered that those who use this process will require different ratios and that the choice of these ratios will be determined by the financial data available and the nature of the problems involved. Ratios are not ends in themselves but, on a selective basis, may help answer significant questions and highlight areas of weakness for the purpose of further investigation and analysis.

2.3.1. Ratio categories.

Ratios may be divided into four main categories: liquidity, solvency, profitability and performance.

1. Liquidity ratios give an indication of how the working capital is managed by the firm and express the firm's ability to meet its current commitments.
2. Solvency ratios indicate how management has financed the capital commitments of the firm and accordingly the firm's ability to meet its long term obligations.
3. Profitability ratios are used to measure the firm's operating and financial efficiency.
4. Performance ratios give an overall indication of how the company has performed with reference to the Stock Exchange. They will be of particular interest to investors and management who wish to maximise shareholders' wealth.

It is essential at the outset to evaluate these categories separately although an overall evaluation will not show how the separate categories are interrelated. This relationship is adequately illustrated by the Du Pont chart. (See Weston and Copeland, 1986:229).

Finally the user must remember that, although individual ratios may give an insight into a particular aspect of the company's well-being, as many ratios as possible must be used in order to obtain an general picture of the financial standing of the company. Hence for the analysis to be effective, a wide profile of ratios must be calculated to facilitate comparison.

As regards the application of ratio analysis, certain rules of thumb have been evolved over a long period of time. Tamari (1978:18) has summarised these rules as follows:-

1. analysing a series of ratios rather than those for one year.

2. carefully studying the notes and explanations attached to the statements.
3. checking the veracity of the items by comparing them with those of previous years; any sudden change being suspect.
4. correct the data for the effects of changes in the price level, particularly to the fixed asset base.

2.3.2 Shortcomings.

As discussed, financial statements have their limitations and, by implication, so too does ratio analysis. It would be erroneous to assume that ratio analysis is a totally reliable and accurate technique for evaluating financial well-being. The limitations associated with the use of ratios can be classified as follows:-

1. Accounting data.

Ratios are constructed from accounting data which may have been compiled according to different accounting policies and methods and the ratios of one company may differ from those of another in the same industry. This would make comparisons difficult. AC 000 (1990) maintains that comparability is an important characteristic of financial statements hence it is important to evaluate the basic accounting data upon which the ratios are based and to reconcile differences whenever they appear.

In addition, the user will need to have at his disposal the average ratios for the industry. Without the industry standards, the user will be unable to make comparisons as to the performance of the company relative to the rest of the industry.

2. Ratios that are interrelated.

If items are closely related to one another in the financial statements, it may mean that certain ratios will be closely related and a judgement based on composite ratios must be made with caution. For example, a high inventory turnover may be an indication that working capital is being adequately managed but it may also signify a shortage of goods for sale and hence the possibility of stockouts.

3. Percentages.

When comparing percentage ratios it is important that the companies examined have similar asset bases. A twenty percent increase in asset turnover from an asset base of R100 000 is not comparable to an increase of ten percent from an asset base of R1 million. Should the success of the two companies be assessed on these returns, it would be misleading to assume that the smaller company is twice as successful as the larger company. It may be impossible for the larger company to increase sales to the point where a twenty percent return on assets is achieved as this level of sales may be unattainable.

4. Historical costs.

As ratios are based on the firm's historical values, analysis is limited as they are not an indication of the firm's future performance. If the firm is in a volatile or fluctuating industry, historical values may mislead management as regards future trends of the firm.

2.4. Conclusion.

The essential purpose of accounting is to provide interim measures of the progress of a business. Initially, these measures should relate to the firm's ability to produce cash for its owners as this is the only asset which may be used to reduce debt in the normal course of business. Ultimately, there is the need to supply information which could be used in assessing management's ability to utilise the firm's resources effectively in achieving the overall goal of creating value for the stakeholder.

The ability of the company to create value for the stakeholder may be assessed with reference to the company's Annual Report. The generally accepted method of evaluating the success or otherwise of the firm in achieving these objectives, is ratio analysis. As this study incorporates the use of ratios in predicting failure, the general nature of the technique has been outlined.

CHAPTER THREE.

LITERATURE REVIEW : FIRM-SPECIFIC FINANCIAL RATIOS.

3.1 Introduction.

The ability to predict bankruptcy is important to a number of people who need forewarning of the impending event. As Altman (1983:71) says,

> Business failure identification and early warnings of impending financial crisis are important not only to analysts and practitioners in the United States. Countries throughout the world, even non-capitalist nations, are concerned with individual firm performance assessment.

Management will need to evaluate the problem so as to apply remedial action. Employees will need to be aware of impending financial difficulties in the company as their welfare depends on the timely payment of wages. Shareholders/lenders of money should be informed of the situation as they may wish to transfer their funds to more profitable operations. Customers will also be inconvenienced by the demise of a company as alternative sources of supply will have to be sought. In fact, all the stakeholders who rely on the redistribution of wealth are dependent on the continued well-being of the firm.

Ratio analysis is a well established aid whose main purpose is the assessment of financial well-being. The technique was evolved from the ratio of current assets to current liabilities which was used at the turn of the century to evaluate credit worthiness. Since then, the technique has been extended to the use of a large number of ratios, grouped into categories, which are intended to highlight different aspects of the business. See Horrigan (1968) for a historical summary of the use of ratio analysis until the mid-sixties.

Since the mid-sixties, specific ratios have been used in an attempt to predict failure culminating with various multivariate models which attempt to establish failure prediction scores. In this chapter a review of the more significant studies of the firm-specific financial variables which are used to model failure, is conducted. Most of these models use the statistical technique of multivariate discriminant analysis when discriminating between failed and non-failed companies.

3.2 Prior research.

A large number of researchers in various countries have conducted research into the reasons for business failure. Due to the fact that the business environment may differ from country to country, the review of the literature on failure prediction is conducted by country.

3.2.1 The United States of America.

The United States of America has been the forerunner in the field of failure prediction. The Great Depression caused a number of articles to be written on the topic, the more significant being those of Fitzpatrick (1932), Smith and Winnakor (1935) and Merwin (1942) who showed that failed firms exhibited substantially different ratios when compared with successful companies. Since the mid-sixties however the topic of failure prediction has enjoyed a great deal of interest in the literature.

3.2.1.1 Beaver.

The first classic research into failure prediction was that of Beaver (1966) whose ultimate objective was the empirical verification of the usefulness of financial statements and not failure prediction, per se. Nevertheless, when researching the problem he found that various financial ratios could discriminate between failed and non-failed companies for up to five years prior to failure.

Classifying failed firms as those which had been declared bankrupt or which had failed to pay dividends on preferred shares or interest on bonds, he isolated a sample of seventy-nine failed companies for further investigation. Paying particular attention to the pairing, Beaver matched these companies by industrial sector and by asset size with non-failed companies. He felt that this was necessary in order to minimise the effects which size and inter-industry differences may have on the relationship between the ratios for the failed and non-failed companies when viewed separately (unpaired). (See Beaver, 1966:76).

Using the financial statements of the selected firms for up to five years prior to failure, Beaver calculated the values of thirty ratios for the chosen companies. The choice of the ratios was based on the criteria of popularity, adequate performance in prior studies and a close affinity to the concept of cash flow.

A comparison of the data for the failed and non-failed firms showed

> that the difference in the mean values (of the ratios) is evident for at least five years prior to failure with the difference increasing as the year of failure approaches.
>
> (Beaver, 1966:81)

Beaver thereafter examined the predictive ability of the ratios using the dichotomous classification test. He arranged each ratio in ascending order and chose a cut-off point, indicating failure, by inspection. The chosen firms were accordingly classified as failed or non-failed and the percentage misclassifications (as compared to the actual) were calculated. The ratio with the lowest percentage of misclassification was regarded as having the best predictive ability.

Beaver found that six ratios were consistent in giving the smallest percentage of misclassification. These were :-

1. cash flow/total debt
2. net income/total assets
3. current plus long-term liabilities/total assets
4. working capital/total assets
5. current assets/current liabilities
6. no-credit interval.

Of these ratios, cash flow to total debt had the smallest misclassification error. This amounted to thirteen percent in the year before failure and increased to twenty-two percent in the fifth year prior to failure. This ratio has subsequently enjoyed a degree of prominence with practitioners due to its ease of application and its high degree of predicted accuracy.

In a subsequent paper, Beaver (1968(a):121) sounded a note of warning to his earlier paper by saying that

> the analysis of ratio components has limited exploratory power because it relies solely upon a comparison of means. Differences in means are difficult to interpret without additional knowledge about ratio distribution.

He advocated that greater emphasis be placed on the pure accounting items in financial statements and that a more empirical approach should be applied to verify *a priori* beliefs.

Using the same data set as his previous paper, he found that the non-liquid asset measures had better predictive ability than the liquid asset measures. This supported his contention that cash flow to debt was a better predictor of failure than liquid asset measures (such as the current ratio). These findings were subsequently empirically confirmed by Gentry, Newbold and Whitford (1985) using logistic regression analysis in conjunction with cash-flow variables.

In his last paper on the subject Beaver (1968(b)) examined the effect of share prices as predictors of failure. Using the same data base as his previous studies, he calculated the rates of return on shares (using market prices) for the failed and non- failed companies for five years prior to failure. He concluded that market prices cannot be used as predictors of failure as no conclusions can be drawn about the difference that exists in the *ex post* rates of return for failed and non-failed firms. His findings point instead to the efficiency of the market because, as he says, "the evidence does not suggest a scheme for beating the market" (Beaver, 1968(b):192). Apart from all else, the paper acknowledged that macroeconomic factors may have a bearing on the prediction of failure.

Although Beaver's work was not directed specifically at failure prediction and lacked statistical rigour (as he himself admits) in the selection of the predictor ratios and with the cut-off point when predicting failure, it nevertheless drew attention once again to the use to which ratios could be put when predicting failure.

3.2.1.2. Altman.

Altman's (1968) initial work on failure prediction was published shortly after that of Beaver. Altman's concern was that ratio analysis as a tool for evaluating company performance was being downgraded, for as he says

> Academicians seem to be moving toward the elimination of ratio analysis as an analytical technique in assessing the performance of the business enterprise. Theorists downgrade arbitrary rules of thumb, such as company ratio comparisons, widely used by practitioners. Since attacks on the relevance of ratio analysis emanate from many esteemed members of the scholarly world, does this mean that ratio analysis is limited to the world of "nuts and bolts".
>
> (Altman, 1968:589).

Altman maintained that Beaver's univariate model was an oversimplification of real life and that a multivariate model would be a better predictor of failure. In support of this contention, he used a sample of thirty-three failed companies which he matched with thirty-three non-failed companies by industry when attempting to establish a multivariate model of failure prediction. The non-failed companies had assets of between one million and twenty-five million dollars.

He thereafter chose twenty-two ratios from five standard ratio categories which he regarded as potentially helpful predictors of failure. Using multiple discriminant analysis and personal judgement, he selected five ratios which he felt were best suited to serve as the predictors in a discriminant function. These appear in a linear discriminant function as follows:-

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

where

X_1 = Working capital/total assets

X_2 = Retained earnings/total assets

X_3 = Earnings before interest and tax/total assets

X_4 = Market value of equity/book value of total debt

X_5 = Sales to total assets

and

Z = Overall Index (or Z-score)

Altman then investigated the predictive ability of the five variables individually by testing their significance in the year prior to failure using an F-test. The first four variables were all significant at the .001 level while the fifth variable was not significant.

Altman concluded that the Z-score could be used as a predictor of failure. A score in excess of 2.99 would clearly indicate a healthy firm whereas a score of less than 1.81 would point to potential bankruptcy. A score between these levels would indicate a "zone of ignorance" due to the probability of misclassification.

The model had a ninety-four percent degree of accuracy in predicting failure in the year prior to failure. This fell to seventy-two percent in the second year prior to failure. Prediction for earlier years proved to be unreliable. From the third to fifth years prior to failure, the model was less accurate in predicting failure than was Beaver's univariate model (where the predictive accuracy, five years prior to failure, was seventy-eight percent).

Although Altman's research was a significant contribution in the field of failure prediction, the predictive ability of the model is fairly limited as it was confined to a group of manufacturing companies whereas a larger sample across the whole business spectrum could have been chosen. In fact, when Altman (1973) calculated the Z-score for a number of railroad companies, the results showed that it was difficult to apply the same cut-off point to firms operating in different industrial sectors and during times in which different economic conditions applied.

In addition, there is little similarity between the predictor variables and those isolated by Beaver (1966). Altman did however not include cash flow/total debt as a variable due to the inconsistent treatment of depreciation by the sampled companies.

Finally, the lack of financial statements for small, or unquoted firms, also imposes limitations on Altman's model. The risk in these firms is usually greatest; thus the need for a suitable prediction model is also greatest. Although it has its limitations Altman's model has been widely used as a useful aid in the prediction of failure.

3.2.1.3 Wilcox.

Wilcox (1971) was critical of the previous approaches to the prediction of failure as he felt that the research was poorly structured and without a conceptual framework. He accordingly sought to adapt the classic model of gambler's ruin when attempting to discriminate between low and high risk firms. Using a probabilistic process, he sought to determine a state of zero liquidity which would constitute failure (or a gambler's ruin).

Wilcox (1976) refined his original model when he focused on the net liquidation value of the firm and the factors which would cause this value to fluctuate. Taking the net liquidation value as the difference between liquidity inflows and outflows, Wilcox defined the inflows as net income minus dividends, and outflows as increases in the book value of assets minus the liquidation value of these assets. Wilcox postulated that the probability of the net liquidation value being reduced to zero was a function of the current wealth, the average adjusted cash flow and their variance. An analogy can be drawn to a bathtub whose tap and plug are both open with the net liquidation value represented by the water level. Should the bath run dry, the firm would have exhausted its net liquidation value and could accordingly be classified as bankrupt.

Wilcox (1976) maintained that the strength of his model lay in the fact that it evolved from a statistical base and not intuitively and that its efficacy had been tested over a long period of time. In addition, he felt that his model had practical application for management - factors which were missing in earlier models.

A criticism of this model is that, while it explained the failure process, it lacked predictive accuracy.

3.2.1.4 Deakin.

Deakin (1972) sought to establish a more efficient failure prediction model than Altman's Z-score model. Following Beaver's approach but for a different time period, he applied a dichotomous classification test of fourteen pre-selected ratios to a paired sample of thirty-two failed and non-failed companies. He found that the ratio of net income to total assets had basically the same predictive ability as the cash flow to total debt.

Deakin thereafter applied multivariate discriminant analysis to the chosen variables and obtained misclassification errors of less than five percent in the three years prior to failure. The misclassification errors for the fourth and fifth years prior to failure were twenty-one and seventeen percent respectively. Deakin also found that misclassification increased when he attempted to reduce the number of predictor variables.

A criticism of this model is that the sample of independent variables was large and a good deal of multicollinearity may well have occurred between the independent variables.

3.2.1.5. Edmister.

Although not seeking to duplicate the prior research, Edmister's (1971) main concern was to develop a model of failure prediction for small businesses. In addition, he used a zero-one regression technique, as opposed to multivariate discriminant analysis, in an attempt to limit multicollinearity in his regression equation. Using an arbitrary stepwise regression procedure, Edmister accordingly excluded a variable from the model if its correlation with an included variable was greater than 0,31. He thereby isolated seven ratios, which had been transformed into zero-one qualitative variables, for inclusion in his regression model.

Edmister concluded that the major factors influencing the predictive accuracy of the model are the statistical technique used when establishing the model as well as the number of ratios which were included in the model.

A criticism of the research is that although Edmister sought to limit the number of ratios for inclusion in the model, the cut- off point for the variable to enter the equation was arbitrarily set. It is therefore difficult to judge the explanatory power of the variable to be eliminated.

3.2.1.6 Libby.

In an encouraging departure from the purely intuitive approach to the selection of the independent variables, Libby (1975) applied principal components analysis for selecting the predictor variables. Using this technique with the fourteen ratios isolated by Deakin (1972), Libby found five independent sources of variation within the selected ratios. These could be represented by profitability, activity, liquidity, asset balance and cash position.

3.2.1.7 Altman, Haldeman and Narayanan.

Altman *et al.* (1977) felt that there was a need to update the original Z-score model for several reasons. The most pertinent were firstly that the changes in the business conditions, made it necessary to review the original model. Secondly, that there was a need to test and assess certain controversial aspects surrounding the use of multivariate discriminant analysis when predicting failure.

As a result of their research, Altman *et al.* isolated seven predictors for inclusion in the new model. The predictive ability of these variables was analysed using multivariate discriminant analysis in the linear as well as the quadratic form. In addition, Altman *et al.* acknowledged that the assumption of equal priors and misclassification costs could bias the cut-off rate. They accordingly varied the cut-off rate and investigated the efficiency thereof.

As the research was undertaken for a private firm, they do not supply the coefficients of the independent variables included in the model. . They do however indicate the seven predictor variables which they use in the discriminant model. These are as follows:-

1. Earnings before interest and tax to total assets.
2. A normalised measure of the standard error of estimated earnings around the ten-year trend.
3. Earnings before interest and tax to total interest payments.
4. Retained earnings to total assets.
5. Current assets to current liabilities.
6. Market value of equity (five-year average)to book value of debt.
7. The total asset value of the firm

Three of these predictor variables (1, 4 and 6) appear in the Z- score model. The other four variables are new inclusions.

Altman *et al.* found this model to be a better predictor of failure than the Z-score model and to be an adequate predictor of failure for up to five years prior to bankruptcy. In addition, the research confirmed that the linear form of the equation outperformed the quadratic form with respect to failure prediction.

Scott (1981:324) has this to say of the ZETA model,

> Of the multidimensional models, the Zeta is perhaps the most convincing. It has high discriminatory power, it is reasonably parsimonious and includes accounting and stock market data as well as earnings and debt variables.

Subsequent to the work by Altman *et al.* (1977), few additional models using multivariate discriminant analysis appear in the literature. The academic discussion is centred on the efficacy of the statistical techniques used in establishing the models, rather than on the predictive accuracy of the model. This aspect is discussed in Chapter Four.

