AN EVALUATION OF FINANCIAL PERFORMANCE OF COMPANIES

"The financial performance of companies is investigated using multiple discriminant analysis together with methods for the identification of potential high performance companies"

by

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ABSTRACT

The objective of this study is to establish whether companies that utilise their resources more efficiently present specific characteristics in their financial profile, and whether on the basis of these characteristics a classification model can be constructed that includes, alongside resource utilisation measures, predictors related to other financial dimensions calculated from published information.

The research proceeds by examining the factors influencing companies' performance, and the reliabilty of published accounts. Discriminant analysis is chosen as the most appropriate technique of analysis. Its applications in the field of financial analysis are discussed and an examination of the discriminant analysis technique is undertaken.

For reasons of comparability and access to a large quantity of information, the analytical part of the study is based on data extracted from a computer readable tape provided by Extel Statistical Services Ltd. It starts by describing the financial variables to be used later on in the study, and proposing a classification framework that would be of assistance in identifying the financial dimensions of importance in relation to the problem under investigation. A discriminant model that correctly classifies 85 per cent of the companies is then constructed. It includes, besides measures of resources utilisation, measures of financial levarege, working capital management, cash position and stability of past performance. The part of the analysis on the identification of potential well performing companies indicates that, although specific characteristics can be noticed up to five year before, it is only possible to construct a classification model with sufficient accuracy one year before a high level of performance is actually reached.

Finally, an index of financial performance based on normal approximations of the z-score distributions from the model used to identify well performing companies is suggested and an assessment of the structural change experienced by companies rising from a less well to a well performaing status is presented.

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INTRODUCTION

CHAPTER 1.

1.1. OBJECTIVES OF THE STUDY.

Financial analysis as a theory of the firm is of fairly recent origin. It is mainly in the late sixties that significant studies appeared in the financial literature, and little work has been done towards formulating a theoretical framework within which most of the problems that financial analysts are confronted with could be approached. As a consequence, most of the published analyses have tried to explain certain phenomena (bankruptcy, bond ratings...etc.) by investigating arrays of possible factors and identifying those that are significant.

The studies published up to now can be classified under two main headings:

1) Development of new theoretical approaches and testing of these new theories.
2) Empirical studies where the relationships between the problem under study and some financial factors are left to be ascertained by some existing statistical techniques.

Our study falls into the second category. Its aim is to test whether successful companies are characterised by specific financial traits. Few studies have attempted to investigate this area and have often been too specific in the type of companies or the choice of financial characteristics they analysed. As a consequence a generalisation of their findings is not possible and a framework on which to base further investigation can not be developed.

The aim of this study is therefore to collect and transform as much information as possible in order to cover most of the financial characteristics of as many companies as possible. This is done for two reasons.

Firstly, it is the author's view that the larger the set of companies analysed, the more significant and the more amenable to generalisation the results will be. So many studies have been criticised on the grounds that the sets of observations were too small or not representative of the population as a whole to permit a generalisation of the findings so that inferences could be made about other companies not in the set being investigated..Secondly, due to the lack of a theoretical framework which could have indicated the financial characteristics to analyse, it was thought that every aspect of the financial profile of companies should be investigated in order to pinpoint the areas of interest.

1.2. BACKGROUND OF THE PROBLEM UNDER STUDY

The performance of companies is a subject that attracts a lot of comments from both financial experts, researchers and management. However, picking out the most successful companies has always proved to be a difficult task. The interest of many parties in firm behaviour have led some publications to present analyses and comparisons of company performance. One of the best known in the U.K. is Times 1000 which lists the 1000 largest U.K. industrial companies in descending order in terms of sales turnover. It also gives details of capital employed, profit before tax and total number of employees. Recently information on European, American and Japanese companies has been added together with details on bank, insurance companies, property companies, building societies and other financial institutions. Another publication, 'Management Today', lists the most performing companies in terms of profitability and growth in profit and dividends.

However useful, these publications give only a limited number of performance indices such as return on capital or profit margin and feature leagues tables based on size or growth rendering difficult the comparison between companies belonging to a same economic sector.

In order to compare the performance of companies within or across industrial sectors, The Financial Times publishes a quarterly summary of the financial results of the major companies reporting during the period. About thirty industrial sectors are covered, each divided into four sections: capital goods, consumer durables, consumer non-durables and miscellaneous. In addition, financial results are reported for banks and other financial institutions. The number of companies comprising each sector is given but their names are not mentioned. In this case again, the information revealed is very small in amount. The Financial Times' summary shows indices related to profits, dividends, cash flow and capital, but fails to include indices related to sales turnover or details of the balance sheet.

A similar type of publication is provided by the Department of Industry, which bases its summary on over one thousand two hundred listed U.K. companies. The companies are classified according to the Standard Industrial Classification but any details about individual companies are not reported.

A more complete publication which is fairly new in this field is issued by Inter-Company Comparison Limited (ICC). It is entitled Industrial Performance Analysis and covers fifty four commercial and industrial sectors. The financial ratios given in the ICC's report on sector performance are based on more than three thousand companies and can be obtained for individual companies. These ratios are related to:

- profitability
- liquidity
- credit given
- profit per employee
- sales per employee
- capital per employee

Hence, the ICC's publication gives a more detailed account of the performance of the companies and the economic sectors it analyses than any of the other publications. But this profusion of information can become confusing since it is rather more difficult to obtain an overall picture of the performance of a firm when the evaluation is based on several indices. For example, a firm may have a high level of profitability, but at the same time be in a very bad situation regarding its liquidity. The problem is then to decide what weight to attach to each of the variables. The situation becomes more complicated as more indices are taken into consideration.

This need to assess company performance has also been felt by financial researchers. A series of articles proposing different criteria of firm performance have been published in the academic accounting and financial journals. These studies can be broadly classified into four categories

1) Use of single ratio and measures of growth
   - value added and return on capital ratio
   - growth in sales, number of employees,assets etc.
2) Use of a hierarchical set of ratios
3) Comparison of a firm's performance on a set of ratios to that of other firms that may be direct competitors.
4) Use of several ratios with associated weight to produce a single index.

Although there is a debate on whether to use value added instead of profit related ratios (Ball, 1968; Beattie, 1970) the use of a single ratio as a mean of evaluating performance is common practice among managers, and are generally accompanied by some measures of growth. However, this practice has been criticised on the grounds that a single ratio cannot reflect every aspect of a company performance and sets of ratios have been proposed to allow a better evaluation of the financial profile of firms. This type of analyses have taken two forms. Bentley (1973)and Vice (1968) proposed the use of a hierarchical set of ratios while Shorrock and Dobson (1979) and Taffler and Sudarsanam (1980) recommended the selection of specific financial ratios and their comparison to those of other firms so as to identify the areas of weaknessess or strength. These analyses often result in conflicting signals being emitted by the different financial ratios considered. Some may indicate areas of strength while others may indicate the opposite. The purpose of indices of performance combining several financial ratios was to overcome this problem. However, they have not been recognised by financial analysts as a reliable mean of assessing company performance. The main reasons for this mis-trust are due to the quite arbitrary manner in which both weights and variables are chosen and to the specificity of the area under study which prevent the generalisation of their use.

1.3. SCOPE OF THE STUDY.

Since the need to assess company performance is evident from the large amount of effort devoted to it, the proposed study will attempt to develop a model based on empirical evidence that will classify companies according to their level of performance.

This study is in fact complementary to the work undertaken in this area, since most of the past studies have focused on the determinants of performance rather than on the effects of a high level of performance on the financial profile of firms.

It is the author's view, that all the financial characteristics of a company should be analysed before a judgment regarding its level of performance can be drawn.

This is demonstrated by the fact that there can be conflict between profitability which is a criterion of company performance widely accepted, and survival. Many firms, especially small firms, go to the wall not because they lack profit but because their cash inflows and outflows are badly timed leading them to run out of cash or credit. Therefore profitability should be matched with solvency. As a consequence, performance criteria should test as well as the efficiency with which the resources of a firm are utilised, its financial strengths in areas such as liquidity, financial leverage, velocity etc.

This is particularly true now, since after times of rapid growth in the fifties and sixties for most companies in Western Europe, the recent tendency is for whole markets to have very small and even negative growth trends. In such situations, companies can no longer rely solely on sales growth to maintain a satisfactory level of performance. Use of assets, liquidity, credit management, financial leverage, long term solvency are of equal importance if a firm is to remain successful.

The theme of the present study will therefore, be of establishing whether companies that have achieved efficient use of their resources exhibit specific characteristics in their financial profiles. If so, a model would then be constructed in order to identify those companies from the rest of the companies on the basis of these differences. Hence this will involve:

1) The selection of a performance criterion as far as efficiency related to the use of resources is concerned.
2) An analysis of the financial characteristics of successful and less successful companies at the single variable and multivariate levels.
3) The construction of a classification model that will include as well as resources utilization measures, other predictors depicting companies financial strengths.

At this stage, it should be noted that the main concern of this study lies with the analysis of financial characteristics and that there will be no attempt to explain the causes of success except if they are projected by financial characteristics.

The information used to carry out the financial analysis is that generally available from published accounts; the reasons for this choice are:

1) To include as many companies as possible in the analysis. The use of more specific information would have certainly lead to smaller samples since the reluctance of companies to give information they are not required by law to publish is well known.
2) To make the results of this analysis usable by any person that has access to companies' published reports.
3) To test whether the information contained in

published accounts is sufficient for a
financial analyst or the public at large
to assess a company's level of performance.

The analysis was undertaken in two phases. Firstly the period of high level of performance is analysed in order to pin point the differences between successful and less successful companies. Secondly, the period preceding success is in turn analysed to test whether potential successful companies exhibit specific financial characteristics and whether they can be identified with a certain accuracy.

The study is divided into seven chapters. The present and first chapter describes the objectives of the study, the background of the problem under study, together with the scope, significance and limitations of this research.

The second chapter discusses the determinants and influencing factors of company performance. The reliability of published accounts as a source of financial data is also examined. Finally, a review of some of the work related to the analysis of company performance together with the choice of the analytical technique and its use in financial analysis are presented.

Chapter three describes the methodology used and proposes a criterion of resource utilization.

In chapter four, the variables used later on in the study are defined. Their utilization in other financial studies is discussed and a classification framework is proposed.

Chapter five is the application of the technique described in chapter three. The companies are analysed and subsequently classified.

Chapter six is a further application of the results of the preceding chapter since based on them an overall index of performance is developed. The structural change undergone by companies reaching a level of high performance is also examined.

Chapter seven is the final chapter. It presents the main conclusions of this research and proposes additional research in the subject.

1.4. SIGNIFICANCE OF THE STUDY.

If the intended analysis is carried out with success, this study would prove to be significant in the following areas:

1) It will add some more weight to the argument that published accounts contain useful information for any party concerned with the behaviour of companies and will show their relevance in relation to the assessment of performance.
2) It will indicate which are the financial characteristics of importance in assessing company performance and whether the applicability of financial statement analysis and statistical techniques in diagnosing the level of performance of companies is verified.

3) The resulting model may help investors, owners, management in capturing a more objective picture of their company regarding use of resources and financial strengths. In the same fashion, a government or ministerial department could use the findings of this study in monitoring the economy as a whole in a very efficient manner.
4) The study will contribute to a better understanding of the performance process, structural change associated with an improving level of performance together with the financial characteristics of potential well performers will serve as the basis for identifying the financial dimensions explaining success.
5) The index of performance will give a precise idea of the situation of a company regarding its performance in relation to the whole population of companies. It will not be necessary to have recourse to direct comparison with other companies.

1.5. LIMITATIONS OF THE STUDY.

The two main limitations of this study are in relation to the nature of the data utilised and to the possible non representativeness of the samples due to the source of the information.

1) Qualitative data regarding management practices, structure and environment of the companies could have been included since these factors have proved to be significant in relation to the analysis of performance. Furthermore, the financial data utilized is limited to that available in the published reports. As a consequence, an inconclusive completion of the study will merely mean that the information available in published accounts is not sufficient in assessing the level of performance of a firm.

2) The source of the data utilized may lead to upward bias in the representativeness of the samples. For ease of access and availability of a large quantity of data, a computer readable tape was used as the source of data. However, it is well known that the "bad" companies tend not to collaborate with agencies providing such services. Therefore, the companies listed on the tape may not be representative of the population as a whole but it is thought that the bias resulting from using the tape will be minute since the proportion of "bad" companies

is quite small.

Although the points mentioned above will limit the depth of this analysis, they might as well give some strength to it. As mentioned earlier, the use of more complete information would have resulted in small samples that would have impeded the statistical validity of the findings or would have necessitated the construction of a data-base which was beyond the scope of this study in terms of time and costs.

CHAPTER 2

FACTORS INFLUENCING PERFORMANCE
AND
CHOICE OF THE ANALYTICAL MODEL

CHAPTER 2

2.1. INTRODUCTION

Before proceeding with the analysis of the differences appearing in the financial profile of well performing firms, it would seem natural to examine the different factors influencing company performance, to question whether published accounts are a reliable source of data and to select the technique of analysis.

As a consequence, the first developments of this chapter will be around:

> "The vast number of influences on performance (that) are at work. Some of these are quantifiable, others are not, some are external to the firm, others are internal and managerial and of the latter, many are subtly interwoven". (Boswell, 1973)

Then the nature of the data derived from published accounts will be discussed. Its use, objective and the controversy surrounding their validity as a reliable source of information will also be investigated. Finally, a description of the main empirical studies on the analysis of company performance will be carried out in order to review the methodologies and criteria of performance employed. The reasons for choosing the statistical technique later on used in the study together with a presentation of its applications in financial analysis will be undertaken.

2.2. FACTORS INFLUENCING COMPANY PERFORMANCE

The explanation of business performance has always been a subject intensively researched but usually the emphasis is on different factors using different approaches. Therefore, a comprehensive answer to the question " what are the factors influencing the level of a company's performance?" remains evasive even though recent studies have attempted to integrate the different theories developed up to now.

Three main fields are involved in the analysis of company performance. They are:

- industrial organisation economics,
- organisation theory,
- business policy.

Each of them approaches the problem of company performance from a different angle but sometimes come to the same conclusions regarding explanatory variables. Recently there have been some attempts to put together the findings of these different fields to come up with a general theory of performance known as the integrative model of company performance.

2.2.1. INDUSTRIAL ORGANISATION ECONOMICS APPROACH

Industrial organisation economists have been concerned with the effects of a company's environment on its performance. Such industry characteristics comprise:

- number of buyers and sellers,
- industry growth,
- existence of substitutes,

- costs structure,
- product differentiation,
- entry barriers.

(They are called industry structure), see Bain (1959) and Scherer (1970).

Numerous studies have linked total industry performance and industry structure. Recently, however, industrial organisation economists have started examining characteristics specific to a company or a group of companies within an industry. This new concept that the pattern of a company or its characteristics should be included among the factors determining the level of performance of a business is well put forward by Porter (1976) when he argued that the firms within an industry often present differences regarding their degree of vertical integration, diversification, marketing policies, etc. Therefore, he concluded that strategies may differ among firms in an industry and that an industry may be composed of strategic groups. That is groups of firms which have similar strategies.

Such an approach to the determinants of company performance can be depicted as in figure 2.2.1. It stipulates that characteristics such as relative market share, product quality and advertisement which are specific to the firm together with structural characteristics such as barriers to entry and concentration of the market have a direct influence on the level of performance of a company.

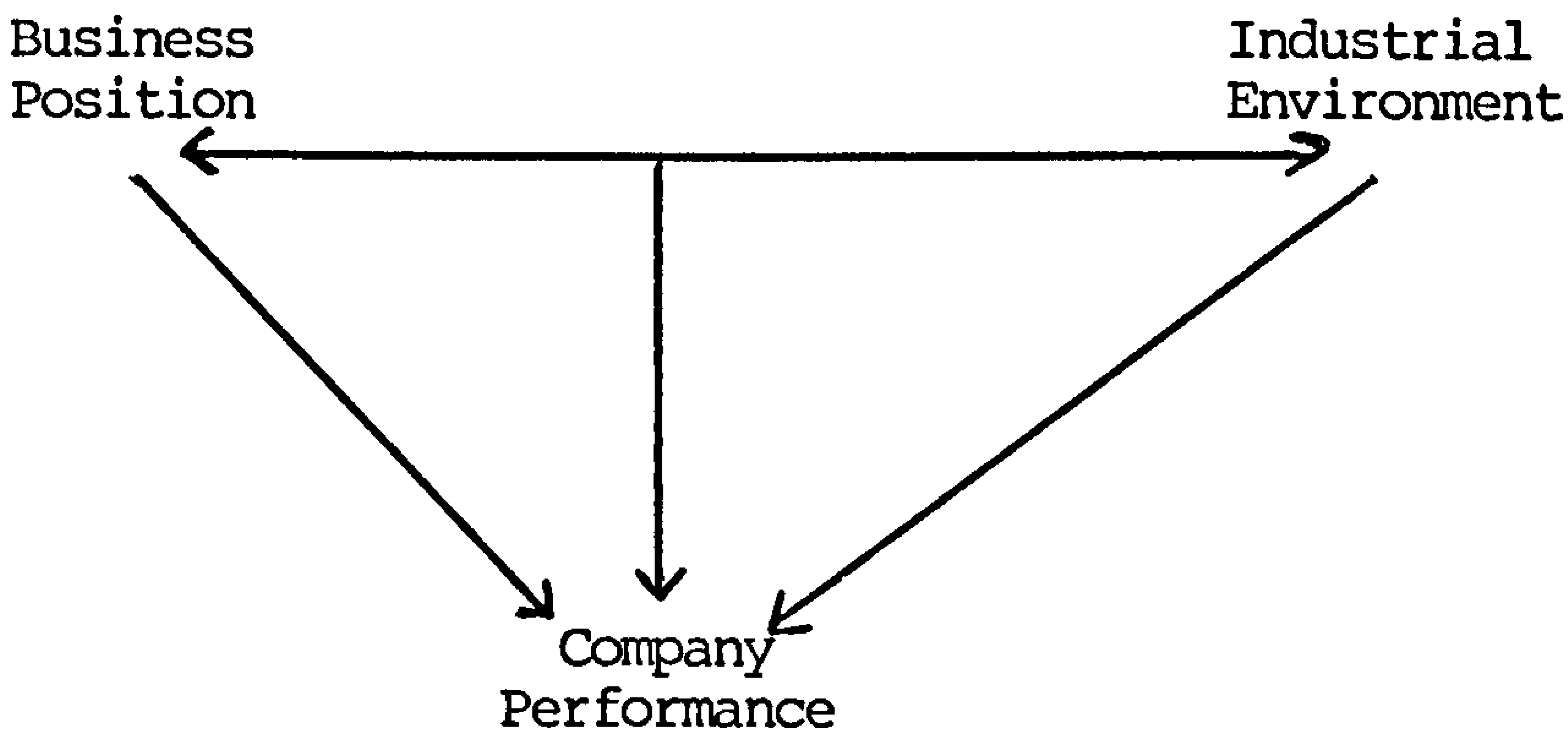


FIGURE 2.2.1. INDUSTRIAL ORGANISATION APPROACH

Empirical evidence seems to give support to the industrial organisation economics model of performance. The profit impact of market strategy (PIMS) model, developed by Schoeffler et al (1974) on data from more than a thousand firms, tried to relate company performance to position in the market and industry structure. Schoeffler et al selected relative market share, product quality and investment intensity to assess the position of the firms. Growth rate was the measure of industry structure. From their study, the structural characteristics of the industries analysed were found to be very significant in explaining company performance.

More recently, Hatten et al (1978) showed the importance of the strategic group concept in explaining the performance of the companies within an industry.

However, the industrial organisation economics model of performance has been widely criticised on the grounds that it fails to recognise that organisation structure and administrative policies are elements to take into account in explaining a firm's performance.

2.2.2. ORGANISATION THEORY APPROACH

Since the fifties, researchers in organisation theory have taken the view that organisations respond to their environments and that as a consequence their level of performance is dependent upon their structure. This theory is known as contingency theory. Dill (1958) used this concept to examine the relationship between organisations and environments. Later Burns and Stalker (1961) showed that the degree of change in the market and in technologies was directly reflected on the internal structure of companies. The organisations with a decentralized structure, characterised by ambiguous roles and lateral communication were found in changing environments. On the other hand organisations typified by centralization, well outlined chains of command and vertical communication were more likely to be encountered in stable environments. The appropriate structure of an organisation is therefore contingent on the specifity of its environments.

The contingency theory approach can be represented as in figure 2.2.2.