3.2.2 The United Kingdom.

The majority of the research in the United Kingdom centred on the application of the research conducted in the United States of America to the United Kingdom situation for as Taffler (1984:199) says, "the UK provides a financial environment ideal for the successful development of statistical models for the assessment of company solvency and performance". See Taffler (1984) for a comprehensive coverage of the topic in the United Kingdom.

3.2.2.1. Lis.

The first research of any note was by Lis (1972), as described by Bolitho (1973), who sought to apply Altman's multivariate approach in the United Kingdom. Using a selection of thirty failed and thirty non-failed companies and multivariate discriminant analysis, he established a Z-score model as follows:-

$$Z = 0{,}063X_1 + 0{,}092X_2 + 0{,}057X_3 + 0{,}0014X_4.$$

where

X_1 = Working capital/total assets
X_2 = profit before interest and tax/total assets
X_3 = retained earnings/total assets
X_4 = net worth/total debt

and

Z = the failure prediction score

The model, using a cut-off rate of 0,037, misclassified only one failed company and five non-failed companies from a paired set of thirty failed and non-failed companies. The research by Lis did show that a failure prediction score could be applied to an environment outside the United States of America but unfortunately no analysis of its predictive ability in actual practice has been published.

3.2.2.2. Taffler and Tisshaw.

The research by Taffler and Tisshaw (1977) centred around the role of the auditor in evaluating the business as a going concern. They felt that the evaluation could best be achieved by determining a Z-score for British companies.

Taking paired sets of forty-six failed and non-failed companies, a selection of eighty ratios and using principal component analysis to aid in the reduction of the predictor variables, Taffler and Tisshaw found that four ratios were significant predictors of failure when tested using linear discriminant analysis. These were:-

1. profit before tax/current liabilities
2. current assets/total liabilities
3. current liabilities/total assets
4. current liabilities/cash operating costs.

This model was almost one hundred percent accurate in predicting failure. In addition, while the failure prediction score of nine for solvent companies remained fairly stable over time, the score for the failed companies declined dramatically, from two in the fourth year prior to failure to minus four in the year before failure.

3.2.2.3. Taffler.

The first comprehensive attempt to arrive at an operational discriminant model which could be used to identify British companies at risk, was by Taffler (1982). His initial concern was that the correct statistical technique be applied in arriving at a failure prediction model but felt that the temporal nature of the ratios needed to be emphasised as well.

Taffler selected twenty-three failed and forty-five non-failed companies for investigation. Using principal component analysis with varimax rotation on a selection of fifty ratios, he found that seven factors explained ninety-two percent of the variance in the independent variable set. Using this information, he applied step-wise linear discriminant analysis to his selected variables and obtained an operational discriminant model, with standardised coefficients, as follows:-

$$Z = 0{,}71X_1 - 0{,}93X_2 + 0{,}32X_3 + 0{,}49X_4 + 0{,}53X_5$$

where

X_1 = Earnings before interest and tax/opening total assets

X_2 = Total liabilities/total capital employed

X_3 = Quick assets/total assets

X_4 = Working capital/net worth

X_5 = Stockturn.

and

Z = the failure prediction score

The model exhibited a high degree of predictive ability and only one of the original failed firms was misclassified. Taffler concludes that his model appeared to outperform the extant United States models and that it exhibits true *ex ante* predictive ability.

3.2.2.4. Robertson.

Robertson (1983) departed from the traditional method of failure prediction as he felt that the pure empirical approach to failure prediction was far too complex for practical application. He accordingly selected five ratios based on their ability to respond to changes in the financial health of the company, and applied a contrived weighting to each ratio. The ratios, with their weighting in parentheses, are as follows:-

1. (sales - total assets)/sales (3,0)
2. profit before tax/total assets (3,0)
3. (current assets - total debt)/current liabilities (0,6)
4. (equity - total borrowings)/total debt (0,3)
5. (liquid assets - bank overdraft)/creditors (0,3).

In doing this, he arrived at a failure prediction score where a decline in the score from year on year is an important indicator when predicting failure. Robertson maintains that the model is not restricted to specific industries and the weightings may be appropriately varied from industry to industry as the need arises. He concludes that

> a drop of forty percent or more in a single year should be investigated without delay and that a further drop of forty percent for a second year running would indicate that a company was unlikely to survive.
>
> (Robertson, 1983:28).

3.2.2.5. Robertson and Mills.

In a more recent publication, Robertson and Mills (1988) expanded on Robertson's original model when developing a new model based on natural selection which is defined as

> the elimination of the unfit ratios and the survival of the fittest in the struggle for existence, depending upon the ability of a ratio to respond to a specific environment.
>
> (Robertson and Mills, 1988:84).

The new model extends across three dimensions. In the first instance the means of the different ratios between the failed and non-failed companies are examined. In this way variables with near-equal means are eliminated. The next step is to calculate misclassification scores and variables with a high misclassification score would be eliminated. The final step is to calculate the rate of change in the variables from year to year in order to test their efficacy over time.

The method proposed above has the benefit of enabling the researcher to mix-and-match and not be subjected to rigid selection techniques. On the other hand, the subjectivity in the selection of predictor variables could result in a different decision when predicting failure. Nevertheless, the literature of the late eighties does indicate a trend to a more subjective approach to failure prediction.

3.2.3. South Africa.

In South Africa, much of the research relating to the use of ratio analysis as a technique for evaluating risk has not been published. Nevertheless, as de lay Rey (1981:1) points out "large sums of money are lost annually in the Republic of South Africa as a result of the financial failure of industrial enterprises". There is thus a need for both a thorough evaluation of corporate failure in the South African context and the publication of the results thereof. In addition, as Strebel and Andrews (1977) point out, financial failure invariably accompanies severe economic recession indicating that the research needs to be expanded beyond the investigation of firm-specific financial ratios only.

The initial research conducted into the reasons for failure in South Africa was conducted by the University of Witwatersrand's Business School.

3.2.3.1. Strebel and Andrews.

In their paper, Strebel and Andrews (1977:1) point out that the ratio of cash flow to total debt, as popularised by Beaver, "has begun to earn recognition as a statistically significant indicator of bankruptcy potential, all on its own."

They applied the cash flow/total debt ratio to sixteen failed companies and compared this ratio to that of thirteen Blue Chip companies. The results clearly showed a downward trend in the ratio for failed companies over time compared to the same ratio for sound companies which remained steady. In addition, it was ninety percent accurate in predicting failure one year in advance of the event. They accordingly saw this ratio as a powerful predictor of corporate failure.

3.2.3.2. Daya.

Daya (1977) expanded on the initial research of Strebel and Andrews. Using the Beaver technique and a matched sample of thirty-one failed and non-failed companies, Daya confirmed the power of cash flow to total debt as a predictor of failure one year prior to failure. On the other hand, net income to total assets appeared to be the best predictor of failure over the five year period. The results however are not conclusive due to certain limitations brought on by the restrictions of the Johannesburg Stock Exchange.

3.2.3.3. Amiras, Ashton and Cohen

Amiras, *et al.*, (1978) used much of the information collected by Daya when attempting to apply the Altman Z-score technique to the South African situation. Recognising that the Altman coefficients could not be directly applied in the South African context, they applied linear regression analysis to a selection of seventeen ratios in an attempt to establish the significant predictors. Five of these ratios were found to be significant.

The significant ratios were then used to obtain a discriminant score (A-score) which was compared to a cut-off point which was set at zero. A value greater than zero was regarded as indicative of failure while a high positive score constituted a strong indication of failure. Amiras *et al.* did point out however, that the closer the A-score was to zero, the more difficult it became to obtain an accurate prediction. Altman would have termed this the "zone of ignorance."

To test their model, they calculated the A-score of twelve selected companies which were regarded by the investment community as being inordinately high risk. Of the 12 sampled, 11 achieved positive A-scores with some of these companies indicating very high positive A-scores, thereby indicating a high possibility of failure.

3.2.3.4. Zevenbergen

In a study of twenty-one South African motor companies Zevenbergen (1978) calculated the value of fifteen ratios for each company. He then calculated the quartile range for each of the fifteen ratios and allocated a score between three (first quartile) and zero (fourth quartile) for each ratio depending on where the individual company was placed on the quartile scale. He felt that companies with the lowest scores were likely to fail.

While this model was the first published attempt at a multivariate model in South Africa, it has various shortcomings. No weighting was applied to the ratios and hence all the ratios are ranked equally. In addition, it made no attempt to define a cut-off point between failed and nonfailed companies. Finally, the method of classifying the ratios by quartiles did not adequately discriminate between companies and this measurement is not sufficiently accurate to pick up the differences between failed and non-failed companies.

3.2.3.5. Immelman.

Immelman (1980), following the lead set by Beaver (1968(b)), attempted to improve on the predictive ability of the models developed in prior research by combining the stock market returns of the various companies with various financial ratios.

The aim of the research was to establish whether the standard deviations of these returns could be effectively used when predicting corporate failure. His overall conclusion was that the market variable in a model did not add significantly to the prediction of failure.

3.2.3.6. de la Rey

The first comprehensive investigation into corporate failure in South Africa was published by de la Rey (1981) who set out systematically to isolate the ratios to be used in his model. de lay Rey used discriminant analysis to test the significance of various combinations of ratios and to obtain a weighting for the ratios for inclusion in the model. In addition, he applied factor analysis to verify the selection of the chosen ratios.

Finally, de la Rey departed from a pure statistical approach to the selection of ratios by incorporating the various combinations suggested by previous researchers. The process was time-consuming and in all a total of one hundred and ninety four combinations were tested and the final choice of ratio was based on intuition.

Eventually, the following model was chosen from the various combinations as it gave the best predictive results:-

$$K = -0{,}06881 + 0{,}01662X_1 + 0{,}0111X_2 + 0{,}0529X_3$$
$$+ 0{,}086X_4 + 0{,}0174X_5 + 0{,}0071X_6$$

where

X_1 = total outside financing/total assets

X_2 = profit before interest and tax/average total assets

X_3 = total current assets plus listed investments/total current liabilities

$X_4 =$ profit after tax/average total assets at book value

$X_5 =$ cash flow profit after tax/average total assets

$X_6 =$ total inventories/inflation adjusted total assets

and

K = failure prediction score

Whilst this model correctly classified 98,6% of his sample one year prior to bankruptcy, it was not as accurate between the second and fifth years prior to bankruptcy. As de lay Rey (1981:17) points out however

> one of the problems is that a South African researcher is unable to find enough businesses of the type and category which he would like to use to bring sophistication to perfection.

In general, the extant South African research is an attempt to replicate some of the research which was conducted in the United States of America. Very little contribution is made to a greater understanding of how failure might effectively be predicted given the unique conditions which prevail in the South African business environment.

3.2.4. Other studies.

A number of other studies outside the United States of America, the United Kingdom and South Africa have been published and Altman (1983) has surveyed this work admirably. Some of these studies warrant mention as the environments in which they were conducted are similar to those in South Africa.

3.2.4.1. Tamari.

Tamari (1964) investigated failure prediction in Israel prior to the research done by Beaver (1966) in the United States of America and his research is therefore mentioned for its pioneering status. Tamari selected six ratios subjectively and by weighting the ratios differently, he obtained an index of risk. By comparing the ex-post risk index of various manufacturing companies for the period 1958-1960, Tamari found that a company with fewer that thirty points was likely to fail, whereas one with sixty points or more was unlikely to fail.

In order to verify the results, Tamari tested the model for (i) a different time period to cater for changes in the economy (ii) firms operating in a non-manufacturing industry (iii) two different countries (the United States of America and the United Kingdom). In all three instances, the model "was able to predict the probability of bankruptcy with only minimal changes, if any". (Tamari, 1978:114)

3.2.4.2. Castagna and Matolscy.

A paper from Australia which warrants discussion is by Castagna and Matolscy (1983) for as Altman (1984:185) says "Australia has certain unique characteristics with huge development potential but with an already established industrial base". As this statement could equally be applied to South Africa, the Australian research may be of interest to South African researchers.

As Castagna and Matolscy (1983:22) say

> We take the view that a company's financial ratios variously "capture" the influences of management policy, macroeconomic factors, and the factors that are specific to the industry in which a company operates.

The ratios which are chosen for inclusion in the model are similar to those used by Altman in his Z-score model. They are:-

1. Earnings before interest and tax to total assets
2. Operating income to operating assets
3. Liquid ratio
4. Total debt to total assets
5. Market capitalisation to total debt

These variables serve as the initial predictor variables. Using discriminant analysis in a model incorporating these variables, the squared value of each variable and various combinations of each of the variables is used to obtain a failure prediction score.

The authors conclude that "the evidence suggests that whilst the model's predictions are not 'perfect', it is currently the best available for addressing this problem in Australia". (Castagna and Matolscy, 1983:24)

3.3. Conclusion.

In this chapter, various models have been discussed which use financial ratios and multivariate discriminant analysis as a means of predicting failure. Irrespective of the variables used and their accuracy in predicting failure, all the models have shown that they may aid in the prediction of failure even though their approach to the problem varies widely.

On the other hand, there are a number of restrictions which have been imposed on these models when they are applied using multivariate discriminant analysis. As Eisenbeis (1977:875) says of the multivariate discriminant analysis papers that have appeared in the literature, "most have suffered from methodological or statistical problems that have limited the practical usefulness of their results". These problems need to be considered when applying a failure prediction model and are accordingly reviewed in the following chapter.

CHAPTER FOUR.

MULTIPLE DISCRIMINANT AND LOGISTIC REGRESSION ANALYSIS.

4.1 Introduction.

In Chapter Three, a broad description of the literature concerning failure prediction models using firm-specific financial variables as the predictor variables was given. Most of these models used multivariate discriminant analysis as the requisite statistical technique.

Barnes (1984) is highly critical of this technique for he maintains that the rigid use of statistical models is a highly undesirable development in failure prediction. He encourages the users of failure prediction models based on multivariate discriminant analysis

> to be critical of new techniques enshrined in statistical sophistication yet devoid of insight into the behaviour of phenomena they claim to be able to control.
>
> (Barnes, 1984:11)

The application of the standard discriminant analysis technique is not without problems and Eisenbeis (1977:875) is of the opinion that one can expect to encounter statistical difficulties more frequently than in any other application areas. He states that problems could arise in the following:-

> (1) the distribution of the variables, (2) the groupdispersions, (3) the interpretation of the significance of the individual variables, (4) the reductionofdimensionality, (5) the definitionsof the groups, (6) the choice of the appropriate *a priori* probabilities and/or costs of misclassification (7) the estimation of classification error rates.
>
> (Eisenbeis, 1977:875).

In general, it is difficult to evaluate the efficacy of models using multivariate discriminant analysis. Although the standard multivariate discriminant analysis procedure provides a general method of classification (failed or non-failed in this case), optimality in prediction is only achieved when the predictor variables are normally distributed. This is not always the case with financial ratios and violation of this condition may bias the tests of significance and the estimated error rates. None of the authors who use multivariate discriminant analysis, except Altman *et al.* (1977) and Taffler (1982), attempt to address a situation of non-normality.

In addition, another critical condition is that the separate samples of failed and non-failed companies have equal variance- covariance matricies. Relaxation of this assumption may affect the significance test for the differences in the group means.

More recent research has used logistic regression analysis when classifying companies as either failed or non-failed. The purpose of this chapter is to review logistic regression analysis as an alternative statistical technique to multivariate discriminant analysis when predicting failure. In addition a comparison is made of the predictive ability of the two techniques with specific reference to the South African situation.

4.2. Prior research

Discriminant, and linear probability functions are closely related and can be used in a number of ways to classify the dependent variables. See Ladd (1966) for an evaluation of the statistical application of the two functions.

Effron (1975), Press and Wilson (1978), Zmijewski (1984) and Noreen (1988) all make a direct comparison of the two techniques. Their conclusions are contradictory. Effron (1975:892) concludes that "logistic regression is shown to be between one half and two thirds as effective as normal discrimination for statistically interesting values of the parameters". Press and Wilson maintain that in almost all discriminant problems at least one of the variables is qualitative, thereby violating the condition of normality and indicating that logistic regression analysis should be used. They conclude that, from the results obtained from their empirical data, logistic regression with maximum likelihood estimation outperformed traditional linear discriminant analysis but feel that it is "unlikely that the two methods will give markedly different results, or yield substantially different linear functions". (Press and Wilson, 1978:705).

Zmijewski (1984) is not so much concerned with the relevant statistical technique as with the fact that non-random samples are used when predicting distress. He maintains that this "can result in biased parameter and probability estimates if appropriate estimation techniques are not used". (Zmijewski, 1984:59). The two biases which he investigates are choice-based sample bias and sample selection bias, both of which could result in erroneous parameter and probability estimates. These conditions arise because researchers are constrained by the low frequency rate of failed firms and by the fact that, even if the firm has failed, certain information pertinent to the problem may be unavailable.

Using probit as the appropriate statistical technique, Zmijewski concludes that choice-based sample, and sample selection bias do occur unless appropriate adjustment measures are used. On the other hand he states that the bias does not affect "the statistical inferences or the overall classification rates" for the financial distress model. (Zmijewski, 1984:80).

Noreen (1988), supports the findings of Zmijewski for he maintains that regression analysis (OLS) performs as well as the log-linear form for the "evidence does not support the use of probit rather than OLS in accounting classificatory studies". (Noreen, 1988:132.)

Joy and Tollefson (1975) and Eisenbeis (1977) both specifically question the application of discriminant analysis to a dichotomous classification problem in empirical research. Joy and Tollefson are concerned that if *a priori* classification is combined with prediction over time it raises methodological issues which do not appear to have been generally recognised. They contend that the statistical technique which should be used will depend on the mean-covariance matrices of the dichotomous samples. Joy and Tollefson conclude that

> for research questions addressed to populations with extremely assymetric (sic) priors it will be very difficult to improve on chance classification and sample results may give a misleading impression of usefulness.
>
> (Joy and Tollefson, 1974:723)

In response to this shortcoming they propose a Bayesian evaluation approach to the problem.

Eisenbeis (1977) makes a thorough evaluation of the problems which he anticiaptes could arise with the application of multivariate discriminant analysis. In essence, he endorses the points raised by Joy and Tollefson as well as expressing concern about the arbitrary selection of the predictor variables. Eisenbeis is also of the opinion that the use of multivariate discriminant analysis does not overcome the problem of multicollinearity which could arise between these variables, should they be arbitrarily selected. In addition, he stresses the need to overcome serial correlation when evaluating time series.