It should be noted, however, that very few empirical studies have related the fit between environment and structure to company performance. Among them, the analysis by

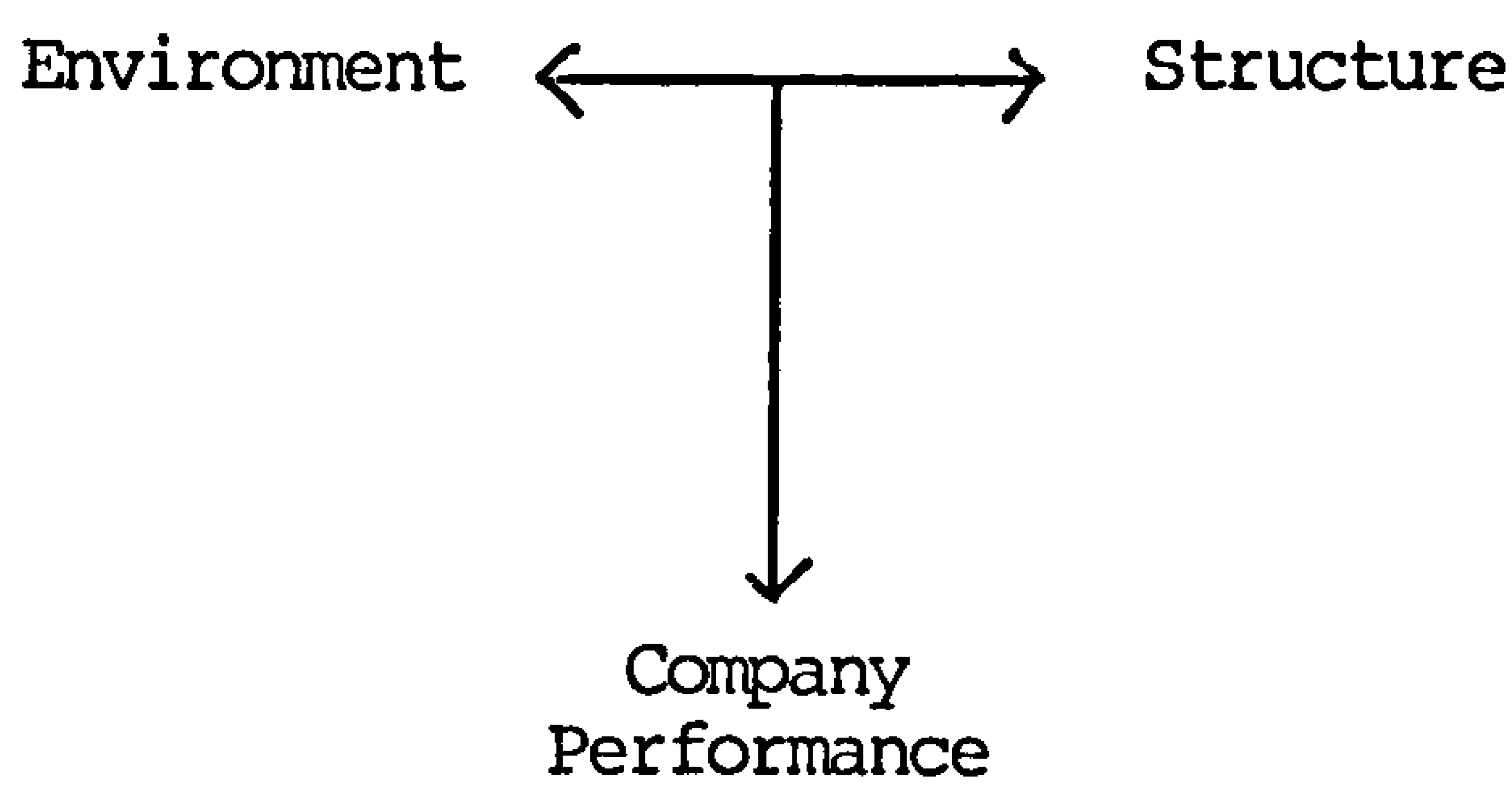


FIGURE 2.2.2. CONTINGENCY THEORY APPROACH

Lawrence and Lorsch (1969) lent some support to the contingency concept. It investigated the relationships between managers' apprehension of their company environments, centralization and decentralization and overall performance in several different environments (i.e. different economic sectors). Lawrence and Lorsch found out that in diverse and dynamic environments, the firms which were decentralized were among the highest performers in spite of their need to channel parts of their resources towards the solution of conflicts typical of decentralized organisations. In stable environments the opposite was observed. The higher performing firms were more centralized, therefore, the need for integration was reduced.

More recently, the relationships between perceived competition, control and decentralization was noted and was found to have a direct influence on the level of performance (Khandwalla, 1973, Negandhi and Reimanm, 1972, Simonetti and Boseman, 1975). These studies suggested that the better the performance of a company, the stronger the observed relationships.

Therefore, the contingency theory approach indicates that:

"the environment places certain requirements
on the firm and some organisation structures
permit more effective coping than others".
(White and Hamermesh, 1981)

However, another school of thought in the field of organisation theory argues that the factors influencing performance are not only the interwoven relationship between environment and structure. Child (1974) suggested that the structure of a company may directly affect its level of performance and that those effects are not contingent on the environment. This approach which insists on the independent influence of company structure has become known as congruency theory since it advocates the importance of the internal congruence of the structural elements of a company in determining its level of performance. Following White and Hamermesh's (1981) developments, the findings of the congruence theory and contingency theory schools of thought can be combined together to arrive at a more general model of performance although in essence each theory emphasises different aspects: the company-environment fit for the contingency theory and the consistency of the internal structure for the congruence theory.

Figure 2.2.3. is a representation of the combination of these two theories.

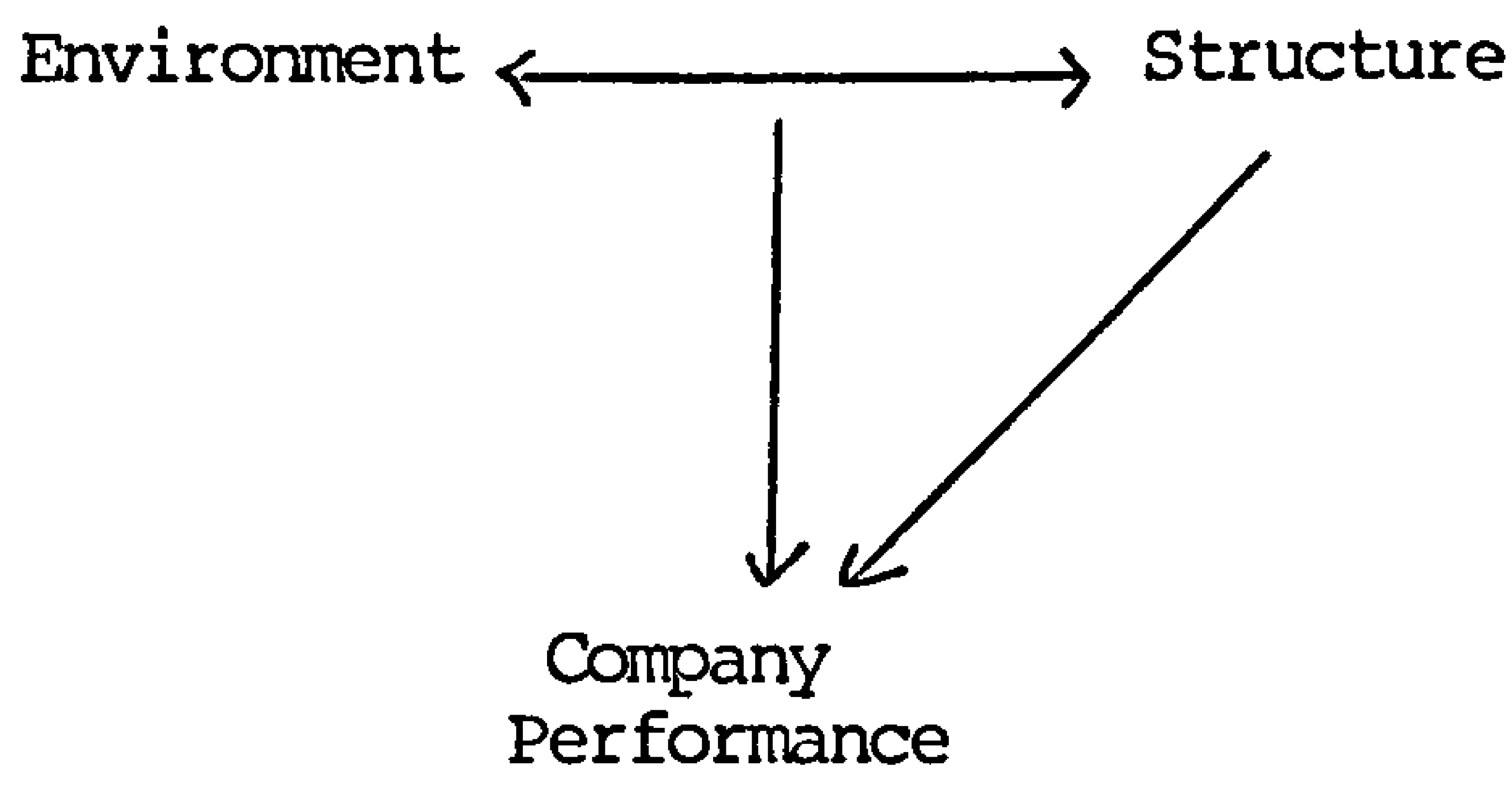


FIGURE 2.2.3: CONTINGENCY AND CONGRUENCY THEORY APPROACH

The interpretation of figure 2.2.3 means that if a company is to perform well it needs its structure to be at the same time appropriate to the company's environment and consistent with itself. If the elements of the structure of a company are not well balanced and consistent with each other, the consequences on the level of performance will be noxious. Likewise a structure badly adapted to the firm's environment will bring about a similar outcome. The only clash between the contingency theory and the congruence theory arises when the constraints imposed on a company by its environments leads to an inconsistent internal structure.

The empirical evidence in support of the organisation theory approach is very limited and has been based on different criteria rendering generalisation difficult. Other criticisms of this approach are regarding the fact that company position and industry characteristics are not included among the influencing factors when evidence from the industrial organisation economists suggests their importance in determining the performance of a firm.

2.2.3. BUSINESS POLICY APPROACH

The business policy approach starts from the fact that organisations have goals and that their management is a continuous process which requires creativity. Therefore, the concept of strategy is central to this field of study.

Strategy has been defined as the pattern of goals and policies and plans laid down to achieve those objectives. Others have described strategy as the pattern in a continuous stream of decisions. Both these definitions stress the purposive aspects of organisations.

As proposed by White and Hamermesh (1981) the concept of strategy can be included in the model of performance described in sections 221 and 222. This would result in the following representation of the industrial organisation economics model (figure 2.2.4.)