Ohlson (1980) felt that the predictive results of multivariate models were influenced by the date on which the financial statements were released to the public and that the results of previous studies were overstated. In addition, in order to overcome some of the problems which he felt were inherent in the use of multivariate discriminant analysis, he introduced the use of probability estimation (conditional logit) into failure prediction models.

Ohlson identified four factors as being statistically significant (although he gives no indication as to how he obtained these factors) in affecting the probability of failure. These were:-

1. the size of the company
2. the measure(s) of financial structure
3. the measure(s) of performance
4. the measure(s) of liquidity.

Using simplicity as a criterion, he chose nine financial ratios, in three different models, to derive three sets of estimates. These models were used to predict failure within one, two and one or two years of the actual event.

Ohlson's conclusion is two-fold. Firstly, the predictive power of a failure prediction model depends on when the financial information is made available and secondly, the predictive power should improve significantly with the incorporation of additional predictors.

Following the approach adopted by Ohlson, Mensah (1984) and Zavgren (1985) use logistic regression analysis as an estimation technique. Zavgren uses both logistic regression analysis and probit to establish a probability of failure as a financial risk measure for the five years prior to failure. Zavgren selects her predictor variables using factor analysis by choosing the ratio with the highest factor loading to represent that factor. She isolated seven factors as potential predictors of failure. The factors (and the variables chosen to represent the factors) are as follows:-

1. return on investment (total income/total capital)
2. capital turnover (sales/net plant)
3. inventory turnover (inventory/sales)
4. financial leverage (debt/total capital)
5. receivables turnover (receivables/inventory)
6. short-term liquidity(quickassets/currentliabilities)
7. cash position (cash/total assets).

These ratios all had a loading of 0.81 or higher.

Zavgren concludes that models which generate a probability of failure are more suited to failure prediction than the dichotomous classification models. Gentry, Newbold and Whitford (1985) concur with this conclusion. In addition, Zavgren found that the efficiency ratios were highly significant predictors of failure over the long run. Zavgren's research compares favourably with the prior research although she does not investigate the non-stationarity of the predictor variables over time.

Hing-Ling Lau (1987) departs from the traditional dichotomous state of failed or non-failed and classifies firms as in one of five states ranging from financial stability (0) to bankruptcy and liquidation (4) thereby highlighting prefailure distress as well as ultimate failure. Using multinomial logit analysis, she determines the probability with which a firm will enter each of the five different states. Hing-Ling Lau thereafter uses the ranked probability scoring rule to evaluate the quality of these predictions.

In recent research, Scherr (1989) feels that incorrect use is made of multivariate discriminant and logistic regression analysis when predicting failure unless the correct consideration is given to the nature of researcher's hypotheses. He proposes that more attention be given to causality in the choice and application of the analysis methods. Scherr (1989:19) concludes that "by properly matching causality and analysis technique...financial position contribute to default" would be obtained. He also suggests that further research into the role which management plays in contributing to failure should be conducted and he proposes that indicies of managerial competence should be established and incorporated into the failure prediction model.

4.3 Statistical techniques.

4.3.1 Multivariate discriminant analysis.

Multivariate discriminant analysis' approach to the problem of group classification can be stated as follows: Given that a population can be partitioned into *k* distinct groups and given a vector of *q* predictor variables such that :-

$$X = (X_1, X_2 \ldots\ldots\ldots, X_q)^t ,$$

multivariate discriminant analysis attempts to determine a discriminant function, known as Fisher's linear discriminant function, for assigning X to one of these groups in such a manner that the chance of misclassification is minimised.

More specifically in the prediction of failure, two samples of failed and non-failed companies,which have n_1 and n_2 companies in each category respectively, are selected from the total population. These two samples are taken to represent the dependent variable. Any number of ratios (predictor variables) are then chosen and the linear discriminant function of predictor variables can be expressed in the form

$$\beta_1X_1 + \beta_2X_2 + \dots\dots\dots\dots + \beta_qX_q$$

or

$$\underline{\beta}^t \mathbf{X}$$

This linear function can subsequently be used to assign a new company to either of the failed or non-failed populations.

4.3.2. Logistic regression analysis.

Logistic regression analysis investigates the relationship between a binary-dependent variable and a set of predictor variables. The dependent variable could be used to represent such conditions as failed and non-failed when evaluating the status of companies.

Suppose that Y_i is a binary random variable which takes the value of 1 for a non-failed company and 0 for a failed company where $i = 1,2,....,n$. Let the probability of success (non-failure) for the *ith* company be denoted by p_i for $i = 1,2,.....,n$. The logistic regression analysis model is formulated in terms of these probabilities as follows:-

$$p_i = \frac{\exp \underline{\beta}^t \underline{X}_i}{1 + \exp \underline{\beta}^t \underline{X}_i}$$

where X_i denotes the vector of q predictor variables and $\underline{\beta}$ the vector of unknown coefficients. This equation can be inverted to obtain the more familiar linear logit equation

$$\log \frac{p_i}{1-p_i} = \beta_0 + \beta_1 X_{1i} + \ldots\ldots + \beta_q X_{qi}$$

$$= \underline{\beta}^t \underline{X}_i$$

In general, for the case of two populations, multivariate discriminant analysis provides a general method of discrimination and classification. This is optimal in respect to minimising the probabilities of misclassification when the predictor variables for the two populations are multivariate normal with equal covariance matrices.

Logistic regression analysis on the other hand, is a technique which provides a model for estimating the probability that an item belongs to a particular group. It can be used in the classification of items and appears to be more robust than multivariate discriminant analysis in certain cases. Empirical studies suggest that classification performance with logistic regression analysis is slightly better than multivariate discriminant analysis when the predictor variables are non- normal.

In the following section, an attempt is made to evaluate the applicability of these techniques to the South African situation.

4.4 Research methodology

In the first instance, a number of public companies which operated during the period 1965 until 1986 were chosen to represent the dependent variable. At the same time, certain financial ratios (independent variables) were selected as being the most likely predictors of business failure.

In the second instance, it is desirable that with such a large selection of independent variables the highly correlated variables be eliminated.

Finally, the predictive ability of the model containing the reduced set of predictor variables was compared using both the discriminant and logistic regression analysis techniques.

4.4.1 The dependent variable.

The selection of the dependent variable centred initially on a group of failed companies. A failed company was defined as a company which had been delisted from the Johannesburg Stock Exchange due to poor financial performance and which was later liquidated. The year of failure was taken as the first year in which the company made a loss even though it may have continued to trade thereafter. In all, twenty-six public companies were found which fulfilled the conditions for a failed company.

The selection of failed companies was then matched by industrial sector and approximate net worth with a set of the same number of non-failed companies. The list of selected companies appears in Appendix 4-1.

4.4.2 The independent variables.

Twenty of the most prominent ratios discussed in the seminal literature on failure prediction were arbitrarily chosen as the initial selection of independent variables. The relevant ratios for each failed company were then extracted from the Bureau of Financial Analysis's data bank for the five years prior to failure. The same ratios, for the corresponding period, were obtained for the non-failed companies.

After a thorough evaluation of the data obtained from the Bureau, six ratios were eliminated due to insufficient data. A list of the selected ratios and their definitions is given in Appendix 4-2. These are also available from the Manual for the Users of the Bureau of Financial Analysis Ratio Service (1984).

There is little doubt that with such a large selection of independent variables a high degree of multicorrelation may be present in the data. This is verified by the correlation matrix which is presented in Appendix 4-3. In addition, a large number of predictor variables makes the model unwieldy; hence it is desirable that the number of independent variables be reduced to managable proportions.

When selecting the predictor variables two unrelated statistical techniques were used to evaluate the interrelationship between the chosen variables. Firstly a factor analysis was conducted on the variables in order to group them into categories with similar characteristics. Taffler (1982:345) concurs, for as he says of factor analysis

> Such variable parsimony not only reduces the complexity of a multivariate statistical model, with little if any decrease in its efficiency, but also reduces the likelihood of sample bias being present in the model's construction.

Secondly, as factor analysis gives no indication of the relationship between the dependent and independent variables, a stepwise regression analysis was conducted on the entire data set in order to evaluate this relationship.

Cognisance of both sets of results was taken when chosing the predictor variables for inclusion in the model. As regards the factor analysis, Lehmann (1985) states that there are three approaches which could be applied when reducing the number of independent variables. Firstly, a single variable may be selected to represent the factor. Secondly, an index based on the major variables may be proposed for each factor and thirdly the factor score, computed from each variable, may be used.

The first approach has merit due to its simplicity and Lehmann is of the opinion that it is by no means inferior to the more complicated methods. It enables the predictor variable set to be reduced to equal the number of chosen factors although Lehmann (1985:571) cautions that the "representative should be both a good variable (well measured and understood) and have a high loading with the factor". It is important to note as well that variables which do not load highly on any factor, should also be included as they are unique to the other variables.

Should stepwise regression analysis form the basis of selection, the step in which the variable entered the equation is of paramont importance.

Using the two techniques in conjunction witth one another, the following procedure was adopted throughout this thesis when selecting the predictor variables. Firstly, the number of predictor variables was limited to the number of factors which appeared in the factor analysis except that if a variable had a low loading on all the factors, it was included as an additional predictor variable.

Secondly, when chosing the requisite predictor variable cognisance was taken of its loading in the factor analysis as well as the step in which the variable entered the stepwise regression equation. A variable with both a high factor loading and an early entry into the stepwise regression analysis was a prime candidate for inclusion in the model. Should the choice of a variable have to be made from a factor where none of the variables had entered the stepwise regression analysis, the variable with the highest factor loading was chosen to represent the factor.

4.4.3 The selection of predictor variables.

As discussed, a factor analysis was conducted on the independent variable set for the five year period. When deciding which factors should be included in the factor analysis, Lehmann (1985) maintains that the most common approach is to examine the eigenvalues of the factors. The normal procedure is to limit the number of factors to the number of eigenvalues which are greater than one and this procedure is adopted in this thesis.

After the factors had been rotated using the varimax technique, four factors emerged with eigenvalues in excess of one. Factor one represents the firm's profitability while factor two is an indicator of the firm's liquidity. Factor three is an indicator of solvency while the final factor can be termed a miscellaneous factor. These factors explained eighty-three percent of the variance in the independent variable set. The factors and their variable loadings appear in Appendix 4-4.

It warrants noting that it could be contended that the factor analysis should be applied to the group of failed companies only, as the factors being sought are those which could point to failure. Needless to say the factors being sought are those from which financial wellbeing may be evaluated; accordingly both groups should be included in the factor analysis. This contention is supported by Taffler (1982) who obtained similar results when applying factor analysis to the two groups separately.

When applying the stepwise regression analysis to the variables, entry into the analysis was limited to those variables with an F- value in excess of one. Seven variables accordingly entered the equation. All of these variables displayed the correct sign and they accounted for sixty-two percent of the variance in the dependent variable. The results of the stepwise regression analysis are given in Appendix 4-5.

Based on the selection criteria, the following predictor variables were chosen:-

1. Operating profit to average operating assets (1607) was chosen to represent factor one as it appeared with a high factor loading (fourth at 0,871) as well as being the first variable to enter the stepwise regression.

2. Current assets to current liabilities (1801) was an automatic choice for factor two as it had the highest factor loading and it entered the stepwise regression in the second step.

3. Total owners interest to total assets (0207) was chosen to represent factor three as it had a high factor loading (0,801) as well as entering the stepwise regression in step three.

4. Profit before tax to total debt (1823) was chosen to represent the final factor as it had the highest loading (0,747) for the factor and it entered the stepwise regression in the seventh final step.

A summary of the chosen predictor variables and certain of their statistical characteristics is given in the following table:-

Table 4-1: The predictor ratios and certain statistical measures.

Ratio	Representing	Mean	Sd Dev	Skewness	Kurtosis
1607	Factor 1	7,92	11,47	-0,42	2,59
1801	Factor 2	3,20	6,39	3,65	12,92
0207	Factor 3	37,92	34,12	-0,97	2,73
1823	Factor 4	3,46	68,30	-2,08	13,34

An immediate observation from the statistics is the negative skewness of three of the variables and high level of kurtosis displayed by 1801 and 1823; this could well indicate the use of logistic regression analysis as a technique when predicting failure using these variables.

4.5 Results.

Multivariate discriminant and logistic regression analysis were performed on the chosen ratios by year using the Biomedical Packages of Statistical Software (1985). The estimated failure prediction score for each company was obtained whereupon the firms were classified as failed or non-failed. It bears mention that where data is absent for a company the Biomedical Packages of Statistical Software excludes the company for consideration. The overall effect is that the number of companies being investigated will be reduced accordingly and indication is given in the results whenever this occurs.

When comparing the two techniques, a firm was classified as failed under multivariate discriminant analysis if its discriminant score fell below the average discriminant score of the two groups. With the logistic regression analysis, a company was classified as failed if its estimated probability was less than 0,5. The classification accuracy of the two techniques appears as follows :-

Table 4-2: Comparison of the classification accuracy of multivariate discriminant and logistic regression analyses for the five years prior to failure.

Year	Multivariate discriminant analysis.		Logistic regression analysis.	
	Failed	Non-failed	Failed	Non-failed
1	20/25 (80%)	24/26 (92%)	23/25 (92%)	25/26 (96%)
2	14/26 (54%)	22/26 (85%)	17/26 (65%)	21/26 (81%)
3	16/26 (62%)	21/26 (81%)	17/26 (65%)	20/26 (77%)
4	10/24 (42%)	19/25 (76%)	10/24 (42%)	20/25 (85%)
5	9/20 (45%)	17/20 (85%)	10/20 (50%)	17/20 (85%)

The main area of concern is in the prediction of failure and logistic regression analysis gives better results for the first three years and the fifth year when failure prediction is the criterion. Where success is concerned however the results are not as clear cut.

A z-test was used to test the hypothesis of a difference between the mean number of correctly predicted failed companies for the two models. When the test was applied to the year prior to failure, a z-value of 1,81 (a p-value of 0,0703) was obtained. This is not significant at the 5% level and suggests that there is insufficient evidence to reject the hypothesis of no difference between the two methods of failure prediction.

Although this method of classification may be adequate when evaluating the mean values between the two groups, it may not be feasible to calculate meaningful results from the small amount of data used in the study. A method which has received wide acceptance under these circumstances, is the jackknife method which offers ways to set sensible confidence limits to fairly complex situations (See Lachenbruch and McKey (1968)).

The basic idea is to assess the effect of each of the groups into which the data have been divided, not by the result for that group alone, but rather through the effect upon the body of data that results from omitting that group. In this instance, the discriminant function can be formed from the $(n_1 + n_2 - 1)$ observations and used to allocate the omitted observation to one of the groups. The procedure is then repeated for all the observations and the number of cases wrongly classified is used to estimate the error rate. This procedure is available from the Biomedical Packages of Statistical Software (1985) when applying multivariate discriminant analysis but is unfortunately not available when applying logistic regression analysis.

The results which were obtained from this method of classification when applied test to multivariate discriminant analysis appear as follows:-

Table 4-3: The jack-knife classification results for the multivariate discriminant analysis.

YEAR	Failed	Non-failed
1	20/25 (80%)	23/26 (83%)
2	13/26 (50%)	21/26 (81%)
3	15/26 (58%)	20/26 (77%)
4	8/24 (33%)	17/25 (68%)
5	9/20 (45%)	17/20 (85%)

The number of correct classifications in this instance is lower than the previous results. In addition, the classification results for the second and fourth years are inconsistent with the declining trend obtained from these results. Difficulties with the jackknife method could arise where the data may have excessively straggling tails. This may well be the case with the data for the failed companies which has lead to the inconsistency in the results.

4.6. Conclusion.

A number of failure prediction models have appeared in the literature. The academic debate no longer centres on the predictive accuracy of these models but rather on the statistical methodology employed in establishing these models. The two most popular statistical methods used are multivariate discriminant and logistic regresssion analysis.

In this chapter, the results obtained from the two methods using South African data are compared. The results suggest that, if predictive ability is the criterion in establishing the model, logistic regression analysis produces better results. This suggests that this technique should be used where no assumptions can be made as to the normality of the predictor variables. When the differences between the two methods were tested statistically, however, there was insufficient evidence to reject the hypothesis of no difference.

On the other hand there were certain shortcomings in the data. The paucity of published statistics for failed companies placed severe restrictions on the data base. The result is that inconsistent predictions are obtained from the data and that no definite conclusions can be drawn as to the most efficient method of failure prediction.

Appendix 4-1: The selected sample of failed and non-failed companies. 1966-1986.

Failed	Years	Non-failed
Tapsa	1970/74	Frasers
Spectro Beheerende	1971/75	Dunnell Ebden
Hepworths	1981/85	Edgars Stores
Lucy's Holdings	1971/75	Lindsay Saker
Fairweather Fashions	1972/76	Charmfit Holdings
Hanhill industeries	1979/83	Chemical Services
Lawsons Motor Group	1969/73	Saficon Investments
Simba Quix	1973/77	T.W.Beckett
Finance Co.for Ind Hold	1973/77	Bristol Industries
The Carpet Manf. Co.	1971/75	Romatex
Bromain Holdings	1980/84	Sinclair Holdings
Hugh Parker	1978/82	Duros
Marshall Industries	1973/77	Griffon Holdings
Tollman Hotels	1969/73	Picardi Hotels
S.A. Selected Holdings	1974/78	Fintec
Dorelle Industries	1976/80	Natal Canvas
Unsgaard and Sampson	1968/71	Coates Bros
Greatrex	1967/70	Hendlers Metal Ind.
Vanite Limited	1966/70	Boymans
Bull Brand Foods	1973/75	Picardi Holdings
Ward and Salomons	1966/70	Stuttafords
Donlewis Investments	1969/73	Schus Holdings
Foodtown	1969/72	Grand Bazaars
Enyati Resources	1982/85	BTR
I.L.Back	1982/85	Veka
Triomf	1980/83	Omnia Fertilisers

Appendix 4-2: The selection of financial ratios.

Ratio	BFA code.
Total owners interest/ Total assets	0207
Total current liabilities/ Total assets	0216
Current assets/Total assets	0237
Current assets/Total debt	0730
Profit before interest after tax/ Total assets	1601
Operating profit/ Average operating assets	1607
Retained earnings/ Average total assets	1633
Profit after interest but before tax/ Total assets	1655
Profit after tax/Total assets	1656
Profit after tax/Average owner's equity	1702
Profit before tax/Interest paid	1712
Current assets/Current liabilities	1801
Profit before tax/Current liabilities	1822
Profit before tax/Total debt	1823

Appendix 4-3 Correlation matrix of the selected independent variables.

	0207	0216	0237	0730	1601	1607	1633	1655	1656	1702	1712	1801	1822	1823
0207	1.00													
0216	-0.64	1.00												
0237	0.53	-0.51	1.00											
0730	0.40	-0.30	0.42	1.00										
1601	0.51	-0.40	0.36	0.09	1.00									
1607	0.32	-0.27	0.41	0.18	0.66	1.00								
1633	0.59	-0.40	0.38	0.14	0.98	0.60	1.00							
1655	0.62	-0.40	0.38	0.14	0.96	0.69	0.97	1.00						
1656	0.61	-0.40	0.37	0.14	0.98	0.64	0.99	0.99	1.00					
1702	0.75	-0.40	0.52	0.10	0.76	0.48	0.78	0.76	0.78	1.00				
1712	0.38	-0.35	0.05	0.04	0.22	0.72	0.20	0.24	0.26	0.21	1.00			
1801	0.39	-0.36	0.49	0.98	0.00	0.17	0.05	0.06	0.06	0.76	0.02	1.00		
1822	0.54	-0.21	0.11	0.44	0.69	0.28	0.76	0.73	0.75	0.47	0.22	0.30	1.00	
1823	0.70	-0.56	0.49	0.74	0.57	0.36	0.62	0.63	0.64	0.45	0.44	0.69	0.74	1.00

Appendix 4-4: Sorted varimax rotated factor loadings.

Ratio	Factor 1.	Factor 2.	Factor 3.	Factor 4.
1601	0,940			
1656	0,927			
1655	0,927			
1633	0.910			
1607	0,871			
1702	0,718			
0730		0,971		
1801		0,938		
0237	0,345	0,518	0,408	
0216			-0,816	
0207		0,319	0,801	
1823	0,401			0,747
1822	0,462			0,743
1712			0,497	0,644

* Loadings less in absolute value than 0,25 have not been recorded.

Appendix 4-5: Summary table of stepwise regression analysis.

Step	Variable Entered.Removed	Coeff	Multiple R Sq	F to Enter.Remove.
1	1607	0,020	0,337	22,37
2	1801	-0,038	0,411	5,43
3	0207	0,007	0,521	9,56
4	1702	-0,001	0,548	2,51
5	1655	0,039	0,564	1,47
6	1633	-0,034	0,596	3,08
7	1823	-0.001	0,618	2,17

CHAPTER FIVE.

FIRM-SPECIFIC NON-FINANCIAL VARIABLES.

5.1 Introduction.

Although management blame economic factors, research has shown that companies in First World countries fail primarily because of managerial incompetence. (Moyer, McGuigan and Kretlow, 1984:717. Campsey and Brigham, 1985:665.). The reasons for failure are summarised in the following table:-

Table 5-1: Classification of reasons for corporate failure.

Underlying causes	Percentage
Incompetence	45,6
Lack of general experience	19,2
Lack of managerial experience	12,5
Neglect, fraud, disaster and other	11,6
Lack of line experience	11,1
Total	100,0

(Source: Moyer *et al.* 1984:717)

As can be seen, incompetence and a general lack of experience account for approximately eighty percent of the reason for failure. These findings are supported by the earlier work of Argenti (1976:122), who isolated twelve reasons which he felt were contributors to impending corporate failure. He maintains that ineffective or poor management leads to mistakes in formulating and/or implementing a strategic plan which in turn leads to the ultimate demise of the company. Past research has mainly been concerned with failure prediction models containing only financial ratios, with little attention given to the non- financial variables which could point to failure.

In this chapter an attempt is made to examine the significance and predictive ability of a selection of firm-specific, non- financial variables in the prediction of corporate failure. In addition, a comparison is made of the predictive ability of these variables to a model using only financial ratios. Finally, an attempt is made to integrate the financial and non-financial variables in a failure prediction model.

5.2 Prior Research.

A large body of research has been concerned with the establishment of failure prediction models based on conventional financial ratios extracted from the relevant company accounts. Limited research has been conducted into the non-financial variables which may be used in the prediction of failure.

Although Ohlson (1980) did not specifically address the need to include non-financial variables in a failure prediction model based on companies in the United States, he maintains that the date of publication of the Annual Report of a company is an important element when forecasting relationships is the criterion. He felt that it is important for a researcher to know whether the failed company had filed for bankruptcy before or after the publication of the Annual Report as "the evidence indicates that it will be easier to 'predict' bankruptcy" with prior knowledge of the event. (Ohlson, 1980:110). He concluded that the use of company financial statements whose publication date had been delayed when predicting failure, overstated the classification accuracy of the specific model.

Lawrence (1983) specifically investigated the significance of a delay in publishing the audited financial statements of American companies. Although not seeking to incorporate this variable into a failure prediction model, he found that a significant number of American companies on the brink of bankruptcy, incurred delays when publishing their annual reports while some only published their reports after bankruptcy. He concluded that by ignoring this variable in the year before failure, statistical bias was introduced into the model.

Whittred and Zimmer (1984) investigated the effect of reporting delays on the Sydney Stock Exchange. They found that the reporting delays of troubled companies for the two years prior to failure, were significantly longer than those for healthy companies. They concluded, however, that the inclusion of this variable in a failure prediction model did not result in any significant improvement in its predictive ability.

Keasey and Watson (1988) found otherwise when they investigated whether delays in submitting financial statements could be used as a variable when evaluating financial distress for small companies in the United Kingdom. Although they concede (1988:54) that "small companies have a high failure rate and a far higher propensity to delay/not submit their accounts", they conclude that in a failure prediction model it is possible to develop cost effective monitoring procedures for small companies.

Peel, Peel and Pope (1986) departed from the traditional approach to predicting corporate failure when they recognised the importance of including firm specific non-financial factors in the prediction of corporate failure. As they say,

> To the extent that such models change analysts' perceptions of companies at risk......., then it is obviously of some importance that variables (other than conventional accounting financial ratios) which may enhance the predictive power of these models should be investigated.
>
> (Peel *et al.* 1986;p.5).

The non-financial variables which they investigated for the year prior to failure, were

1. the lag, and changes in the lag, in publishing financial statements.
2. director resignations and appointments.
3. director shareholdings.

They tested the significance of eight financial and non- financial predictor variables using a sample of thirty-four failed and forty-four non-failed companies, using conditional logit analysis. In the main, the research indicated that at a 0,05 level of significance, the addition of non-financial variables to a conventional failure prediction model leads to a marked improvement in the model, both in terms of explanatory and predictive powers. In particular, the lag in publishing the financial statements was identified as a significant predictor when combined with conventional financial ratios.

Merks (1986), using Peel *et al.* (1986) as a basis, evaluated the significance of certain non-financial variables using South African data for the period 1972 to 1986. He found that three variables, namely, changes in director shareholdings, the lag in publishing financial statements and shareholder approval for directors to increase gearing could be significant contributors in a model using multiple regression.

Peel and Peel (1988) sought to extend the predictive ability of the model of Peel *et al.* (1986) by using a multivariate logit function to investigate the probability of four possible outcomes, namely, that the company is healthy or that it will fail one, two or three accounting periods into the future. The multilogit function assumes that the data available from the various years prior to failure are valid. Should this be the case, it seems reasonable to assume that a decision maker would receive consistent signals from the various years of data.

The research confirmed that the time lag between the accounting year end and the date on which the financial statements were published was a significant factor in a failure prediction model. In addition, although they found that the error rates were comparatively high for the second and third years prior to failure, the use of a multivariate logit model added a new dimension to failure prediction as it could be used to adopt an ex-ante approach to the problem. This contention is supported by Keasey, McGuinnes and Short (1990).

Court (1991), when investigating the position in South Africa, confirmed that certain non-financial variables appear as significant predictors of failure and enhance the predictive ability of a failure prediction model containing only financial variables.

5.3 The firm-specific non-financial variables.

In the first instance the significance of the non-financial variables was investigated.

5.3.1 Research methodology.

A selection of failed and non-failed companies was chosen to represent the dependent variable. At the same time, a number of firm-specific, non-financial variables which could point to failure were selected to represent the independent variables. The significance of these variables was then examined using logistic regression analysis. Finally, the predictive ability of the significant non-financial variables was thereafter compared with the model established in Chapter Four.

5.3.1.1. The dependent variable.

A selection of failed and non-failed companies for the period 1965 to 1986 was obtained to represent the dependent variable. These are the same companies as those used in Chapter Four. See Appendix 4-1 for a list of the selected companies.

5.3.1.2 The independent variables.

Three groups of firm specific non-financial variables were selected for further investigation. The criterion for selection was that the variables were obtainable from the Annual Report.

Group One: Publication of financial statements.

The financial year end of a company can be determined from its Annual Report. The date on which the financial statements are finally signed by the auditors as a fair presentation of the financial standing of the company can be ascertained from the Auditors' Report. For a financially sound company this delay should be fairly consistent over time. It could be that the longer the delay, the more problematic the auditing process. This may indicate, inter alia, that all is not well with the company.

An increased delay could be imposed by either of the parties concerned. Management may attempt to delay publication of the financial statements in order to rectify those items which could cause adverse interpretation from investors and hence have a negative effect on the share price. Secondly, the auditors may delay the process of publication as they seek to satisfy themselves regarding the going concern concept or other matters which may cause qualified audit reports.

The overall inference to be drawn is that the duration of the delay may be construed as having a good news/bad news informational content. An increase in the lag from year to year may well signal a company in financial distress.

Group Two: Director resignations and appointments.

The number of directors on the boards of companies will vary from year to year and may change for a number of reasons during the year. There will be normal attrition through such factors as death, inability of non-executive directors to attend board meetings due to pressure of work and director resignations after normal term in office. On the other hand there could be changes to the composition of the Board, either in an attempt to strengthen a potentially failing company by adding skilled executives, or by resignations from those directors who perceive that the company will fail in due course and who wish to avoid the stigma of having been associated with a failed company.

For a successful company the size and composition of the board of directors could be expected to vary little from year to year. Director resignations would be by rotation and the position would be filled either by reappointment or by a new appointment. On the other hand, a company which is in danger of failing may find that the size and constitution of the board will change dramatically over a short period of time. Changes to the board of directors other than by rotation could signal a company in financial distress.

An attempt was made to determine from the managing director's report the reason for appointment or resignation. Natural attrition or rotation was disregarded and only where it could be ascertained that the appointment or resignation was for other reasons, was this regarded as a change in the variable.

Group Three: Director Shareholdings.

Share option schemes exist in most companies and employees share equally in these schemes. Most executive directors should have sufficient confidence in their company to purchase shares in the company and the Company's Act requires that the nature of director shareholdings be published in the Annual Report. The movement in these shareholdings may well have an informational content.

A reduction in directors' shareholdings could be an indication that the company is experiencing financial difficulties and that the directors regard their investment as suspect. On the one hand, directors hold a privileged position in the company and the sale of shares well in advance of failure may constitute insider trading. If directors act responsibly then the sale of shares, which constitute insider trading, will be minimal. On other the hand, the reverse may be true. A director may purchase shares which come on the market in anticipation of bolstering the share price so that the potential bad news effect on the market may be minimal. Nevertheless even a small change in director shareholdings could be construed as an indication that all is not well with the firm.

Based on the preceding discussion, the delay in days between the financial year end and the publication of the Annual Report, as well as the CHANGE in the delay from year to year, were selected to represent the first group. The number of director appointments and resignations, as well as the RATIO of director appointments and resignations to the number of directors on the board, were selected to represent the second group. Finally, the number of shares held annually by directors as well as the CHANGE in their annual shareholding were chosen to represent the third group. A list of these variables with their corresponding codes is given in Appendix 5-1.

5.4 Results.

The significance of the selected non-financial variables was examined using logistic regression analysis for the three years prior to failure. The results for the year prior to failure appear in the Table 5-2.

The results show that the delay in publishing the financial statements and the number of shares held by directors are significant predictors of failure at the 5% level of significance. For the remaining group, neither director appointments and resignations or director appointments and resignations as a proportion of the number of directors is significant.

Table 5-2: Logistic regression analysis of the non-financial variables in the year before failure.

Variable	Coeff.	Std error	T-Stat.	2-Tail Sign.
Constant	-9,786	3,869	-2,529	0,017
Delay in publishing financial statements	0,068	0,029	2,408	0,022
Change in delay in publishing financial statements	- 1,582	3,818	-0,414	0,681
Director appointments and resignations/No of directors	3,542	9,855	0,359	0,722
Director appointments and resignations	1,202	1,566	0,767	0,449
Dir. shareholding	0,002	0,001	2,193	0,036
Change in director shareholding	0,003	0,003	0,838	0,409

The same pattern occurred in the second year prior to failure as shown in Appendix 5-2. In this instance, only the lag in publishing the Annual Report was significant at the 5% level. In the third year prior to failure, none of the variables was significant at a 5% level as can be seen in Appendix 5-3. For this reason, the third and earlier years were excluded from the investigation.

It is interesting to note that when the two variables from Group Two were included separately in a model with the two significant variables from the first step, both appeared as significant predictors of failure with the same level of significance (0,021). As a result it was decided to include director appointments and resignations as a predictor variable. The results of the logistic regression analysis using the selected non-financial predictor variables is presented in the following Table:-

Table 5-3: Logistic regression analysis on the three selected non-financial variables

Variable	Coeff.	Std error.	T-Stat.	2-Tail Sign.
Constant	-8,456	3,051	-2,771	0,008
Delay in publishing financial statements in year prior to failure	0,059	0,022	2,605	0,012
Director appointments and resignations	11,158	4,604	2,423	0,021
Director shareholding in year prior to failure	0,002	0,001	2,303	0,028

As can be seen, all of the chosen variables are significant at the 3% level. This would seem to indicate that these variables are suitable for use as predictors of failure. Finally, the predictive ability of these variables was compared to the model containing only financial ratios, which was developed in the previous chapter. The results appear in the following Table:-

Table 5-4: A comparison of the classification accuracy of the selected financial and non-financial variables using logistic regression analysis.

	Financial *		Non-financial	
Year	Failed	Non-failed	Failed	Non-failed
One	23/25 (92%)	25/26 (96%)	21/22 (95%)	18/19 (95%)
Two	17/26 (65%)	21/26 (81%)	16/21 (76%)	14/19 (74%)

* These are the results from Chapter Four.

It will be seen that the number of companies being classified for the non-financial variables is appreciably less than those for the failed companies. This is due to the fact that the information on the non-financial variables is missing in a number of instances and these companies have accordingly been omitted from the analysis.

Furthermore, the table demonstrates that the classification accuracy of the two sets of variables are similar and that neither is clearly superior to the other. This would tend to suggest that the prediction of failure could be achieved with the use of a fairly wide spectrum of microeconomic predictor variables and not only those confined to the financial information contained in the Annual Report.

5.5 The firm-specific non-financial and financial variables combined.

Finally the two sets of variables were combined with the intention of obtaining a model which gave the best results when predicting failure. In this instance the dependent variables are the same companies used in Chapter Four while the independent variables are the financial ratios isolated previously and the non-financial variables isolated earlier in this chapter. A list of the enlarged set of independent variables is given in Appendix 5-4.

5.5.1 Research methodology.

Consistent with the previous chapter, factor and stepwise regression analyses were conducted on the enlarged set of variables to aid in the selection of predictor variables for inclusion in the model. The predictive ability of the chosen non- financial and financial variables was then examined using both logistic regression and multivariate discriminant analysis.

5.5.2. The selection of predictor variables.

Once again it was considered necessary to evaluate the relationship between the independent variables when selecting the predictor variables. In the first instance, the correlation between the enlarged set of variables was examined. The correlation matrix of the financial variables has been presented in Appendix 4-3 while that of the non-financial variables is given in Appendix 5-5. Further investigation showed that the financial and non-financial variables were only minimally correlated with the change in delay in publishing the Annual Report and profit before tax to current liabilities being the highest at -0,522.

After the factors had been rotated using the varimax technique, six factors emerged with eigenvalues in excess of one which explained eighty percent of the variance in the factor space. The results of the factor analysis appear in Appendix 5-6.

Factor one represents a profitability ratio although it does contain the non-financial ratios associated with the delay in publishing the Annual Report. Factor two is a liquidity ratio while factor three reflects changes to the board of directors.

Factor four is indicative of the firm's solvency. Factor five represents the lag in publishing the Annual Report although it does contain a number of financial ratios but all with relatively low factor loadings. Factor six represents the trading activity in director shareholding.

A stepwise regression analysis was simultaneously conducted on the data set. As before, a variable was allowed to enter if it had a F-value in excess of one. Eleven variables, which accounted for eighty-six percent of the variance in the dependent variable, accordingly entered the stepwise regression analysis. The results of the stepwise regression analysis appear in Appendix 5-7.

Consistent with the selection criteria proposed in the previous chapter, a single variable was chosen to represent the requisite factor. These are as follows:-

1. Profit after tax but before interest to total assets was chosen to represent the first factor as it was highly loaded with the factor (0,943) as well as being the first variable to enter the stepwise regression.
2. Current assets to total debt was chosen to represent the second factor as it was highly loaded with the factor (0,958) and entered third in the stepwise regression.
3. Director appointments and resignations, was chosen as the third factor for, although it had a smaller factor loading than director appointments and resignations to the number of directors (0,964 as against 0,961), it entered the stepwise regression before the latter variable in fourth position.
4. Profit before interest to interest paid was chosen to represent the fourth factor as it is the only variable in factor four with a high factor loading (0,864).
5. The change in the delay in publishing the Annual Report was chosen to represent factor five as it had the highest loading (0,706) as well as entering the stepwise regression analysis at the seventh stage.
6. Director shareholding was chosen to represent the sixth factor for, although it had a smaller factor loading than the change in director

shareholding (0,706 compared to 0,729), it entered the stepwise regression during the sixth stage ahead of director shareholding.