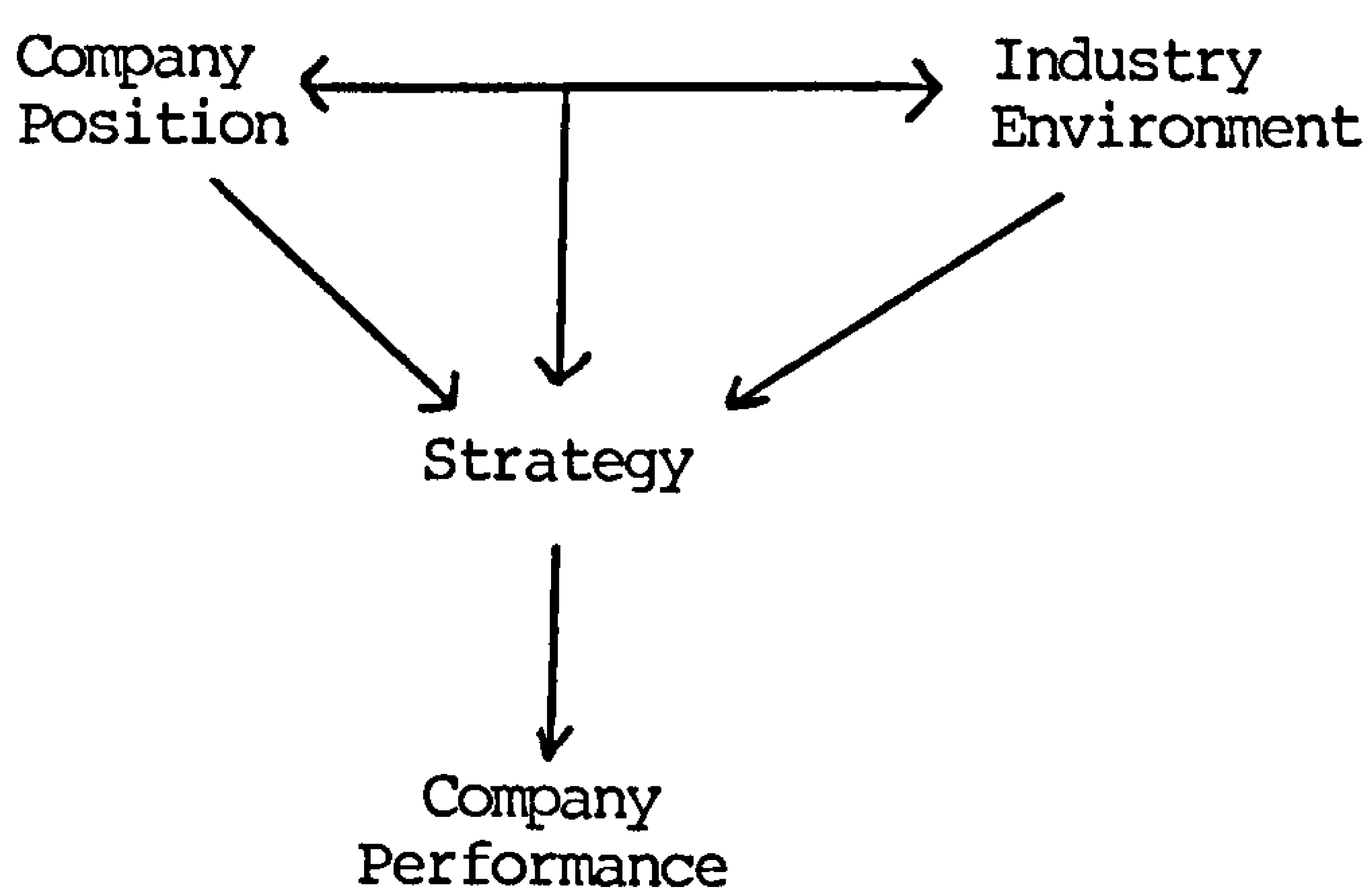


FIGURE 2.2.4. INDUSTRIAL ORGANISATION APPROACH INCLUDING STRATEGY

Such a model indicates that strategy is the decision taken by the management to respond to its company's industrial environment and position but other factors might influence the strategy of a firm. The business policy approach suggests that factors such as management preferences and values, corporate pressure and expectations of environmental changes play an important role in the strategy followed by a firm and that business concerns which have the same position and compete in the same industry environments may have different strategies (White and Hamermesh, 1981). Thus the industry environment and company position although having a decisive influence are not the sole deciding factors of a company's performance.

In the same fashion, the organisation theory model can be modified to take into consideration strategy (figure 2.2.5.).

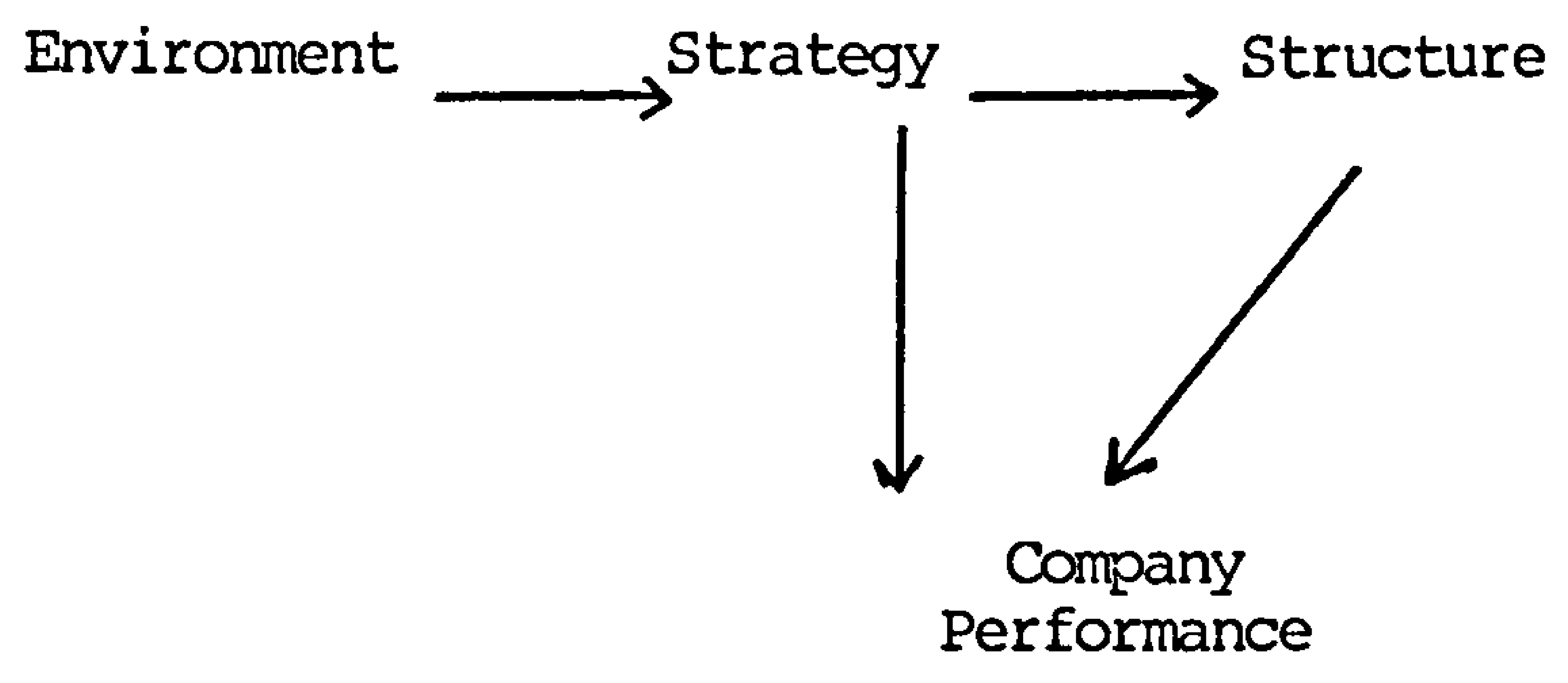


FIG. 2.2.5: ORGANISATION THEORY APPROACH INCLUDING STRATEGY

Figure 2.2.5 reveals that the perception of its environment by a company is translated into its strategy and that in turn its organisation structure will depend upon the strategy chosen.

The relationship between strategy and structure has been widely analysed (Chandler, 1968; Rumlet, 1974 among others). The results from those studies indicates that structure is very much influenced by strategy.

2.2.4 INTEGRATIVE APPROACH

Some researchers have attempted to integrate the findings of several fields. The studies cited above are a step in that direction. Some other studies by organisation theorists have used concepts inherent to industrial organisation economics (Pfeffer and Leblebici, 1973, Khandwalla, 1973). In the same way, the concept of structure has been included in the framework of industrial organisation economists (Williamson, 1975). Some attempts were even made to bring together ideas from business policy and industrial organisation economics (Porter, 1979). However, most of the work done in order to propose an integrative framework has taken into account the findings of two of the three areas of research described above.

Very few researchers have tried to integrate the findings of the three fields. Although Bower's (1970) study was not related directly to performance, it established the influence not only of the environment and business position on the strategies of a firm but also on its structure. Therefore, Bower's developments indicate that the organisation structure has an impact on the strategy followed by companies. Later White and Hamermesh (1981) extended the findings of Bower to include performance and proposed an integrative model of performance depicted in figure 2.2.6 As they stated:

> "From industrial economics comes the idea of assessing industry attractiveness and business strengths and weaknesses. Organisation theory draws our attention to organisation structure and the environment. Business policy provides the essential concept of strategy as the proactive mediation of industry and competitive factors and organisation potential".