A summary of the chosen predictor variables and certain statistical characteristics of these variables are summarised in the following table:-

Table 5-5: The predictor ratios and certain statistical measures.

Ratio	Representing	Mean	Sd Dev.	Skewness	Kurtosis
1655	Factor 1	1,01	15,82	-1,70	3,49
0730	Factor 2	274,16	655,26	3,86	13.94
DAR	Factor 3	1,41	2,43	2,05	4,01
1712	Factor 4	10,51	94,02	4,89	28,97
CLAG	Factor 5	0,20	0,29	1,75	5,65
SH	Factor 6	744,65	1188,01	1,94	3,42

Finally, the statistical significance and predictive ability of the chosen financial and non-financial variables was examined using both logistic regression and multivariate discriminant analysis and the results evaluated.

5.6 Results.

As can be seen from Table 5-6, when these variables were combined in a failure prediction model, the predictive ability of the model proved disappointing for the year before failure although there was a marked improvement two years before failure. The results are presented in the following Table:-

Table 5-6: Classification accuracy of model containing the selected financial and non-financial variables using logistic regression and multivariate discriminant analysis.

	Logistic regression analysis		Multivariate discriminant analysis	
Year	Failed	Non-failed	Failed	Non-failed
One	17/21 (81%)	17/19 (90%)	16/21 (76%)	19/19 (100%)
Two	16/19 (84%)	13/16 (81%)	16/19 (84%)	12/16 (75%)

The results from the two prediction techniques are very similar although, for the sample to hand, logistic regression analysis gives marginally better results for failure prediction in the year prior to failure. On the other hand, the predictive ability of the model is rather disappointing. If the predictive accuracy of the model is the criterion, it is interesting to note that when the three financial variables to enter first in the stepwise regression analysis (operating profits/average operating assets, total owners interest/total assets and current assets/current liabilities) are included in a model with the selected non- financial predictors, substantially better results are obtained. These are presented in the following Table:-

Table 5-7: Predictive ability of a selection of financial and non-financial variables using logistic regression analysis and multivariate discriminant analysis.

	Logistic regression analysis		Multivariate discriminant analysis	
Year	Failed	Non-failed	Failed	Non-failed
One	21/21 (100%)	19/19 (100%)	19/21 (91%)	19/19 (100%)
Two	18/21 (86%)	14/18 (78%)	16/21 (76%)	17/18 (94%)

In this instance the predictive ability of the logistic regression analysis in the year before failure improves dramatically to one hundred percent. The predictive ability of the multivariate discriminant analysis also improves.

5.7. Conclusion.

It is well accepted that the main reason for corporate failure is managerial incompetence. In essence, ineffective or poor management leads to mistakes which ultimately result in the failure of the company. In the past, financial ratios have generally been used in models to predict failure. Nevertheless one can reasonably assume that certain non-financial variables could also be incorporated in failure prediction models.

This chapter has shown that certain non-financial variables are adequate predictors of corporate failure. It can reasonably be concluded that the inclusion of non-financial variables in a model to predict failure will enhance the predictive ability of the model.

When the chosen non-financial variables were included with certain financial ratios in a model, the predictive accuracy of the model improved for the given samples from 92% (for the financial variables only) to 100% in the year prior to failure.

It could be concluded that the high predictive ability of the model is unduly influenced by the relatively small size of the data base rather than by the suitability of the chosen variables. In addition, the results may have been biased by the classification technique and more realistic results could possibly have been obtained with the use of the jackknife classification technique.

Ideally a control sample should be used to establish the model and a different sample used to test the model. Unfortunately, South Africa suffers from the lack of a comprehensive data base from which these samples could be drawn and the existing sample of failed companies is barely sufficient to cover the test sample. It would be desirable therefore to re-evaluate the predictive ability of the model obtained above on a broader data base once this becomes available.

Appendix 5-1: The selection of non-financial variables and their corresponding codes.

Variable	Code number.
Delay in publishing financial statements	LAG
Change in delay in publishing financial statements	CLAG
Director appointments and resignations	DAR
Director appointments and resignations/Number of directors	DARN
Director shareholding	SH
Change in director shareholding	CSH

Appendix 5-2: Logistic regression analysis on the non-financial variables two years before failure.

Variable	Coeff.	Stderror	.T-Stat.	2-Tail Sign.
Constant	-4,115	1,682	-2,446	0,020
Delay in publishing financial statements	0,034	0,015	2,347	0,025
Change in delay in publishing financial statements	1,001	1,588	0,632	0,533
Director appointments and resignations/Number of directors	-5,318	8,507	-0,625	0,536
Director appointments and resignations	1,153	1,630	0,707	0,485
Dir. shareholding	0,001	0,001	1,586	0,123
Change in director shareholding	0,0006	0,001	0,061	0,952

Appendix 5-3: Logistic regression analysis of the non-financial variables three years before failure.

Variable	Coeff.	Stderror	.T-Stat.	2-Tail Sign.
Constant	-1,307	1,292	-1,060	0,298
Delay in publishing financial statements	0,013	0,011	1,200	0,240
Change in delay in publishing financial statements	0,160	2,460	0,006	0,995
Director appointments and resignations/Number of directors	-5,226	6,176	-0,846	0,405
Director appointments and resignations	0,983	0,995	0,988	0,332
Dir. shareholding	0,0002	0,0005	0,437	0,665
Change in director shareholding	0,913	1,006	0,907	0,372

Appendix 5-4: The selection of independent variables.

Variable	Code
Total owners interest/ Total assets	0207
Total current liabilities/ Total assets	0216
Current assets/Total assets	0237
Current assets/Total debt	0730
Profit before interest after tax/ Total assets	1601
Operating profit/ Average operating assets	1607
Retained earnings/ Average total assets	1633
Profit after interest but before tax/ Total assets	1655
Profit after tax/Total assets	1656
Profit after tax/Average owner's equity	1702
Profit before tax/Interest paid	1712
Current assets/Current liabilities	1801
Profit before tax/Current liabilities	1822
Profit before tax/Total debt	1823
Delay in publishing financial statements	LAG
Change in delay in publishing financial statements	CLAG
Director appointments and resignations	DAR
Director appointments and resignations/ Number of directors	DARN
Director shareholding	SH
Change in director shareholding	CSH

Appendix 5-5: Correlation matrix of non-financial variables

	DAR	DARN	LAG	CLAG	SH	CSH
DAR	1,00					
DARN	0,97	1,00				
LAG	0,22	0,27	1,00			
CLAG	0,11	0,14	0,44	1,00		
SH	0,17	0,27	0,19	0,03	1,00	
CSH	0,00	0,01	-0,11	-0,09	0,42	1,00

Appendix 5-6: Sorted rotated factor loadings.

Variable	Factor loading.					
	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
1601	0,952					
1655	0,943					
1656	0,941					
1633	0,932					
1702	0,811					
1607	0,806					
0207	0,550	0,449	-0,260	-0,260	0,434	
LAG	-0.503				0,291	
1801		0,959				
0730		0,958				
1823	0,493	0,691				
0237	0,515	0,516			0,349	
DARN	0,964					
DAR	0,961					
1712	0,864					
CLAG					0,706	
1822	0,443			0,273	-0,631	
CSH						0,729
SH						0,706
0216	-0,452	-0,379		-0,397	-0,469	

Appendix 5-7: Summary table of step wise regression analysis.

Step no	Variable to Enter.Remove.	Coeff	Multiple R. SQ	F to Enter Remove.
1	1655	0,031	0,382	21,67
2	1633	-0,023	0,594	17,77
3	0730	-0,001	0,675	8,17
4	DAR	-0,1258	0,700	2,73
5	0216	-0,005	0,733	3,74
6	SH	-0,001	0,760	3,37
7	CLAG	-0,264	0,800	5,89
8	DARN	1,153	0,813	1,98
9	LAG	-0,003	0,835	3,45
10	1702	0,001	0,848	2,36
11	1607	0,856	0,856	1,25

CHAPTER SIX

ECONOMIC VARIABLES AND THE BUSINESS FAILURE RATE.

6.1. Introduction.

The previous chapters have focused on the firm-specific, microeconomic factors which contribute to business failure. Six variables were found to be significant predictors of failure. On the other hand, as Altman (1983:83) observes,

> the importance of microeconomic issues and the attendant large number of analytical studies have obscured the relevance and influence of macroeconomic influences on the business failure phenomenon.

Therefore, rather than continue to concentrate on the firm- specific causes of failure, it is appropriate that consideration be given to the macroeconomic factors which contribute to business failure.

General economic conditions have a direct bearing on the activities of individual firms. During periods of economic recession, money and capital market conditions are significant factors in the financial well-being of a firm. Participants in these markets may be unwilling to extend credit to those firms which are mismanaged or which are financially unstable. This could lead to failure and ultimately liquidation.

In addition, as South Africa is classified as a developing nation, it relies to a large degree on external resources in the development of its internal economic structure. Should these resources be denied, due to the adverse perceptions of the internal situation in South Africa, the economy may not realise its full potential. This will impact adversely on the smaller, more marginal firms in the economy and they will be the first to suffer from this economic deprivation. This will also lead to an increase in the business failure rate.

In this chapter the macroeconomic variables which could contribute to the business failures are discussed and an attempt is made to isolate those variables which could be used as predictors of the business failure rate.

6.2. Prior research.

Limited research has been conducted into the macroeconomic factors which contribute to the business failure rate. Norton and Smith (1979) were the first to concern themselves with the fact that the predictive ability of failure prediction models could be affected by macroeconomic factors. They used multivariate discriminant analysis when comparing failure prediction based on ratios obtained from historical costs with ratios which had been adjusted to cater for fluctuations in the general price level. Although their results were generally inconclusive, they did highlight the need to relate the firm-specific financial ratios to the general level of prices in the economy.

Rose, Andrews and Giroux (1982) were the first to enquire directly into the effect of macroeconomic variables on business failure. They contend that it would seem reasonable

> that macroeconomic indicators also may be helpful predictors of individual firm failure, since any given firm may have a higher propensity to fail in times of economic recession than in times of economic prosperity.
>
> (Rose *et al.*, 1982:20)

Starting from a data base of twenty-eight macroeconomic variables, six variables (some in their lagged form) were found to be significant predictors of the business failure rate at the 0,05 level when using linear regression analysis. The six variables, with the figures in parentheses denoting the degree of lag per quarter, are as follows:-

1. The Standard and Poor (S&P) composite index. (2).
2. Gross domestic private investment/Gross national product.(3)
3. Profits after tax/Income originating in companies. (0).
4. Prime rate. (4).
5. Ninety-day treasury bill rate. (4).
6. Retail sales/Gross national product. (0).

The results appear quite promising with a coefficient of determination of 0,912. Rose *et al.* conclude (1982:31) "that economic conditions influence business failure and, indeed, may play a highly significant role in the failure process".

Altman (1983) also examined the aggregate effect of various economic variables on the business failure rate by using failure statistics compiled by Dun and Bradstreet over the period 1951 - 1978. The categories of economic variables which Altman felt ought to have a bearing on the business failure rate and the variables chosen to represent them can be summarised as follows:-

1. Economic growth activity as represented by the growth in real gross domestic product and corporate profits.
2. Money market activity as represented by the growth in the money supply.
3. Capital market activity as represented by the rate of change in the S&P index and a risk premium represented by the differential between Moody's Aaa and Baa bonds.

4. Business population changes as represented by the growth in new business incorporations.
5. Price level changes as represented by changes in the gross national product price deflator.

Altman (1983:90) analysed the aggregate influences on the business failure rate within the "first difference, quarterly, regression models with emphasis on the distributed lag properties of a number of explanatory variables". In addition, he used the percentage changes in the variables (where appropriate) to remove the exponential trend effect over time which could arise in this type of analysis. In order to achieve his objective Altman examined the second degree polynomial equation for each independent variable specification individually and thereafter observed the structure, the amount and the significance of the various lagged periods' coefficients.

The findings of Altman's research indicated that four variables contributed cumulatively to a greater propensity to fail and are all significant at the 5% level. See Altman (1983:93) for a detailed analysis of the results. The significant variables are the percentage changes in:-

1. real gross domestic product,
2. the Standard and Poor index,
3. the money supply,
4. new business incorporations.

Altman (1983) concludes that the overall results are quite encouraging and that the predictor variables show relatively good explanatory power. Altman however does not attempt to link these variables with the firm-specific variables which contribute to corporate failure which he had evaluated in his prior research. He felt that whereas the firm-specific financial ratios can be assigned specifically to a dichotomous dependent variable, the macroeconomic variables relate to both failed and non-failed firms and cannot be assigned to an individual firm. For this reason, Altman makes no attempt to combine the macro- and microeconomic variables in obtaining an overall model for the prediction of corporate failure.

Although Mensah (1984) did not address himself exclusively to the effect of economic variables on a failure prediction model, he was concerned that the pooling of data over time pays little attention to economic conditions during the relevant periods. He felt that this oversight could well affect the predictive accuracy of the model as it gives rise to non-stationarity in the predictor variables. The macroeconomic conditions which Mensah contends will contribute to non-stationarity in these variables are inflation, interest rates leading to credit availability and the business cycle.

Mensah accordingly examines the accuracy of a failure prediction model containing financial ratios over four distinct periods of the business cycle. He concludes that the accuracy and structure of predictive models will differ according to the economic environment as well as the industrial sector for which the model is constructed.

6.3 Research methodology.

The technique of time series regression analysis was used when evaluating the impact of the economic variables on the business failure rate. The purpose is to determine which of these variables have a significant impact on the rate at which businesses fail. The significant variables will then be used in the prediction of the future rate of business failure as this rate forms an integral part in the development of the overall model of failure prediction.

When applying this technique, there are a number of points which need to be borne in mind. Firstly where a large selection of the independent variables are being evaluated, some of the variables may be linearly or nearly linearly related. For this reason, some form of variable reduction is desirable. Secondly, due to the sequential nature of the data, the effect of a number of the predictor variables may only be felt after a lapse of time and it will be necessary to investigate the significance of these variables in their lagged form as well.

Finally, a certain degree of autocorrelation may be present in the series. If this is the case, some adjustment procedure would have to be implemented in order to overcome the problem.

6.3.1. The dependent variable.

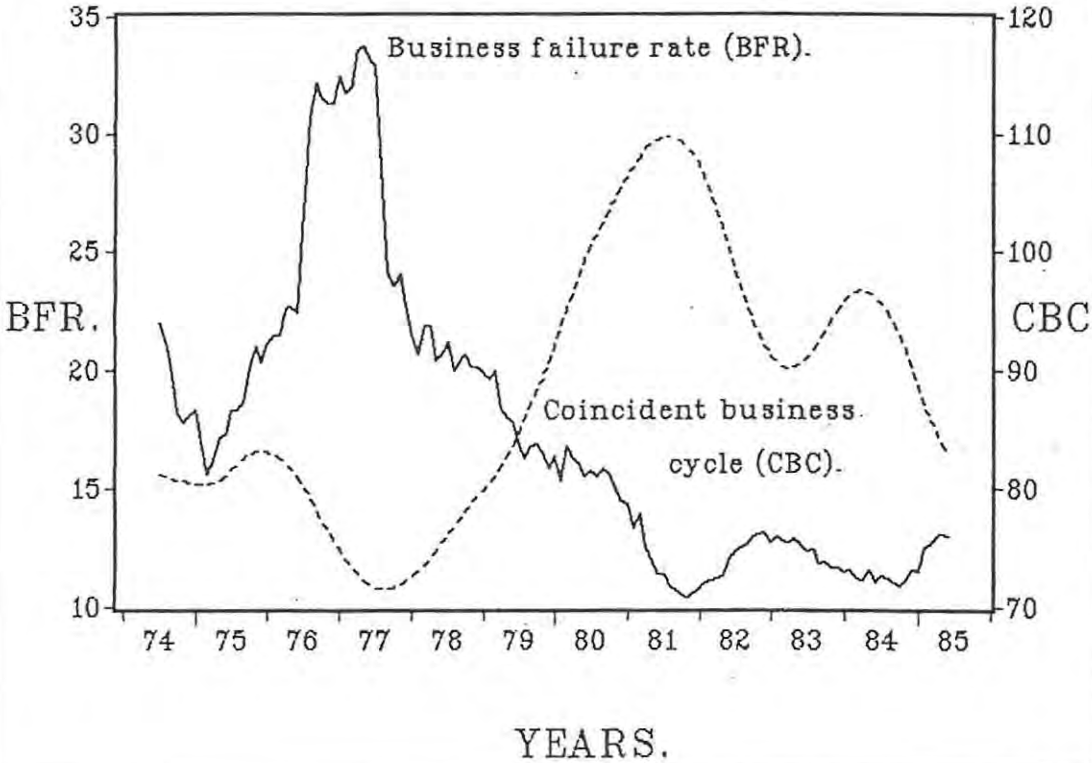
When relating the well-being of the firm to the macroeconomic environment, the chosen dependent variable is the business failure rate observed on a monthly basis. The period between 1974 and the end of 1985 was chosen as the period under investigation. The reasons were:--

1. The Companies Act was changed in 1974, making it easier for companies to be registered.
2. The period has seen South Africa move through periods of both economic upturn (boom) and downturn (recession).
3. This period has been characterised by increasing political instability within South Africa;
4. International pressures on South Africa have escalated since the mid-

seventies.

The business failure rate was obtained as follows. The monthly liquidations and insolvencies were obtained from the Registrar of Companies. The total of these was then divided by the number of registered companies at the end of the period and adjusted in order to obtain the business failure rate per 10 000 companies. A graphical representation of the business failure rate and the coincident business cycle appears in the following figure:

Figure 1. The business failure rate and the coincident business cycle. 1974-1985



From the figure, it can be seen that the business failure rate peaks during 1977 at about THREE AND ONE HALF percent of the total population. It drops thereafter to a low in 1982 of approximately ONE percent of the population. From then, until the end of 1985, the trend appears to be upward although at a significantly lower rate than in 1977. In addition, the figure supports the contention of Rose *et al.* (1982:21) that a downturn in the business failure rate and the business cycle are negatively correlated.

6.3.2 The independent variables.

When evaluating the independent variables which could be used in a failure prediction model in South Africa, the same categories of variables used by Altman (1983) will constitute the basis of this investigation. The time interval on the other hand will be monthly as opposed to quarterly. In addition, it will be necessary to include additional categories of variables to model the unique socio-economic and political situation in South Africa. The categories and the selection of macroeconomic variables are as follows:-

6.3.2.1 Economic growth activity.

It is logical to expect that the overall level of demand in the economy is positively correlated with the level of economic activity; during boom periods a firm's revenue and profits should increase. These increases should be beneficial to the firm experiencing liquidity problems and ultimately lead to a reduction in the business failure rate. The converse should happen during periods of recession.

The gross domestic product is a universally accepted measure of the overall level of demand and hence revenue in an economy. Unfortunately, the data relating to the gross domestic product are only published on a quarterly basis and it is proposed that an alternative measure be evolved to reflect economic growth activity. To this end the average earnings yield of industrial sector shares, multiplied by the industrial share price index, is proposed as a surrogate for both economic activity and corporate profits. This will be referred to as the corporate profit index.

6.3.2.2 Money market activity.

Money market activity relates to the overall level of liquidity in the economy which in turn is influenced by the cost of short-term credit in the market place. It can be expected that during periods of "tight" money conditions, the rate of interest to money market participants will increase. This "credit-rationing" effect usually discriminates against the smaller firms and those whose solvency is threatened due to their weakened bargaining position. As a result, the business failure rate should increase during periods of high interest rates.

The rate of change in the money and near-money supply has been chosen as an indication of the availability of money in the money market, while the real rate of interest has been chosen to reflect the cost of these funds.

Over the longer term, should the solvency of a firm become questionable, it may become impossible to raise funds on the money market and medium term credit becomes the only source of finance. In order to take account of this development, total advances from the banking sector to the private sector has been used to represent the demand for medium term credit.

6.3.2.3 Capital market activity.

Stock price movements are critical to the marginal firm listed on the Johannesburg Stock Exchange. A drop in the overall share price index, due to a decline in economic activity, could adversely affect a firm seeking to raise additional capital. If the index drops too low the marginal firm may be precluded from raising funds via this avenue, thereby placing its continued existence in jeopardy. On the other hand, during periods of buoyant economic conditions, the market will relax the restrictions placed on firms with unfavourable leverage ratios and make it easier for funds to be raised by the highly levered firm.

It is proposed that overall capital market activity be measured by using the number, and value, of shares traded on the Johannesburg Stock Exchange. These variables should be negatively correlated with the business failure rate.

6.3.2.4 Business population statistics.

It is understandable that in buoyant economic conditions the number of new firms to be established will increase. On the other hand, Altman (1983) maintains that over fifty percent of all firms fail within five years of being established. During a recession newly established firms should be more susceptible to failure and the period between establishment and failure would accordingly be reduced.

Unfortunately the "age" of businesses within the South African context is impossible to establish. Statistics are published on the number of new business formations but, as these figures are directly used in establishing the business failure rate, it would be inappropriate to include them as one of the independent variables together with the business failure rate.

6.3.2.5 Price level changes.

Inflation is a common economic dilemma. The reasons for a sustained increase in the general level of prices are diverse and could be explained by a number of economic factors.

An increase in the overall price level will assist the technically insolvent firm. The argument is that as highly levered firms are able to repay their (fixed interest) debts with cheaper money, they are able to delay the onset of failure and continue to operate. In addition, during periods of high inflation, the uneconomical firm whose product has a low elasticity of demand, may find it easier to pass price increases on to the consumer. Thus, firms are able to improve upon their liquidity position and remain in business for a longer period of time.

General price increases are given by the consumer and production price indices and the percentage changes in these indices have been chosen to measure inflationary conditions in the South African economy.

6.3.2.6 Socio-economic factors.

There can be little doubt that the mining sector has played a significant role in the socio-economic development of this country and that the well-being of the industrial sector depends to a large extent on a prosperous mining sector. Gold, along with the discovery of other precious minerals, has been the mainspring of South Africa's economic growth. The gold mining industry not only provides employment for thousands of people, it is also the major foreign currency earner in the country. For this reason, the state of the South African economy depends to a large extent on the price of gold on the international markets. A high dollar gold price will have a positive effect on the confidence in the economy and is accordingly used to reflect socio-economic conditions in South Africa.

On international markets, South Africa is slowly losing her competitive edge due to a number of economic and political factors. The overall measure which relates the real wealth of the South African economy to its trading partners, is the terms of trade which compare the price of a country's exports to the cost of its imports. As the terms of trade decline, the input costs of import-oriented firms will increase relative to the revenue generated by the firm thereby reducing profitability. This will certainly be to the disadvantage of the marginal firm and the business failure rate should increase accordingly.

6.3.2.7 Socio-political factors.

The policies of the South African government have lead to increased political unrest locally which continues to persist. On the other hand, isolation from abroad has abated over the past few years. The net result however is that the economy has not enjoyed the real growth it should have experienced and it is necessary that some variable be used to represent the socio- political environment which is unique to the South African situation.

Three variables have been proposed to represent this category. In the first instance, if the perception of foreigners is of an increased likelihood of political instability locally, the number of visitors to the country would decline accordingly. Hence changes in the number of visitors to South Africa has been chosen to represent the external perception of this country over the short term.

By the same token, the longer term effect could be evaluated by using the number of emigrants from, and the number of immigrants to South Africa. If the perception is that the situation within the country will become increasingly untenable, the number of emigrants should exceed the number of immigrants. Hence the ratio of emigrants to immigrants has been selected as an independent variable.

Finally, there has been a steady decline in the exchange rate of the Rand vis-à-vis the world's major currencies. This can to some extent be ascribed to the entrenched political instability in South Africa. As the dollar is the world's major trading currency, the rand-dollar exchange rate has been chosen as an overall measure of external perceptions of the political situation in South Africa.

Negative trends in number of visitors and the exchange rate and a positive trend in the ratio of emigrants/immigrants could tend to point to lower than normal real growth in the economy. This would ultimately have an adverse effect on the business failure rate.

A summary of the fourteen economic variables chosen for further investigation are given in Table 6-1.

The data for these variables were obtained on a monthly basis from the Quarterly Bulletin published by the South African Reserve Bank and from the Bulletin of Statistics published by Central Statistical Services. Where applicable, year on year percentage changes were used in order to eliminate any trend effect over time. In addition, a thirteen month moving average was used on all of the variables to eliminate any seasonal fluctuations in the variables.

Table 6-1. The categories and economic variables used in the investigation of the business failure rate.

CATEGORY	ECONOMIC VARIABLE	CODE
General economic activity	Index of corporate profits	CP
Money market activity	Change in money supply	MON
	Real rate of interest	RT
	Total advances from banking sector	TOT
Capital market activity	Index of share prices	VOS
	Index of share transactions	ST
	Index of bank debt	BD
General price level	Consumer price index	CPI
	Production price index	PPI
Socio-economic conditions	Gold price	GPD
	Terms of trade	TT
Socio-political conditions	Number of visits by foreigners	VT
	Ratio of emigrants to immigrants	PAE
	Exchange rate	XR

6.3.3 The selection of predictor variables.

In the first instance, the correlation between the independent variables was investigated in order to evaluate the degree of inter-correlation between the chosen variables. The correlation matrix appears in Appendix 6-1. Thereafter, a factor and stepwise regression analysis was applied to the selection of independent variables.

After the factors had been rotated using the varimax technique, four factors with an eigenvalue in excess of one emerged from the data set. These factors explained approximately ninety percent of the variance in the independent data set. The factor loadings for these variables are given in Appendix 6-2.

Factor one can be characterised as an indicator of money market activity although it is difficult to explain the presence of the emigrant/immigrant ratio. Factor two relates to the general level of economic activity but biased towards the foreign sector. Factor three reflects capital market activity while factor four relates to the political environment.

From the stepwise regression analysis it was found that the index of total advances from the banking sector was the first variable to enter the regression analysis and explained sixty-six percent of the variance in the dependent variable. The second variable to enter was visits by foreigners which accounted for a further twenty-two percent of the variance. The only other variables to make a meaningful contribution to the variability in the dependent variable were the consumer price index and the value of share transactions. These four variables explained ninety-five percent of the variability in the business failure rate. The results of the regression analysis appear in Appendix 6-3.

From these results, the following were chosen as the predictor variables:-

1. The variable with the highest loading for factor one was total advances from the banking sector (TOT). This variable was also the first to enter

in the stepwise regression analysis and it was accordingly chosen to represent factor one.

2. None of the highly loaded variables for factor two made sizeable contributions to the stepwise regression. On the other hand the index for corporate profits (CP) was loaded across all four variables and following Lehmann's (1985) recommendation it was selected to represent factor two.
3. The variable with the highest loading for factor three was the value of share transactions (VOS) which entered the stepwise regression at step four. It was therefore selected to represent factor three.
4. Visits by foreigners (VT) had the highest loading for factor four and it entered second in the stepwise regression; hence it was chosen to represent factor four.

The variables and some of their statistical characteristics are given in the following table:-

Table 6-2: The predictor variables and certain statistical measures.

Ratio	Representing	Mean	Sd Dev.	Skewness	Kurtosis
TOT	Factor 1	22,98	15,25	0,23	-1,48
CP	Factor 2	0,02	0,14	-0,05	-1,47
VOS	Factor 3	34,77	55,03	0,57	-0,70
VT	Factor 4	1,68	8,73	-0,42	-0,28

6.4 The results.

The effect of the predictor variables on the business failure rate was examined using the technique of least squares regression analysis. All the variables were found to be highly significant for the period 1976 to the end of 1985 as the following table shows:-

Table 6-3: Ordinary least squares results of the selected variables on the business failure rate.

Variable	Coefficient	Std. Error	T-Stat	2-Tail Sig
C	27,2558	0,3376	80,74	0,000
TOT	-0,3598	0,0110	-32,79	0,000
CP	-5,5677	1,3045	-4,27	0,000
VOS	-0,0257	0,0031	-8,15	0,000
VT	-0,3762	0,0200	-18,76	0,000
R-squared	0,9242	Mean of dependent var		17,3523
Adj. R-squared	0,9216	S.D. of dependent var		6,4945
S.E. of regression	1,8183	Sum of squared resid		380,2270
Durbin-Watson stat	0,2658	F-statistic		350,7660
Log likelihood	-239,4692			

These variables explained ninety-two percent of the variance in the dependent variable. Although the predictor variables appear highly significant, there is obvious evidence of serial correlation due to the low Durbin-Watson statistic (0,27). There is little doubt that certain of these variables could be more significant in their lagged form.

In order to establish the significant lagged structure of the four variables, a polynomial distributed lag structure was incorporated into the regression analysis. The degree of the polynomial selected was two and twelve lags were chosen in order to account for the annual nature of the data. The period examined was from the middle of 1977 to the beginning of 1983 as this constituted a typical business cycle. The results of the polynomial distribution lag on the four variables are shown in Appendix 6-4.

As can be seen from the diagrams, all the variables were more significant in their lagged form. Total advances from the banking sector was most significant when lagged for two months. The index for corporate profits, value of share transactions and visits by foreigners were most significant when lagged for three months.

The significance of the lagged structure of the variables was once again examined using times series regression analysis. The results appear in Table 6-4.

As expected, the variables were all significant in their lagged form but predictive ability of the model declined slightly. On the other hand the Durbin-Watson statistic improved to 0,53. Nevertheless there is still an unacceptably high level of serial correlation and in order to adjust the data for the presence of serial correlation, the Cochrane-Orcutt (1949) procedure (first-order autoregressive correction - AR(1)) was incorporated into the regression analysis. The results appear in Table 6-5.

Table 6-4: Ordinary least squares table of selected variables in their lagged form on the business failure rate.

Variable	Coefficient	Std. Error	T-Stat	2-Tail Sig
C	23,3062	0,3810	61,17	0,000
TOT(-2)	-0,2429	0,0134	-18,19	0,000
CP(-3)	-14,0137	1,7301	-8,09	0,000
VOS(-3)	-0,0090	0,0030	-3,01	0,004
VT(-3)	-0,3201	0,0286	-11,20	0,000

R-squared	0,9211	Mean of dependent var	16,3536
Adj. R-squared	0,9162	S.D. of dependent var	4,6383
S.E. of regression	1,3427	Sum of squared resid	117,1845
Durbin-Watson stat	0,5314	F-statistic	189,6058
Log likelihood	-117,3596		

Table 6-5: Ordinary least squares table of lagged selected variables on the business failure rate using AR(1) specification.

Variable	Coefficient	Std. Error	T-Stat	2-Tail Sig
C	16,6987	2,2897	5,76	0,000
TOT(-2)	-0,0819	0,0707	-1,16	0,252
CP(-3)	-7,7244	5,2361	-1,48	0,145
VOS(-3)	0,0062	0,0090	0,70	0,489
VT(-3)	0,1246	0,1567	0,80	0,430
AR(1)	0,8216	0,0443	18,53	0,000

R-squared	0,9750	Mean of dependent var	16,3536
Adj. R-squared	0,9731	S.D. of dependent var	4,6384
S.E. of regression	0,7613	Sum of squared resid	37,0916
Durbin-Watson stat	2,0692	F-statistic	499,4875
Log likelihood	-77,0971		

In this instance, the predictive ability of the model improved to ninety-seven percent while the serial correlation was eliminated as the Durbin-Watson statistic is at an acceptable level (2,07). This would indicate that the AR(1) process has successfully accounted for the serial correlation which is evident in the series. On the other hand, the T-values of the selected variables dropped dramatically and none of these variables were significant at the ten percent level. In order to overcome this problem, the predictor variables were examined individually. Interestingly, total advances from the banking sector was highly significant while the predictive ability of the model was minimally affected as the following table shows:-

Table 6-6: Ordinary least squares table of chosen predictor variables on the business failure rate.

Variable	Coefficient	Std. Error	T-Stat	2-Tail Sig
C	18,6276	1,2068	15,44	0,000
TOT(-2)	-0,1497	0,0374	-4,00	0,000
AR(1)	0,8314	0,0343	24,20	0,000
R-squared	0,9722	Mean of dependent var		16,3536
Adj. R-squared	0,9713	S.D. of dependent var		4,6384
S.E. of regression	0,7845	Sum of squared resid		41,2378
Durbin-Watson stat	1,8746	F-statistic		1172,4510
Log likelihood	-80,8058			

The results would tend to indicate that total advances from the banking sector could effectively be used as a predictor of the business failure rate when modelled in conjunction with the AR(1) process. Of the remaining variables, visits by foreigners was significant at the one percent level while the index of corporate profits was significant at the five percent level. The value of share transactions was not significant (p-value of 0,113). These results are presented in Appendix 6-5.

6.5. Conclusion.

It is apparent that certain economic variables and the business failure rate are closely correlated. Based on this investigation, four economic variables were isolated for further investigation. These are:-

1. Total advances from the banking sector
2. An index of corporate profits
3. An index of the value of share transactions
4. Visits by foreigners.

These variables explained ninety-two percent of the variance in the dependent variable; nevertheless a high degree of serial correlation was evident in the model. When this was eliminated using the Cochrane-Orcutt procedure, the four variables lost their significance although the variance explained by the variables improved to ninety-seven percent.

On the other hand three of the variables were significant at a five-percent level when regressed individually on the business failure rate. Of these total advances from the banking sector, which represent a money market activity (cash flow), appeared as the more significant of these variables. It is accordingly used as the predictor variable when assessing the business failure rate. This is justified by the fact that research in South Africa has shown that cash flow can be used exclusively as a predictor of corporate failure (Strebel and Andrews, 1977). In addition, other studies have shown that cash flow is widely used as a variable in the prediction of corporate failure (Altman, 1984). It is understandable therefore that it would be a significant predictor of the business failure rate.

Appendix 6-1: Correlation matrix of the macroeconomic variables.

	CPI	CP	BD	GPD	MON	PAE	PPI	RT	ST	TT	TOT	VOS	VT	XR
CPI	1,00													
CP	0,46	1,00												
BD	-0,42	-0,28	1,00											
GPD	0,03	-0,01	0,56	1,00										
MON	0,68	0,26	0,34	-0,34	1,00									
PAE	0,58	-0,39	-0,33	0,50	-0,64	1,00								
PPI	0,54	0,78	0,28	0,38	0,07	-0,11	1,00							
RT	-0,10	-0,61	-0,44	-0,63	0,24	-0,20	-0,71	1,00						
ST	-0,03	-0,34	0,36	0,78	-0,42	0,35	0,18	-0,28	1,00					
TT	0,65	-0,03	0,32	-0,48	0,75	-0,80	-0.18	0,51	-0,19	1,00				
TOT	0,25	-0,33	-0,38	-0,36	0,42	0,04	-0,18	0,65	-0,20	0,34	1,00			
VOS	0,17	-0,28	0,51	0,81	-0,19	0,24	0,27	-0,33	0,94	-0,05	-0,12	1,00		
VT	-0,24	-0,28	0,30	0,16	0,18	0,07	-0,36	0,09	0,06	-0,03	-0,15	-0,02	1,00	
XR	0,22	-0.51	-0,32	0,40	0,40	-0,08	-0,34	0,83	-0,08	0,52	0,89	-0,06	0,04	1,00

Appendix 6-2: Sorted rotated factor loadings.

Variable code.	Factor 1.	Factor 2.	Factor 3.	Factor 4.
MON	0,87			
TOT	0,87	0,38		
PAE	-0,84		0,31	
CPI	0,81			0,48
BD	0,60	-0,46	0,57	
XR		0,94		
TT		0,87		
RT		0,81	-0,34	-0,38
CP	0,35	-0,65	-0,25	0,58
VOS			0,98	
ST			0,93	
GPD		-0,36	0,87	
PPI		-0,43	0,26	0,78
VT				-0,79

*. Factor loadings of less than 0,25 are not recorded.

Appendix 6-3: Summary table of stepwise regression analysis.