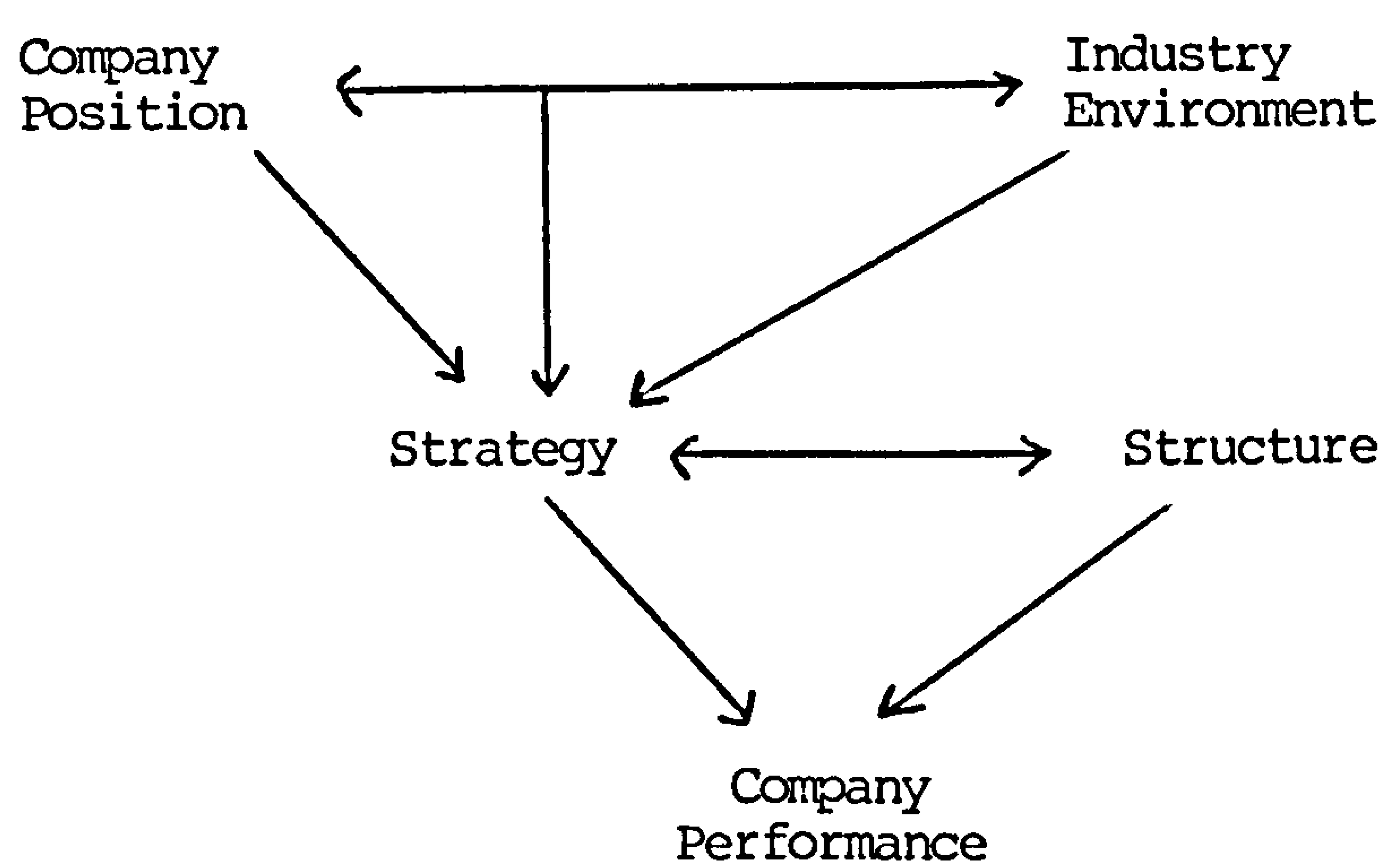


FIGURE 2.2.6. INTEGRATIVE APPROACH

The integrative model of figure 2.2.6 links together the concepts of company position, industry environment, organisation structure and strategy and relates them independently or in connection to performance. The central concept of strategy that represents the way in which a firm is managed according to industry conditions and its position in the market, affects directly performance. In turn, the structure of the company will be modified according to strategy but at the same time it puts some constraints on the choice of strategy. The integrative model has not to the knowledge of the author received any confirmatory empirical support but as White and Hamermesh (1981) argue the links between parts of the models have separately been tested and empirical evidence lends support to the theoretical conceptualisation as we have seen.

In summary, the main influencing factors on the level of performance of a firm are:-

- Industry environment.
- Company position.
- Strategy.
- Organisation structure.

More specific variables would be:-

A) Industry environment

- number of buyers and sellers,
- industry growth,
- existence of substitute,
- costs structure,
- product differenciation,
- entry barriers.

B) Company position

- Relative market share.
- Product quality.
- Investment intensity.

White and Hamermesh (1981) define some of the variables that could be included under the headings strategy and organisation structure. Note that some of these measures relate the relationship existing between the different units comprising a company.

C) Strategy

- R & D leader and follower
- Product pricing.
- Product quality.
- Full line or narrow line.
- Regional, national or international activities.
- Investment intensity.
- Value added.

D) Organisation structure

- Shared resources: Extent to which the different unit of the company shares key functional services.
- Co-ordinating devices:. Control and information system mechanisms between the different units of the company.
- Incentive Compensation.
- Autonomy: Extent to which a unit of the company can take a decision on its own (decentralization).

2.3. ASSESSING PERFORMANCE

Several parties are concerned with the activities of a company. Among them the most important are:

the owners of the Company,

the employees,

the society as a whole,

the creditors,

the financial institutions,

the customers,

the Government,

the management,

the competitors.

However, each of them may have different interests and would certainly appraise the firm's performance in relation to their own interest. For example a bank manager or a creditor would equate the performance of a company to its ability to pay back loans that it received or will receive. Solvency would be their criterion for evaluating performance. The owners of a business firm would certainly show more concern about the return they are getting on their invested capital. Hence, returns on share holders fund and dividend paid will be their criteria of performance. The management may have a different view on performance from that of the owners. Generally, their criteria are profitability and optimal use of resources, but other achievements in areas such as market penetration, growth, well balanced financial structure, may be if not as important at least complementary to the above criteria.

Competitors would certainly look at the same type of areas to assess the strengths and the weaknesses of a particular company. The customers would be more interested in the capability of a company to supply them with a steady flow of products or services. Hence their criterion should be the reliability of a company in fulfilling its orders on time and quality of products etc. For the employees, performance could mean a firm which would provide them with good job security, a good working environment and good pay.

Regarding the two parties that are not dealing directly with a company, the government and the society as a whole, their evaluation of a company performance could take on a completely different meaning although the government may share some common views with the management regarding the optimal use of national resources. Factors such as creation of jobs or revitalizing of an economic area may be for the government criteria of performance along side an efficient use of resources. For the society as a whole, a successful company could be a company that would bring to the community maximum benefits (employment, higher standard of living, etc...) at minimum social costs (pollution, stresses on the environment and the community etc..)
From the points mentioned above, two types of performance criteria are generally used by the parties involved in the life of a company :

1. Financial and economic criteria.
2. Social criteria.

One of the aims of this study will be to select a criterion that could be acceptable to most of the parties. Due to the controversial aspects of social criteria and to the difficulty in evaluating them, the criterion that will be defined in Chapter Three will be chosen among the economic and financial criteria. Besides the availability of data will be a restricting factor to take into consideration.

2.4. PUBLISHED ACCOUNTS AS A SOURCE OF DATA

As a large sample of companies would certainly increase the significance of the study, the source of the information should be as accessible as possible. Furthermore, the resulting model should be such that a person without any access to particular information about a company could use it. As a result, the most appropriate source of information is the report published annually by companies for their members and the public at large since the reluctance of companies to provide information other than that they are required by law to publish is well known (Mulando, 1981).

At this stage, one should therefore ask the question whether published financial records and the financial variables calculated from them give the information needed for the purpose of this study in sufficient quality and quantity.

In order to clarify this point, the literature on the purposes of published accounts together with the controversy surrounding the reliability of published accounts as a source of information will be briefly reviewed.

2.4.1 PURPOSES OF PUBLISHED ACCOUNTS

The purpose of published accounts is a very debatable subject. The first views on company reports were that they should depict in financial terms as closely as possible the utilisation of the company's resources and the position of the owners and creditors. Such a definition was not accepted by all the parties concerned with accounting practices. However, there seems now to be some agreement on the objectives of published accounts. The argu ment is that business concerns are run by professional management and that as a consequence, one of their obligations is to account to the owners of the companies. The published accounts are then designed for this end. This users orientated approach is known as the "users' approach". The fact that other parties besides the owners of a company could need information about a company was recognised. Therefore, a more appropriate definition of the purposes of published accounts is that they should be laid out in a fashion understandable by the recipients and divulge sufficient information in order for them to reach the conclusions they are looking for on a specific company (Chambers 1966). But the users of company accounts can be very varied. In order to get a better understanding of the information available in published annual reports, it would seem useful to find out who may be the users - seven different categories of users are defined by the Steering Accounting Committee, namely, equity/investor group, the loan creditor group, the employees, the analyst/advisor group, the business contact group, the government and the public at large. The examination of the requirements of each of these groups will indicate to us whether they are common information needed by all of them or whether providing them with adequate information will result in crammed accounts hardly readable and too costly for the companies.

a) THE EQUITY/INVESTOR GROUP:

Published reports serve them in assessing management achievements. They will guide them in their decision to buy or sell. Such items as price of shares and dividend policy should thus be among the information disclosed in order to predict the probable future results of their company.

b) THE CREDITOR GROUP:

Two categories emerge from this group: long term creditors and short term creditors. The need of the long term creditors is in the credit standing of companies. Their interest lies with the firm's profitability, earning power and financial leverage. The information should be such as to allow them to estimate whether a firm is going to default or not.

The short term creditors are more concerned with the current liabilities of companies. Their interest is more with their stake than with the continuity of the company. Therefore, they need information about the priority of the various claims and the nature of the realisable assets.

c) EMPLOYEES:

Published accounts should carry the information they need to assess their job security and prospects.

d) ANALYSTS/ADVISERS GROUP:

The information required by this group is very much dependent upon the use it will make of it and as it contains a large variety of users such as financial analysts, researchers, stockbrokers, journalists, financial advisers, it may need if not more, at least as much information as that needed by all the other users'group.

e) THE BUSINESS CONTACT GROUP:

This group is constituted of customers, competitors, suppliers etc... The information it requires is similar to that needed by the creditor and management group.

f) THE GOVERNMENT:

This includes all ministerial departments and local authorities. The information needed can be very much varied. Data such as wages, exports, imports, total assets, profit, turnover, capitalisation and number of employees, may be required to draw general statistical tables. More specific information might be needed by certain departments such as the tax department.

g) THE PUBLIC:

This group includes any person who, for his personal use, requires data on a company.

The number of possible users of published accounts is large but some sort of common needs can be noticed. This is particularly true of the users that are the most affected by the activities of companies.

2.4.2 RELIABILITY OF PUBLISHED ACCOUNTS.

The main criticisms regarding the reliability of published records are related to the nature of the data published and to the diversity of methods used to calculate certain items of the accounts.

It is argued that the quantity of information required by law to be published is too little to be of intrinsic worth to any user and that the accounts are prepared mainly for the benefit of shareholders. Therefore, they contain specific information which may not be useful to all the users. However, a certain number of financial analysis studies using published accounts have proved to be very significant in their own field.

The criticisms regarding the possibility of using different accounting methods to calculate certain items of the balance sheet, and the profit and loss account are stronger since the final results of a company can be greatly affected. Stamp and Marley (1970) pointed out that the problem lies with the availability of a wide range of accounting principles and the lack of legal or professional enforcement regarding the techniques to use. At present, it seems that in practice accountants have chosen flexibility rather than uniformity, which could result in the impossibility to compare accounts of different firms or at least lead to inconsistent and useless comparative results. Therefore, the users of published reports are misguided and may take a decision that they would not have reached if more complete information was available.

To illustrate this argument a few examples related to the main areas of controversy will be presented below, namely, asset depreciation and valuation of inventories.

The two most commonly used methods of depreciation are the straight line method and the declining balance method. Using the straight line method results in an equal amount of depreciation being deducted every year over the entire life of the asset. The declining balance method consists of deducting a constant proportion each year but this amount is removed from the already depreciated value of the asset. Therefore, the amount depreciated in the first year is high and then consistently declined for the following years.

Each of these methods has legitimate economic reasons for its application. For instance, the straight line method is more suitable when the costs of operating a particular asset are constant over its entire life or when the value of an asset is decreasing constantly over time. The declining balance method on the other hand, is more desirable when the asset loses most of its value during the first years (cars, trucks etc.) or when the operating costs are higher in the latter years of the asset working life.