Step no	Variable Entered.Removed	Coeff.	Multiple R Sq	F to Enter.Remove
1	TOT	-0,210	0,660	229,0
2	VT	-0,346	0,878	207,7
3	CPI	-1,337	0,935	103,9
4	VOS	-0,047	0,952	41,1
5	PAE	-0.013	0,958	15,7
6	ST	0,073	0,960	5,9
7	GPD	0,091	0,960	1,4
8	BD	-0,322	0,962	4,8
9	TT	0,236	0,963	2,7
10	XR	-0,052	0,967	9,3
11	CP	13,555	0,968	2,1
12	PPI	-0,618	0,968	3,8

Appendix 6-4: Lagged distribution schedule.

```
---------------------------------------------------------------------------=========
:*                        :       :  0  -0.21492   0.03554  -6.04719
:    *                    :       :  1  -0.17243   0.02170  -7.94629
:         *               :       :  2  -0.13373   0.01168  -11.4482
:            *            :       :  3  -0.09882   0.00890  -11.1043
:                *        :       :  4  -0.06771   0.01247  -5.42843
:                   *     :       :  5  -0.04039   0.01610  -2.50846
:                      *  :       :  6  -0.01686   0.01792  -0.94110
:                         *       :  7   0.00287   0.01758   0.16304
:                         :  *    :  8   0.01880   0.01513   1.24267
:                         :    *  :  9   0.03094   0.01108   2.79220
:                         :     * : 10   0.03929   0.00840   4.67728
:                         :      *: 11   0.04384   0.01375   3.18796
:                         :      *: 12   0.04460   0.02515   1.77320
------------------------------------------------------------------------------------
                          0         Sum -0.56450   0.03589 -15.7292
====================================================================================
      Lag Distribution of CPR3        Lag    Coef       S.E.      T-Stat
====================================================================================
:        :*                       :  0    1.89548   6.35174   0.29842
:      * :                        :  1   -3.59903   3.79940  -0.94726
:   *    :                        :  2   -7.56338   1.88904  -4.00383
: *      :                        :  3   -9.99758   1.30542  -7.65851
:*       :                        :  4   -10.9016   2.02454  -5.38474
: *      :                        :  5   -10.2755   2.70271  -3.80192
:  *     :                        :  6   -8.11922   3.02822  -2.68119
:     *  :                        :  7   -4.43278   2.97309  -1.49097
:        :*                       :  8    0.78382   2.59852   0.30164
:        :    *                   :  9    7.53057   2.15532   3.49394
:        :          *             : 10    15.8075   2.35597   6.70953
:        :                *       : 11    25.6145   3.71429   6.89621
:        :                       *: 12    36.9518   5.91655   6.24550
------------------------------------------------------------------------------------
         0                          Sum   33.6945   6.17011   5.46093
====================================================================================
      Lag Distribution of VOSR3       Lag    Coef       S.E.      T-Stat
====================================================================================
:             :           *       :  0    0.01475   0.00499   2.95865
:             :   *               :  1    0.00527   0.00271   1.94224
:           * :                   :  2   -0.00235   0.00124  -1.90122
:      *      :                   :  3   -0.00813   0.00145  -5.62230
:  *          :                   :  4   -0.01204   0.00224  -5.37888
: *           :                   :  5   -0.01411   0.00274  -5.14512
:*            :                   :  6   -0.01432   0.00284  -5.04548
:  *          :                   :  7   -0.01268   0.00251  -5.04811
:     *       :                   :  8   -0.00918   0.00179  -5.13505
:         *   :                   :  9   -0.00383   0.00094  -4.07271
:             :  *                : 10    0.00337   0.00166   2.02730
:             :          *        : 11    0.01243   0.00367   3.38571
:             :                  *: 12    0.02334   0.00624   3.74295
------------------------------------------------------------------------------------
              0                     Sum  -0.01747   0.00745  -2.34553
====================================================================================
      Lag Distribution of VTR3        Lag    Coef       S.E.      T-Stat
====================================================================================
:  *     :                        :  0   -0.05212   0.08467  -0.61560
: *      :                        :  1   -0.06268   0.04761  -1.31647
:*       :                        :  2   -0.06663   0.01772  -3.76052
:*       :                        :  3   -0.06397   0.00735  -8.70277
: *      :                        :  4   -0.05470   0.02281  -2.39806
:   *    :                        :  5   -0.03882   0.03217  -1.20696
:     *  :                        :  6   -0.01633   0.03475  -0.47007
:        :*                       :  7    0.01277   0.03062   0.41689
:        :     *                  :  8    0.04847   0.02033   2.38408
:        :         *              :  9    0.09079   0.01055   8.60619
:        :              *         : 10    0.13972   0.02822   4.95032
:        :                   *    : 11    0.19526   0.05936   3.28946
:        :                       *: 12    0.25741   0.09816   2.62242
```

Appendix 6-5: Ordinary least squares schedule of selected variables.

(a) visits by foreigners.

Variable	Coefficient	Std. Error	T-Stat	2-Tail Sig
C	13,7978	0,8005	17,23	0,000
VT(-3)	0,2608	0,0856	3,05	0,003
AR(1)	0,8683	0,0186	46,47	0,000

R-squared	0,9723	Mean of dependent var	16,3536
Adj. R-squared	0,971	S.D. of dependent var	4,6384
S.E. of regression	0,7834	Sum of squared resid	41,1180
Durbin-Watson stat	1,9562	F-statistic	1175,9630
Log likelihood	-80,7040		

(b) index of corporate profits

Variable	Coefficient	Std. Error	T-Stat	2-Tail Sig
C	14,6508	0,9435	15,23	0,000
CP(-3)	-10,6980	4,8275	-2,21	0,030
AR(1)	0,8766	0,0243	36,02	0,000

R-squared	0,9709	Mean of dependent var	16,3536
Adj. R-squared	0,9701	S.D. of dependent var	4,6384
S.E. of regression	0,8036	Sum of squared resid	43,1546
Durbin-Watson stat	1,8685	F-statistic	1118,8860
Log likelihood	-82,3959		

(c) index of the value of share transactions

Variable	Coefficient	Std. Error	T-Stat	2-Tail Sig
C	12,6972	1,2980	9,78	0,000
VOS(-3)	0,1329	0,0083	1,61	0,113
AR(1)	0,9042	0,0192	46,99	0,000
R-squared	0,9708	Mean of dependent var		16,3536
Adj. R-squared	0,970	S.D. of dependent var		4,6384
S.E. of regression	0,8046	Sum of squared resid		43,3795
Durbin-Watson stat	1,9168	F-statistic		1112,9090
Log likelihood	2,5779			

CHAPTER SEVEN

THE NON STATIONARY AND STATIONARY MODELS COMBINED.

7.1. Introduction.

In Chapters Four and Five, a thorough evaluation of the microeconomic variables which could be used in the prediction of failure was made. In addition to these variables, it is generally accepted that the probability of failure will increase during adverse economic conditions. Accordingly in Chapter Six, an investigation of the macroeconomic variables which impact on the business failure rate was undertaken. In this chapter, an attempt is made to develop a model which integrates the two sets of variables when predicting failure.

Should an attempt be made to integrate the two categories of variables in a comprehensive model of corporate failure, attention needs to be paid to the nature of the dependent variables. The microeconomic variables are firm-specific and may be apportioned specifically to a failed or a non-failed company. The macroeconomic variables on the other hand are market related and constitute the systematic risk inherent in the environment. These variables are not unique to a specific firm. For this reason it is not feasible to combine the predictor variables in a single failure prediction model and the model will need to be evolved over two stages.

7.2 Prior research.

El Hennaway and Morris (1983) acknowledge the fact that economic factors may have a bearing on the predictive ability of the model and although their main concern was with the temporal instability of certain ratio characteristics, they state that their

> secondary objective was to widen the data frame from which

> the models were derived to include general economic and industry indicators with the intention of producing a universally more acceptable model.
>
> (El Hennaway and Morris, 1983 :209)

They accordingly included two dummy economic variables with three chosen financial variables in their prediction model to obtain an adjusted failure prediction score.

Goudie (1987), when investigating failure prediction in the United Kingdom, focused on what he believes are the two central issues. The first is that there be a maximum period of forewarning of impending failure. The second is that the projective efficiency of the model be enhanced with reference to future macroeconomic developments.

Goudie begins with a general evaluation of the ratios which affect corporate failure. His final selection of discriminating variables is based on a cash flow framework as this is regarded by a number of researchers as the significant factor in the prediction of corporate failure (Donaldson (1962), Beaver (1967), Blum (1974), Helfert (1982) and Gentry *et al* (1985)). Goudie accordingly chose the following five ratios as his predictor variables:-

1. post-tax rate of return on equity assets (0,399)
2. working capital/gross assets (0,207)
3. retentions plus depreciation/total net assets (0,307)
4. post-tax income less interest/post-tax income (0,516)
5. percentage change in debt/equity (0,2)

The figures in parentheses represent the scaled coefficient for each variable. Goudie observes that, in general, the absolute correlation coefficients between these ratios were all below 0,3 except for the relationship between the profitability- capital gearing relationship (ratios 1 and 5) which had a coefficient of 0,75. These variables were all significant at a five percent level.

The predictor variables were then used to calculate a discriminant score for each company for the year prior to failure and the results compared to a cutoff rate, or critical value, of 0,47. The cutoff rate was obtained by using a loss ratio of 40:1 and an odds ratio of 1:25. The model achieved satisfactory predictive results overall and correctly classified ninety percent of the companies.

In order to extend the period of forewarning of failure, Goudie constructed pro-forma statements for each of the companies under investigation based on their projected cash flows. The relevant ratios are then extracted from the pro-forma statements and the discriminant function used to calculate the predicted z-score for each company for n-years ahead. Based on the calculated discriminant score, firms can be classified as either financially sound or in severe financial difficulty. The object of obtaining the discriminant score is to isolate those companies, *ceteris paribus*, which could suffer financial difficulties; hence where necessary the appropriate action may be taken.

Goudie finally integrates the company-specific model into the Cambridge Growth Project's disaggregated industry-level model of the United Kingdom economy. The model assumes that certain assumptions on the United Kingdom economy must be made which are based specifically on the following variables:- (i) The exchange rate (Pound/Dollar) (ii) The twenty-year debenture rate (iii) Percentage increase in nominal earnings of companies (iv) Percentage increase in government expenditure (v) Percentage increase in a world production index.

From these assumptions, projections are obtained on the following variables:-

1. The growth rate in the gross domestic product.
2. The ratio of unemployment to the economically active population.
3. Public sectorborrowing as a percentage of the gross domestic product.
4. The balance on the current account.
5. The nominal rate of inflation.
6. The nominal increase in industry profits.

Although Goudie does not specifically indicate how the integration is achieved, he states that

> we would expect the number of companies experiencing financial difficulty to be directly related to these broad economic indicators, and it is towards this that the discriminant model is directed.
>
> (Goudie, 1987:76).

In summary, the research has shown promising results in being able to extend the period of forewarning of impending company failure. In addition, the projective ability of the model is further strengthened by reference to macroeconomic conditions. Although the approach adopted by Goudie is an advance on the previous research, he admits that the paper lacks statistical precision.

7.3 Research methodology.

As indicated, the methodology will need to address the differences which appear in the dependent variables. As the microeconomic dependent variable is dichotomous while that for the macroeconomic variables is continuous, it is not feasible to combine the two sets of variables in a single failure prediction model. If the two sets are to be used in conjunction with one another, use will have to be made of a model which is developed in two stages.

During the first stage, the significant micro- and macroeconomic variables are isolated separately. In Chapter Five, six variables were found to be the most suitable predictor variables in the failure prediction model in the year prior to failure. These are:-

1. Total owners interest/Total assets
2. Operating profit/Average operating assets
3. Current assets/Current liabilities
4. Director appointments and resignations
5. The change in delay in publishing the Annual Report
6. Director shareholdings.

In Chapter Six, four macroeconomic variables were found to be significant predictors of the business failure rate. On the other hand, a large degree of serial correlation was present in the model. When this was corrected using the Cochrane-Orcutt procedure, the four variables were no longer significant at the five percent level of significance. Nevertheless, further investigation showed that a model containing only total advances from the banking sector, lagged for two months, could adequately be used when predicting the business failure rate.

During the second stage, use is made of the business failure rate and predictor variables established previously. The macroeconomic variable is used to estimate the business failure rate whilst the microeconomic variables are used to calculate the discriminant (failure prediction) scores.

The prior results have indicated that either of the two statistical techniques, logistic regression or multivariate discriminant analysis, could be used in the South African context when predicting failure. In this chapter, use is made of a different discriminant analysis technique, that of Bayes-Fisher, when attempting to predict failure. As this constitutes a departure from the established techniques and from those used in Chapter Four, multivariate discriminant analysis is initially used when obtaining the relevant failure prediction scores. Following this, the Bayes-Fisher discriminant analysis technique is used when predicting failure.

Once having established the relevant discriminant score, it is essential that the question of classification be resolved. The earlier chapters assumed that the probability of failure or non- failure were equal (0,5) and that no cost be attributed to the misclasification of an observation, as the intention was only to compare the efficiency of the statistical techniques used when predciting failure.

The classification procedure adopted in this chapter took account of different prior probability estimates (odds ratio) and the cost of misclassification (loss ratio) when calculating the cutoff rate. The prior probability estimates were obtained from the relevant business failure rates and varied from one percent of all registered companies up to a maximum of ten percent. The establishment of misclassification costs is highly subjective and was set at 40:1 as this accords with the loss ratios set by Taffler (1982) and Goudie (1987). In addition, classification results were obtained for a loss ratio of

35:1 which is the same as that set by Altman *et al.* (1977).

7.3.1 Multiple discriminant analysis.

When using this technique in the prediction of failure, the normality and equal variance-covariance matrices, Σ, of the populations is assumed. Under this assumption the classification rule that minimises the expected cost of misclassification is given by allocating a particular observation,x , to the non-failed company group if

$$(Z_x - \tfrac{1}{2}(\bar{Z}_1 + \bar{Z}_2)) > \lambda$$

where $\bar{Z}_1$ and $\bar{Z}_2$ are the observed mean discriminant function scores for the non-failed and failed companies respectively, and $Z_x = (\mu_1 - \mu_2)^t \ \Sigma^{-1} x$, the linear discriminant function, where $\mu_1$and μ_2 are the means of the non-failed and failed company populations respectively.

Failing this, allocate x to the group of failed companies. In this instance

$$\lambda = \ln \frac{C(1 \mid 2)\, p_2}{C(2 \mid 1)\, p_1}$$

where

p_1 and p_2 are the odds ratios for the non-failed and failed companies respectively

$C(1 \mid 2)$ is the cost of misclassifying a failed company.

$C(2 \mid 1)$ is the cost of misclassifying a non-failed company.

The six predictor variables from Chapter Five were used in the classification of the non-failed and failed companies for the two years prior to failure. The loss ratio $C(1 \mid 2)$:$C(2 \mid 1)$ was initially set at 40:1; thereafter a ratio of 35:1 was also investigated.

The prior probability of failure of a company p_2 was varied from one to ten percent and the cutoff points were calculated from

$$\lambda \quad + \quad \frac{(\bar{Z}_1 + \bar{Z}_2)}{2}$$

7.3.2. The Bayes-Fisher discriminant analysis.

In the Bayes-Fisher discriminant technique (Haung and Li, 1991) knowledge of the probability density functions of the populations, failed or non-failed companies, is not required. Use is made of the business failure rate estimated previously as the prior probabilities of the populations.

In particular, assume that we have two random samples from the non-failed and failed company populations consisting of the three financial variables and three non-financial variables, which are denoted by G_1 and G_2 respectively. Let the means , covariance matrices and prior probabilities of G_1 and G_2 be denoted by μ_i, v_i and p_i (for $i = 1,2$) respectively. Consider a six-by-one vector random variable consisting of the three financial and three non-financial variables of G_1 and G_2. A company with associated values x must be assigned to either G_1 or G_2. In this manner a Bayes-Fisher discriminant function is obtained from

$$l(x) = 2p_1 \, p_2 \, x^t \; (p_1 \, v_1 + \; p_2 \, v_2)^{-1} \, (\mu_1 - \mu_2)$$

With this method a range of predictor variable coefficients is obtained rather than a single set of coefficients as is the case with the multiple discriminant analysis. Finally, the cutoff point (K) is obtained by minimising the expected cost of misclassification (ECM) where

$$ECM = p_1\,C\,(2 \mid 1)\ \text{Prob}\,(I(X) > K \mid G_1) + p_2\,C\,(1 \mid 2)\ \text{Prob}\,(I(X) < K \mid G_2)$$

where $C\ (2 \mid 1)$ and $C\ (1 \mid 2)$ are the costs of misclassification defined previously, and K the relevant cut-off score

7.4 Results.

7.4.1 The multiple discriminant analysis.

The six predictor variables were used to calculate a company's discriminant score when evaluating failure. The linear discriminant function obtained for the year prior to failure was

$$Y = 0{,}0696X_1 + 0{,}1875X_2 - 0{,}5126X_3 - 0{,}3812X_4 - 0{,}6958X_5 - 0{,}00075X_6$$

where

X_1 = Total owners interest/Total assets

X_2 = Operating profit/Average operating assets

X_3 = Current assets/Current liabilities

X_4 = Director appointments and resignations

X_5 = Change in delay in publishing Annual Report

X_6 = Director shareholding

and

Y = the discriminant score

Using this discriminant function with different values of the business failure rate and a cost ratio of 40:1, various discriminant scores were obtained. From these scores a company is classified as successful if Y is greater than the cutoff point; otherwise it was classified as a failure.

The classification accuracy of the model is given in the following table:-

Table 7-1: Cutoff points and classification results of selected companies for different levels of the business failure rate in the year prior to failure.

Business failure rate	Cutoff point	Success (19)	Failure (21)
0,01	0,6193	19	15
0,02	1,3226	19	18
0,03	1,7383	19	19
0,04	2,0364	19	20
0,05	2,2700	18	20
0,06	2,4629	18	20
0,07	2,6277	18	20
0,08	2,7721	18	20
0,09	2,9008	18	20
0,10	3,0172	18	21

The figures in parentheses are the number of companies being classified.

At a business failure rate of one percent of the total population, the model correctly classified seventy-one percent of the failed companies whereas it correctly classified all the non- failed companies. The classification accuracy of the model improved to one hundred percent of the failed group at a business failure rate of ten percent. At this level the classification accuracy of the non-failed group was ninety-five percent.