The difference resulting from using either of these two methods can be demonstrated by an example. The two formulae giving the amount to deduct each year using the straight line method and the proportion to deduct each year using the declining balance method are respectively as follows:

$$D = \frac{1}{p} \quad (C - S)$$

and

$$= 1 - \sqrt[p]{\frac{s}{c}}$$

where p is the number of years of working life

s the estimated resale price

c the initial cost of the asset.

Take an asset, say bought for £320,000 with an estimated working life of five years, its resale value at the end of its expected life is estimated to be £10,000. Using the declining balance method ensues in a much larger amount being deducted in the first year as the table below indicates. In fact, this amount is more than two and a half times higher that that given by the first method. The effect of employing one or the other method on the company profit can be paramount if the depreciating assets are expensive and ill-use of one of the methods may lead to the publishing of profits that are at variance with the economic state of the firm.

The other area of controversy that will be examined is concerned with the evaluation of stocks. An accountant can use three different methods, namely the average, first in first out (FIFO) and last in first out (LIFO) methods. When the economic climate is characterised by a period of changing prices, the use of any of these methods can have a substantial effect on the profits of a firm. In times of rising level of prices, as is the case now, the FIFO method will boost the profit of the firm since the remaining inventories will be much higher while the products or raw materials taken from the stocks will be less expensive.

	Straight Line Method	Declining Balance Method
Asset Value at Beginning of Year 1	£320,000	£320,000
Depreciation for Year 1	- £ 62,000	- £160,000
Asset Value at Beginning of Year 2	£258,000	£160,000
Depreciation for Year 2	- £ 62,000	- £ 80,000
Asset Value at Beginning of Year 3	£196,000	£ 80,000
Depreciation for Year 3	- £ 62,000	- £ 40,000
Asset Value at Beginning of Year 4	£134,000	£ 40,000
Depreciation for Year 4	- £ 62,000	- £ 20,000
Asset Value at Beginning of Year 5	£ 72,000	£ 20,000
Depreciation for Year 5	- £ 62,000	- £ 10,000
RESALE VALUE	£ 10,000	£ 10,000

At the other end, the LIFO method will give smaller profit results, while the profits will be between these two values when the average method is used.

Once again, the possible affects on the profitability of a firm due to the use of different accounting principles is highlighted.

Another area that is affected is the valuation of fixed assets. Through a simple re-evaluation, an accountant can increase or decrease the net worth of a firm according to the method chosen. In this respect as in others the role of inflation in accounting can play a significant role. The controversy as to whether to use historical figures or current values has been discussed in depth by Lee (1974). He has shown that the bias appearing in certain financial ratios, especially profitability ratios, because of the under-valuation of assets and equity due to inflation is very limited. The same conclusion can be reached about the fact that accountants under-report companies profit in order to avoid taxes.

The few points mentioned above are some of the weaknesses of published accounts in regard to their reliability. However, some suggestions have been put forward to improve their reliability. Notes accompanying the accounts have been seen as a necessity if the users are to have a precise knowledge of the firm's position (Myre (1946), Stamp and Marley (1970), Mulondo (1981)). These notes would include information such as the different accounting methods utilised existing contracts etc. But more important is the need for more uniformity which would solve a lot of comparison problems. (Mulondo, 1981; Lev, 1974).

Nevertheless, even though there is space and need for improvement, published accounts in their present forms are a good proxy to the economic reality of firms. Several significant studies based on published information have made major contributions to the field of financial analysis. Therefore, it would seem that the similarities in the way accounts are evaluated are outweighing the differences and that published reports remain an invaluable source of financial data.

2.5 EMPIRICAL STUDIES ON COMPANY PERFORMANCE.

Although the performance of companies is a topic widely researched, very few empirical studies are devoted to the influences of performance on firms financial characteristics. The great majority of these analyses try to identify the main influencing factors associated with performance. Even though they are not directly concerned with the main purpose of the present research it would seem worth while to examine the most significant of them together with those that are more related to our analysis in order to examine the criteria of performance and methodology employed.

Child (1974) attempted to identify managerial and organisational factors that were associated with company performance. His criteria of performance were:

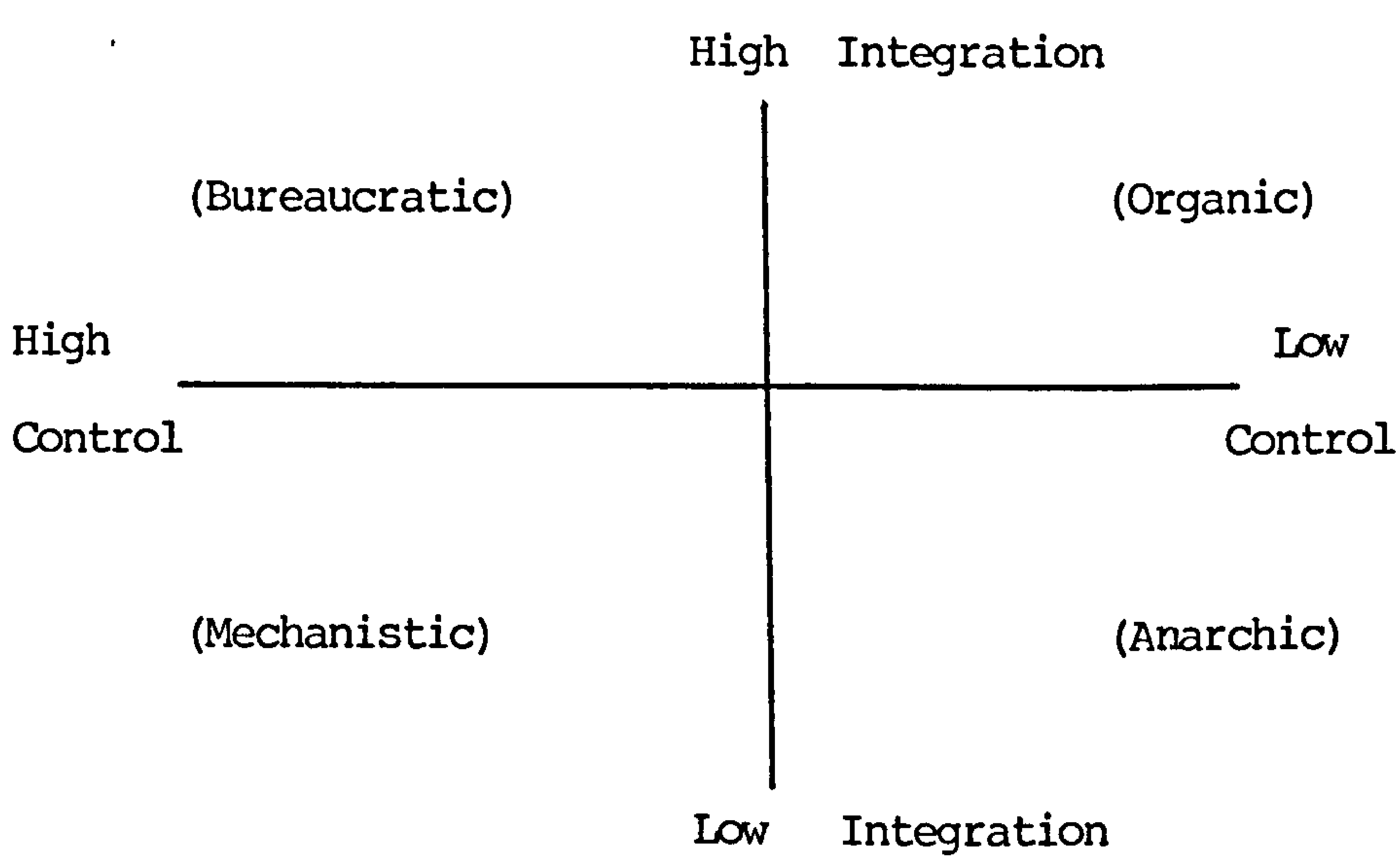
1. Net income to net assets.
2. Profit margin.
3. Growth in income.
4. Growth in net assets.
5. Growth in sales.

The statistical technique used by Child was correlation analysis whereby each of the five criteria defined above was correlated to each of the variables analysed. He examined six of the performance determinants generally found in the universalistic theory, namely:

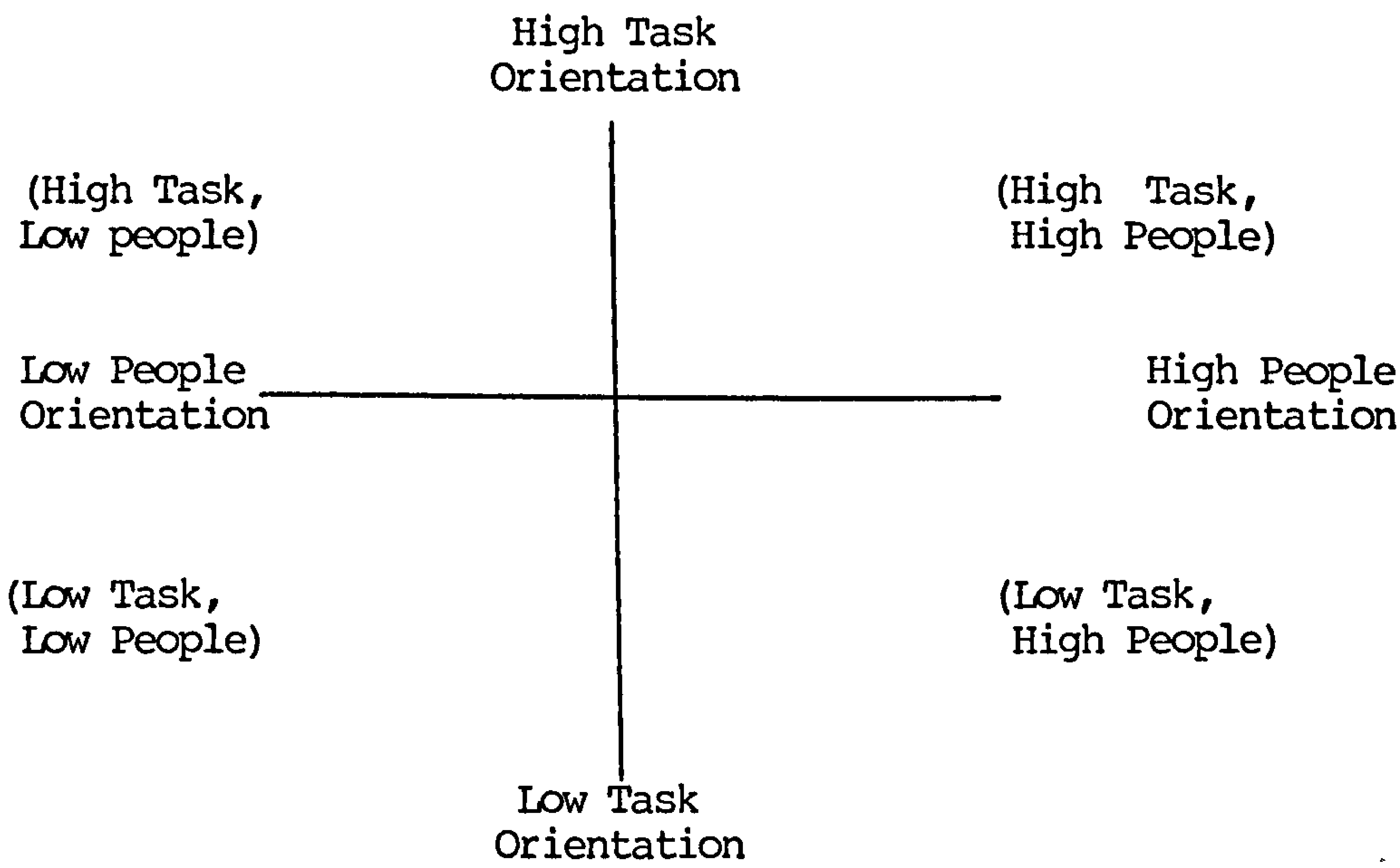
- Management Youth
- Company Objectives
- Ownership and Control
- Allocation of manpower resources
- Size
- Bureaucracy

The results of his study lent some limited support to the universalistic approach in that youthful management was significantly associated with high rates of growth, low level of bureaucracy were favourable to attain more rapid growth, and objectives priority and resources allocation help determine the achieved level of performance. However, company size and the concentration of ownership with control were not found to be significantly related to performance.