For the case of the second year prior to failure, the discriminant function was found to be

$$Y = 0{,}0496X_1 + 0{,}1471X_2 - 0{,}2386X_3 + 0{,}203X_4 - 1{,}514X_5 - 0{,}00024X_6$$

Once again, the various discriminant scores were calculated and the classification accuracy, using the same cost ratio, is given as follows:-

Table 7-2: Cutoff rates and classification results of selected companies for different levels of the business failure rate in the second year prior to failure.

Business failure rate	Cutoff point	Success (18)	Failure (21)
0,01	2,1619	18	11
0,02	2,8652	17	15
0,03	3,2810	16	15
0,04	3,5790	14	16
0,05	3,8126	14	18
0,06	4,0055	13	18
0,07	4,1704	12	18
0,08	4,3147	11	19
0,09	4,4434	10	19
0,10	4,5598	9	19

In this instance the results are naturally poorer than those for the year prior to failure although the same trend exists as for the previous year.

Since the choice of a cost ratio is subjective, classification results were obtained for comparative purposes using a loss ratio of 35:1. These results appear as follows:-

Table 7-3: Cutoff rates and classification results of companies for different levels of the business failure rate in the year prior to failure.

Business failure rate	Cutoff point	Success (19)	Failure (21)
0,01	0,4857	19	15
0,02	1,1891	19	18
0,03	1,6048	19	18
0,04	1,9028	19	19
0,05	2,1364	19	20
0,06	2,3293	19	20
0,07	2,4942	18	20
0,08	2,6385	18	20
0,09	2,7672	18	20
0,10	2,8836	18	20

As can be seen there is little difference in the classification results when varying the loss ratio. Once again, the results for the second year prior to failure were computed and appear as follows:-

Table 7-4: Cutoff rates and classification results of selected companies for different levels of the business failure rate in the second year prior to failure.

Business failure rate	Cutoff point	Success (18)	Failure (21)
0,01	2,0284	18	10
0,02	2,7317	17	14
0,03	3,1474	16	15
0,04	3,4455	14	15
0,05	3,6791	14	16
0,06	3,8720	14	18
0,07	4,0368	13	18
0,08	4,1812	12	18
0,09	4,3099	11	19
0,10	4,4263	10	19

7.4.2 The Bayes-Fisher discriminant analysis.

When applying the Bayes-Fisher discriminant analysis technique, different coefficients are obtained for each level of the business failure rate. The coefficients for the two years prior to failure are given in Appendix 7-1.

The relevant failure prediction scores were obtained for various levels of the business failure rate under the assumption of a 40:1 loss ratio. The classification results are presented in the following table:-

Table 7-5: The cutoff points and classification results of selected companies for different levels of the business failure rate in the year prior to failure.

Business failure rate	Cutoff point	Success (19)	Failure (21)
0,01	0,1539	19	20
0,02	0,3510	19	21
0,03	0,5151	19	21
0,04	0,6560	19	21
0,05	0,7635	19	21
0,06	0,8457	19	21
0,07	0,9326	19	21
0,08	0,9995	19	21
0,09	1,0570	19	21
0,10	1,1066	19	21

The results of the Bayes-Fisher discriminant analysis appear highly satisfactory and are an improvement on the results obtained for the multivariate discriminant analysis. Perfect classification accuracy is obtained for successful companies. Similar results were obtained for the failed companies except at the very lowest level of the business failure rate (0,01). Interestingly enough, these results are similar to those which were obtained when investigating failure prediction using microeconomic variables and assuming equal prior probabilities and misclassification costs.

The results for the second year prior to failure were also obtained. These appear to be satisfactory as well and are given in the following table:-

Table 7-6: The cutoff points and classification results of selected companies for different levels of the business failure rate in the second year prior to failure.

Business failure rate	Cutoff point	Success (18)	Failure (21)
0,01	0,1385	14	15
0,02	0,2796	14	15
0,03	0,4107	14	16
0,04	0,5370	14	16
0,05	0,6545	14	16
0,06	0,7674	14	16
0,07	0,8716	14	16
0,08	0,9677	14	16
0,09	1,0565	14	16
0,10	1,1385	14	16

7.5. Summary.

This chapter has attempted to construct a usable, yet comprehensive model of corporate failure which embodies all of the relevant variables which influence the success or otherwise of a business organisation. Emphasis has been placed on the practical application of the model. The method of establishing the model is different from the traditional method whereby a model using a number of predictor variables and a single cutoff rate, was used to classify companies at risk of failure.

In addition, although the macroeconomic variables which impact on a potentially failed comapny have been acknowledged, limited integration of these variables in a traditional model has been attempted. Where integration has been achieved, the application of the model is limited to those researchers with access to techniques/data which are not freely available.

The model proposed in this thesis is developed in two stages and encompasses a range of cutoff points whereby where companies at risk may be classified. In the first stage, the microeconomic and macroeconomic variables which could be used as predictor variables in a failure prediction model were established. During the second stage, the chosen variables were used to predict failure using two different statistical techniques.

Initially, multivariate discriminant analysis was used to obtain a failure prediction score. This was then compared to a cutoff point which was established with reference to the relevant business failure rate. Thereafter, the Bayes-Fisher discriminant analysis technique was used to obtain a discriminant score for various levels of the business failure rate which, once again, was compared to its relevant cutoff point. The classification results obtained for the Bayes-Fisher method of discrimination proved highly satisfactory.

The intention is that the model proposed in this thesis will enable the researcher to obtain a failure prediction score with adequate reference to existing micro- and macroeconomic variables and the Bayes-Fisher discriminant technique. The discriminant score which is obtained will be compared to its relevant cutoff score for the appropriate level of the business failure rate and the company classified accordingly. The ultimate decison whether the company will fail or not will be left to the researcher.

Appendix 7-1: The discriminant score coefficients using Bayes- Fisher discriminant analysis for (a) the year before failure (b) the second year prior to failure.

(a) the year before failure

Business failure rate	0207	1607	1801	DAR	CLAG	SH
0,01	0,0063	0,0186	-0,1417	-0,1765	-0,3720	-1,20E-5
0,02	0,0103	0,0305	-0,1843	-0,2522	-0,5297	-1,62E-5
0,03	0,0136	0,4000	-0,2093	-0,2947	-0,6617	-2,46E-5
0,04	0,0164	0,0480	-0,2274	-0,3204	-0,6710	-3,63E-5
0,05	0,0189	0,0550	-0,2419	-0,3366	-0,7043	-5,04E-5
0,06	0,0212	0,0612	-0,2540	-0,3467	-0,7250	-6,59E-5
0,07	0,0232	0,0667	-0,2643	-0,3528	-0,7373	-8,22E-5
0,08	0,0251	0,0761	-0,2733	-0,3562	-0,7438	-9,91E-5
0,09	0,0267	0,0788	-0,2811	-0,3576	-0,7462	-1,16E-4
0,10	0,0283	0,0801	-0,2880	-0,3579	-0,7456	-1,33E-4

(b) the second year prior to failure.

Business failure rate	0207	1607	1801	DAR	CLAG	SH
0,01	0,0035	0,0069	-0,0408	-0,0105	-0,1957	-4,97E-5
0,02	0,0066	0,0140	-0,0707	-0,0311	-0,3403	-7,21E-5
0,03	0,0092	0,0205	-0,0932	-0,0357	-0,4549	-8,65E-5
0,04	0,0114	0,0264	-0,1107	-0,0394	-0,5488	-9,71E-5
0,05	0,0134	0,0318	-0,1245	-0,0473	-0,6272	-1,06E-4
0,06	0,0152	0,0368	-0,1254	-0,0545	-0,6937	-1.13E-4
0,07	0,0167	0,0414	-0,1442	-0,0610	-0,7506	-1,19E-4
0,08	0,0181	0,0456	-0,1514	-0,0669	-0,7997	-1,24E-4
0,09	0,0194	0,0495	-0,1572	-0,0723	-0,8422	-1,28E-4
0,10	0,0206	0,0530	-0,1619	-0,0773	-0,8792	-1,32E-4

CHAPTER EIGHT

CONCLUSION

8.1. Introduction.

A large number of researchers have developed failure prediction models which are based solely on firm-specific financial ratios. Although the majority of these models are easily applicable, the diversity of ratios and the different statistical techniques used when establishing them raises doubt as to their practicality.

One model which has enjoyed prominence is the Altman Z-score model. The model produces a discriminant score which can subsequently be used to classify companies at risk of failure. On the other hand, the model is confined to the financial ratios which influence failure and ignores a host of variables which could also influence the success or failure of a business. The more recent models have been extended to include the firm- specific non-financial variables which can be used as predictors of failure. In addition, certain models have been developed which take account of the macroeconomic variables which may affect business failure.

This thesis has concentrated on producing a comprehensive, yet simple model of corporate failure. Use is made of both micro- and macroeconomic predictor variables when constructing the model. The intention is that the model be applied by practitioners involved in the evaluation of financial well-being.

8.2 Synopsis of thesis.

The model presented in this thesis has been developed with the view to isolating those companies which MAY fail in the future. Once having isolated a potential failure, the researcher will need to use intuition when making the final decision. The central theme of the thesis is that the variables which are used in the model be readily available to researchers. For this reason, extensive use has been made of the Annual Reports of certain companies as well as certain readily obtainable economic variables.

Two categories of variables need to be evaluated when analysing why companies fail. The first category is the microeconomic variables. These are firm-specific and can be further broken down into financial and non-financial variables. The second category is the macroeconomic factors. These influence the business failure rate and ultimately have a bearing on the individual company at risk of failure.

There is an important difference in these two categories. On the one hand, a downturn in the general level of economic activity is not firm-specific and will affect all the participants in the economy in differing degrees. On the other hand the firm-specific variables can be specifically allocated to either a failed or a non-failed company; hence the incorporation of economic variables into the failure prediction model will need to be treated separately to the firm-specific variables.

In order to overcome the problem of dissimilar dependent variables, use was made of the Bayes-Fisher discriminant method. In this instance, the prior probability of failure is obtained from the business failure rate. This is then used to calculate the cut-off rate to be compared to the appropriate discriminant score for predicting whether a company would fail or not. Due to the fact that the business failure rate will vary according to economic conditions, a range of discriminant score coefficients and cut-off points, rather than a single set of coefficients and cut-off point (as in the past) was obtained.

The model presented in this thesis is not unique when attempting to combine the micro- and macroeconomic variables which could be used in a failure prediction model. The need to achieve this is readily acknowledged in the literature, although no model for which the predictor variables are readily obtainable and which is easily applicable is available. On the other hand, the model is unique in producing a RANGE of discriminant score coefficients with their corresponding cut-off points which are dependent on general economic conditions.

8.3 Summary of findings.

As two categories of variables were evaluated, the findings are summarised accordingly.

8.3.1 The microeconomic variables.

This category was further sub-divided into the financial and non- financial variables.

8.3.1.1 The firm-specific financial ratios.

Fourteen financial ratios which are readily available to researchers were selected to represent the selection of independent variables. In order to aid in the reduction of the variables and in the selection of the predictor variables, factor and stepwise regression analysis was conducted on the fourteen variables. Based on these results four predictor variables were chosen for inclusion in the failure prediction model. These were:-

1. Operating profit/Average operating assets

2. Current assets/current liabilities
3. Total owners interest/total assets
4. Profit before tax/total debt

These variables can be classified as the activity, liquidity, solvency and profitability components of a set of financial accounts. These predictors were then used to evaluate the efficiency of multivariate discriminant and logistic regression analysis as statistical techniques in predicting failure.

The logistic regression analysis achieved superior results when predicting failure for all of the five years prior to failure. On the other hand, a z-test indicated that there was insufficient evidence to suggest that either technique was superior to the other. The overall conclusion is that logistic regression analysis cannot be regarded as a superior statistical technique to multivariate discriminant analysis when failure prediction is in question. Nevertheless, it appears to be a more robust technique under certain circumstances.

In the main the predictive ability of the chosen variables was satisfactory in the year prior to failure although the results for earlier years were disappointing.

8.3.1.2 The non-financial variables.

Three groups of non-financial variables which relate to the delay in publishing the annual report, director resignations and appointments and director shareholdings, were investigated.

A number of variables were chosen to represent these groups and their significance examined using logistic regression analysis. From the analysis three variables emerged as significant predictors of failure at the 5% level. These were:-

1. the change in delay in publishing the financial statements
2. director appointments and resignations
3. director shareholdings

It is interesting to note that a model containing these variables gave comparable results (95,0% to 92,0%0) to the failure prediction model containing only financial ratios.

8.3.1.3 The financial and non-financial variables.

An evaluation of the combined financial and non-financial variables was then undertaken. Factor and stepwise regression analysis were again used in an attempt to isolate the more significant variables and aid in the selection of predictor variables. After due consideration of the results, six variables were chosen as the predictor variables:-

1. Profit before interest after tax/ Total assets
2. Current assets/Total debt
3. Profit before interest/Interest paid
4. Director appointments and resignations
5. Director shareholdings
6. The change in delay in publishing the financial statements

The first three variables are indicative of the profitability, liquidity and solvency levels of a company which can be obtained from a set of financial statements. The remaining variables relate to the non-financial activity of a company and are also available from the Annual Report. The predictive ability of the variables was then evaluated using multivariate discriminant and logistic regression analysis. In this instance, the ability of the model to predict failure proved disappointing in the year prior to failure. Both the multivariate discriminant and logistic regression analysis provided inferior predictive results to the model using only financial variables. The results for the second year prior to failure however, were a substantial improvement.

In an attempt to improve on the predictive ability of the model the selected financial ratios were replaced by those used in the earlier model - *viz.* operating profits/average operating assets, total owners interest/total assets and current assets/current liabilities. In this instance, the predictive ability of the model improved dramatically and the model using logistic regression analysis produced perfect predictive ability.

8.3.2 The macroeconomic variables.

Six categories of economic variables were chosen to represent the independent variables when investigating the business failure rate in South Africa. Fifteen economic variables were accordingly chosen to represent these categories. Factor and stepwise regression analysis were again used to evaluate their interrelationship and to aid in the selection of predictor variables. From the results four variables were chosen to represent the macroeconomic variables. These were:-

1. total advances from the banking sector
2. the index of corporate profits

3. the value of share transactions
4. visits by foreigners.

Due to the sequential nature of the data the relationship between the variables was examined using a polynomial distribution lag. The more significant lags were then examined using least squares regression while the Cochrane-Orcutt procedure was incorporated to account for serial correlation. In the final analysis, a model containing only total advances from the banking sector (lagged for two periods) is an adequate predictor of the business failure rate.

8.4 The combined variables.

Having isolated the significant variables in the prediction of failure and of the business failure rate, a model which combined both sets of variables was evolved using two stages. In the first stage the business failure rate is estimated using the variable total advances from the banking sector (lagged for two periods). In the second stage, two different statistical techiques are used to obtain discriminant functions and cut-off points relating to the business failure rate obtained during the first stage. In this way, sets of discriminant functions and cut-off points are obtained depending on the state of the economy and the failure prediction score for each company compared to its relevant cut-off point.

The results which were obtained appear to be satisfactory, particularly in the case of the Bayes-Fisher discriminant analysis. In this instance, the model appeared to be an accurate predictor of business failure except for very low levels of the business failure rate. At this level, economic conditions are not as harsh as one would expect at a higher level of business failure and one could anticipate that companies would continue to operate due to the benign economic conditions which would not be the case during a downturn in the economy.

8.5 Conclusions and implications of the research.

The reasons for business failure are wide and varied and as business failure affects the various stakeholders in different ways, it is important that its prediction be achieved with a reasonable degree of accuracy.

To establish a failure prediction model which is so esoteric that it may only be used by its author, will serve of little use to practitioners when attempting to predict failure. In addition, to confine a failure prediction model to one set of predictor variables and to ignore the other variables capable of predicting failure would be equally erroneous. Goudie (1987) is the only prior research which attempts to combine all the predictors of failure in a failure prediction model. The model developed in this thesis also takes cognisance of all of the areas of failure prediction and arrives at a discriminant score which can then be compared to a predetermined cut-off point.

The model has easy application and has been developed not so much for its accuracy in predicting failure (although this is highly satisfactory), but rather as a guide in isolating potential failure candidates. A discriminant score will need to be calculated and compared to the cut-off scores obtained from Table 7-6. If the discriminant score is below the cut-off point, the indication is that the relevant company may well fail. Thereafter, intuition will need to be used when making the final assessment.

The implications for further research are varied. A great shortfall in the research is the limited availability of the data as only a limited number of publicly quoted companies have failed over the last two decades. Nevertheless, the sample size is similar to previous research. (Altman, 1968. Marais, 1979. Castagna and Matolscy (1981). Taffler (1982)). Ideally, one would like to choose a sample of failed companies and develop a failure prediction model based on this sample and the chosen predictor variables. Thereafter, one would like to apply the model to a control sample of companies and compare the results of the two samples. For this reason, once additional data on failed companies becomes available it would be desirable to test the model using the data obtained from these failed companies.

The relaxation of apartheid control regulations makes South Africa more acceptable to the outside world. This could have a beneficial effect on the economic environment which could affect the economic variables investigated in this thesis. Future research could be conducted on the effect of changes in the economy on the business failure rate, once the changes have become entrenched in the economic system.

The inconsistent nature of the pure accounting values contained in financial statements may also influence the results obtained from the various models of failure prediction. Research needs to be undertaken which sets out to standardise the definitions of the ratios used in failure prediction and thereby the values of the discriminant scores and cut-off points obtained. In this way the results obtained from the various models would be universally applicable and hence more comparable over different environments. On the other hand, standardisation may only prove possible when universal consensus is reached by the accounting profession as regards the consistent application of stated accounting policies.

The rigid application of statistical techniques in predicting failure is to be questioned. The various techniques which are used are subject to assumptions being made about the nature of the data being investigated. Satisfactory results could be obtained under the assumptions set down in the methodology whilst these results may not prove to be as satisfactory should the stated assumptions be varied. This is fairly evident from the abundance of "satisfactory" failure prediction models found in the literature. Hence, there is a very real need to standardise the procedure and assumptions which are used when predicting failure.

Finally, it is difficult to model a phenomenon which is influenced by such a large set of factors along purely mathematical grounds. This thesis has suggested that the final decision be left to the interested party. Future research could well focus on how the decision-maker reaches his final decision. This could well add to a better understanding of the nature of the non-financial variables in failure prediction.

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