Lansley et al (1974) examined the relationship between organisation and management style and their influence on company performance measured in both human and financial terms. They defined four different organisation structures and four different management styles as presented below.



<u>ORGANISATION STRUCTURES</u>



MANAGEMENT STYLES

Their criteria of performance were divided in two groups:

1. Performance in human terms:

   (1) Satisfaction: with job and company

   (2) Information: effectiveness of communication system.

   (3) Change: effectiveness of firms response to change.

2. Performance in commercial terms:

   (1) Profitability

   (2) Growth in sales

Two types of companies were analysed, building firms and printing companies - the methodology used was based on a visual inspection of plots. Results of the study indicated that both organisation structure and management style are significant predictors of performance for the printing industry with the most successful firms being characterised by a bureaucratic structure and a high task orientation. On the other hand, this relationship was only valid between management style and performance as far as the building industry was concerned with high task and high people orientated firms being the highest performers. However, an investigation to test whether the building companies had appropriate organisation structure in relation to their type of task and the subsequent classification of firms into the appropriate and inappropriate structure classes revealed a strong relationship between structure and performance.

Schoeffler et al (1974) in their profit impact of market strategies (PIMS) study based their performance criteria on the return on investment ratio. They singled out thirty seven distinct factors which were significantly related to profitability and built a regression function that explained eighty percent of the variation in profitability. Among those thirty seven factors three categories of determinants proved particularly useful, they were market share, investment intensity and company characteristics.

The analyses revealed that companies possessing a substantial share of the market together with those selling high quality products were among the top performers. Concerning investment intensity, Schoeffler et al pointed out that firms with high investment to sales ratio tended to have a low return on investment ratio. The last categories of factors related to the characteristics of the parent company such as size and diversity. The larger and the smaller companies (size is measured by the volume of sales) tended to achieve a higher profitability than the medium sized firms did. The same conclusions were reached concerning diversity with the business concerns experiencing a low or a high degree of diversity being the most successful. The explanations for these phenomena were that, in regard to size, large companies benefited from economics of scale while the smaller took advantage of their greater flexibility. As far as diversity was concerned, the effectiveness of diversified companies might have been due to their ability to deal in different fields while at the other end, the advantages of specialisation ended in higher profit. Companies in the middle group benefited from neither of these advantages.

Bass et al (1978) attempted to relate structural and firm-related variables to performance expressed as profitability. Their analytical model was based on multiple regression analysis. The function they derived was of the form:

$$p_i = b_o + b_1\, a\, s_i + b_2\, c_i + b_3\, g_i$$
$$+ b_4\, m\, s_i + b_5\, s_i + b_6\, d_i + u_i$$

where:

p_i = the ratio of net income after taxes to shareholders fund of firm i averaged over five years.

Structural Variables

as_i : weighted average of industry advertising to sales ratios in firm i's product markets.

c_i : weighted average of the four-firm concentration ratios in firm i's product markets.

g_i : weighted average of changes in industry demand in firm i's product markets.

Firm-Related Variables

ms_i : weighted average of firm i's market share in its product markets.

s_i : size of firm i.

d_i : diversification of firm i.

u_i : disturbance term.

Pooling together the data from sixty three companies, the structural and firm-related factors explained slightly more than 24 percent of the variation in profitability. However, using a partly constrained model, Bass et al noticed a lack of homogeneity across industry. Their partly constrained model explained 42.3 percent of the variation in profitability. They concluded that market share had a direct impact on performance in agreement with the finding of the PIMS study (Schoeffler et al, 1974) and that size has the expected sign. However, the relation between diversification and profitability was not clearly established since the sign of its coefficient varied across industry.

Gillingham (1980) analysed the attribute profiles of the U.K. wool industry and the Canadian leather accessory industry. He compared the attribute profiles of profitable and unprofitable firms and found that both industries differed significantly on sixteen common attributes. Using stepwise discriminant analyses, Gillingham could distinguish profitable from unprofitable firms in the U.K. wool industry with an accuracy of 94.4 percent. His final discriminant function contained nineteen variables from an initial set of one hundred and thirty four. Then using the same variables, a discriminant analysis was performed on the Canadian leather accessory firms and resulted in 100 percent accuracy. However, the results of this study as Gillingham pointed out, should be interpreted with caution since the variables did not satisfy the assumptions underlying valid application of discriminant analysis and since the sign of the coefficients of twelve variables was not stable across industries.

The work undertaken by the Centre for Interfirm Comparison (Harrington and others, 1981) is more related to the present research in that both management practices and financial variables are investigated. Basing their criterion of performance on the return on investment ratio, they selected from a previous study (Harrington and others, 1977) which will be described later, sixteen management practices that differentiated more between successful and unsuccessful firms. Then, the companies investigated were divided into two groups according to their answer (yes/no) to the question corresponding to each of the sixteen management practices. The financial characteristics of the companies in each group were in turn compared. The methodology used was t-test analysis and each financial characteristic was represented by a financial ratio or a measure of growth or a measure of size.

The results of the analysis indicated that from an original list of one hundred and three, twenty two financial variables were found to have significant differences between companies following successful and unsuccessful management practices. These variables were related to specific financial aspects of the firm:

Current assets: All the elements of current assets were found to have higher turnovers for the successful firms except for debtors which was lower.

Fixed assets: The variables associated with this financial aspect gave

> "a picture of plant which is modest in extent but which is being used extensively" (Harrington & others, 1981)

Value added: The value added financial ratios confirmed the relationship between success and high productivity yet they suggested that successful companies do not undertake as much of their own production as less successful firms although they carry out their own production highly efficiently.

Overheads and research and development: The tendency was for successful firms to have higher turnover of overhead labour costs but smaller turnover of research and development costs.

Production labout costs: Successful firms have lower production labour costs in relation to sales and cost of goods sold together with lower growth of employees. However, they have significant higher growth in production labour costs per employee involved in the production process.

Harrington and others summarised their findings in the following words:

> "This would seem to indicate that successful firms manage to combine high earnings and high growth of earning with low labour costs and low growth of employees. This adds up to a convincing picture of carefully planned and skilfully executed policies."

A previous study published by the Centre for Interfirm Comparison (Harrington and others, 1977) was divided in two parts. The first was concerned with analysis of firms financial characteristics in relation to overall performance. The second attempted to identify management practices that were influencing the level of the companies performance.

The first part of this analysis is particularly related to the present study since financial characteristics are related to an overall indice of performance. Therefore we will confine our discussion to it. The success of each of the two hundred and forty firms studied was measured by the ratio of operating profit to operating assets. The financial characteristics were represented by a list of one hundred and three variables including financial ratios, trend measures and size measures. The selection of the variables was based on the pyramid of ratios (a description of it is given in Chapter 3). Using correlation analysis, each of the one hundred and three variables were correlated to the return on capital ratio. This analysis was undertaken for seven different industrial sectors. However, the first four sectors were grouped into a single industry: the manufacturing section.

The number of variables significantly related to the overall indice of performance varied from forty six, sixteen, eighteen and seven, according to the industry classification. However, it should be pointed out that the whole set of variables could not be calculated for all the industries.

Harrington and others found a closer relationship between profit margin and return on capital than between capital turnover and return on capital. In most of the cases profit margin explained about 90 percent of the variation in the performance criterion. Concerning costs, the major cost ratio cost of goods sold to sales and general overheads to sales, were significantly negatively related to the indice of overall performance. Regarding assets, the good utilisation of firms current assets was more important than was good utilisation of fixed assets in relation to performance. However, growth and size were not found to be closely linked to return on assets.

These are the broad conclusions of Harrington and others study, a more detailed analysis examining the relationship between the performance criterion and more specific ratios was also undertaken in order to identify more specific significant financial characteristics.

This study proved again that high performance firms present specific financial characteristics.

Another study worth mentioning is by Haslem and Longbrake (1971). They analysed the financial characteristics of extreme high and low quartile profitability groups of commercial banks. From an initial set of forty six ratios, covering such characteristics as (1) gross revenue and profitability (2) asset composition (3) deposit and capital and (4) expenses , Haslem and Longbrake selected eight variables using stepwise discriminant analysis. This final discriminant function was as follows:

$$Z = 0.560\ X_{56} + 0.308\ X_{57} + 0.285\ X_{58} - 0.536\ X_{61} - 0.587\ X_{62} - 0.223\ X_{67} - 0.317\ X_{72} + 0.098\ X_{83}$$

where

X_{56} = interest on time and savings deposits to total operating revenue.

X_{57} = net occupancy expenses of bank premises to total operating revenue.

X_{58} = all other expenses to total operating revenue

X_{61} = net gains or losses on loans, securities and "all others" to total operating revenue.

X_{62} = net increases (decreases) in valuation reserves to total operating revenue.

X_{67} = net losses or recoveries and profits on securities to total securities.

X_{71} = "other" securities to total assets

X_{83} = furniture and equipment expenses to total operating revenue.

The function correctly classified 86.5 percent of the banks into their true profitability group. These eight variables were then entered into a multiple regression analysis of the ratio of net income after taxes to total capital accounts which was the criteria of profitability used for the classification of the banks into the four groups prior to the discriminant analysis. The regression analysis was performed on the whole sample of bank and resulted in a very significant R^2 since 73.9 percent of the variation in the dependent variable was explained by those eight variables.

Haslem and Longbrake concluded their article by stressing the importance of operating expenses and non operating items in determining bank profitability.

The above mentioned studies are an indication of the possible ways in which the analysis of firm performance can be undertaken. Different criteria of performance have been used but most of the articles reviewed included among them a return on capital ratio. The techniques of analysis also varied widely from univariate to multi-variate statistical methods.

The studies analysing firms financial characteristics in relation to performance, although very interesting, were too specific regarding:

1) the nature of the variables analysed. Harrington and others, (1977, 1981) used very detailed information in the construction of their financial ratios and failed to cover every aspect of a firm financial profile (e.g. working capital dimension, financial leverage dimension etc.)

As a consequence, their findings can be used mainly by people having access to inside information of companies and have little value for persons relying on published accounts. Furthermore, other firm financial dimensions need to be analysed.

2) the type of business analysed. Haslem and Longbrake (1971) were concerned with bank performance. The nature of banks operations make their finding too specific to be generalised to all sorts of business concerns.

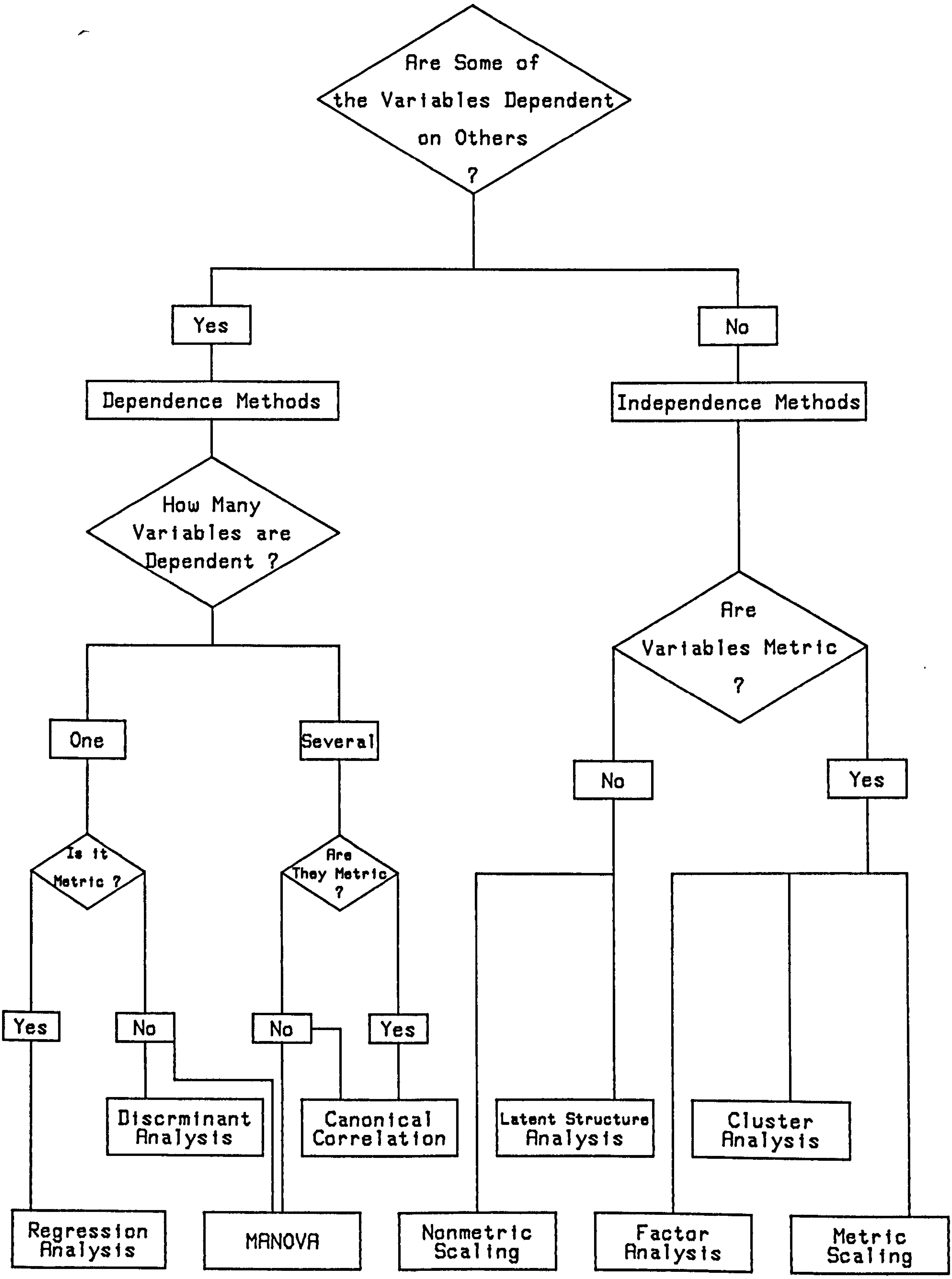
2.6. CHOICE OF THE ANALYTICAL TECHNIQUE

Having set the aims of the study, the most appropriate analytical technique has to be selected. Most of the empirical studies reviewed have used univariate methods of analysis but for four, even though most of them have recognised the multi-variate nature of the data analysed.

To recognise the inter-relationships between the variables is particularly important in our type of study since, as it has been shown on theoretical and empirical grounds, multi-variate methods have the ability of exploiting the information content of seemingly insignificant variables on an univariate basis (Cochran, 1964; Cooley and Lohnes, 1962; Altman, 1969).

Sheth (1971) presents a diagram helping in the selection of the appropriate multi-variate methods according to the nature of the data and the aim of the analysis. Although its

Figure 2.6 : A Selection Diagram for Multivariate Methods



selection suggestions were primarily intended in the field of marketing research, the general ideas can be applied in the present study.

The problem we are presented with consists of establishing whether the population of well performing companies differ from that of the less well performing companies according to a set of combined financial indicators. Therefore, the answer given to the first question (see fig. 2.5) " Are some variables dependent on others ? " is affirmative. The response to the second question, " How many variables are dependent ? " is one. As a consequence the choice of possible techniques is limited to regression analysis, disciminant analysis and multi-variate analysis of variance. But, since our dependent variable which is the level of performance achieved by a firm is non metric, as it can take only one of two values (high performance and low performance) the multi-variate methods left are multi-variate analysis of variance and disciminant analysis.

If the purpose of the study was just to test the difference between two populations on a multi-variate basis, the multi-variate analysis of variance technique (MANOVA) would be the more appropriate method since its aim is to test the null hypothesis

$$H_o : \mu_1 = \mu_2$$

in the two group case where μ_1 and μ_2 are the mean vectors of population 1 and population 2 respectively.

MANOVA is based on the separation between group centroids. By assigning weights to the independent variables, the variability between groups is maximised relative to the variability within groups. A criterion is then derived known as Wilks' lambda and accordingly the null hypothesis is accepted or rejected. In our case the rejection of the null hypothesis would imply that differences in level of performance have a direct impact on the financial profile of firms.

However, our analysis is to continue further since the final goal is to identify well performing firms. The appropriate multivariate method in this case is discriminant analysis. Furthermore, a test for the difference between mean vectors is performed as the initial stage of any discriminant analysis, and the importance of each variable in relation to the overall discriminatory power of the model can be assessed. Therefore, this latter technique is the most suitable for the purposes of the present study.

Discriminant analysis, as it will be described in more detail in Chapter 3, has as primary objective the prediction of an individual's likelihood of belonging to a particular group based on several measurements. The technique requires the pre-definition of the groups, in our case the well performing and the less well performing groups of companies.

Having chosen the method of analysis, the next section of this chapter will be devoted to its application in the field of financial analysis.

2.7. APPLICATIONS OF DISCRIMINANT ANALYSIS IN FINANCIAL ANALYSIS.

The extensive use of the discriminant technique in the field of financial analysis is fairly recent although its first application can be traced as far back as the late fifties (Walter, 1959). It was in the late sixties that its application to the problem of company failure established it as a powerful tool of analysis. Its use was then extended to the prediction of bond ratings and to the analysis of common stocks.

2.7.1. DISCRIMINANT ANALYSIS AND COMPANY FAILURE

Extensive research on the problem of company failure was initiated by the substantial losses produced by such an event to the owners, creditors, employees and the community at large. Firstly analysed on an univariate basis (Beaver, 1967), the prediction of company failure was improved by considering simultaneously several financial ratios with the use of discriminant analysis (Altman, 1968).

Altman's discriminant function which proved to be the best performer was as follows:

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

where

X_1 = working capital over total assets

X_2 = retained earnings over total assets

X_3 = earnings before interest and taxes over total assets

X_4 = market value of equity over book value of total debt

X_5 = total asset turnover.

The discriminant model accurately classified ninety - five percent of the companies one year prior to failure. However, its effectiveness declined rapidly as the number of years before bankruptcy increased.

Daniel (1968) derived the following discriminant function from two samples of fifteen failed and non-failed firms each:

$$z = 1.829\, X_1 - .048\, X_2 + .485\, X_3 + .009\, X_4 + .272\, X_5 + 0.26\, X_6 + .470\, X_7 + .010\, X_8 - .072\, X_9 + .158\, X_{10}$$

where

X_1 = net profit after taxes

X_2 = long term liabilities

X_3 = inventory over sales

X_4 = sales over fixed assets

X_5 = net working capital over total assets

X_6 = long term liabilities over total liabilities

X_7 = net profit after taxes over net working capital

X_8 = long term liabilities over net working capital

X_9 = inventory over current assets

X_{10}= net working capital over net worth.

He selected these variables out of an initial set of forty six including thirteen financial statement classifications and thirty three financial ratios. Three selection methods were considered : correlation analysis, factor analysis and regression analysis. The best discriminant function was obtained using the variables selected by a stepwise regression analysis. The model mis-classified only one failed company as non failed. Tested on a hold out sample four failed companies were mis-classified indicating a high level of accuracy. This study reinforced the validity of discriminant analysis as a method of identification of failing companies.

In an attempt to reduce the rapid decline of the predictive ability of the discriminant models as the number of years prior to failure increase, Deakin (1972) derived a discriminant function for each of the five prior to failure using the variables Beaver (1967) used in its study namely :

- Non liquid assets:
- X_1 cash flow to total debt
- X_2 net income to total assets
- X_3 total debt to total assets

- Liquid assets to total assets:
- X_4 current assets to total assets

- X_5 quick assets to total assets
- X_6 working capital to total assets
- X_7 cash to total assets
- Liquid assets to current debt:
- X_8 current assets to current liabilities
- X_9 quick assets to current liabilities
- X_{10} cash to current liabilities
- Liquid asset turnover:
- X_{11} current assets to sales
- X_{12} quick assets to sales
- X_{13} working capital to sales
- X_{14} cash to sales

The samples of failed and non-failed companies comprised twenty two companies each. The results of the discriminant analyses indicated a percentage of correct classification equal to 95%, 95.5% and 95% for the first, second and third year, before failure respectively with a marked increase in the rate of mis-classification in years four and five prior to failure since the rate of correct classification dropped to 79% and 83% respectively. Although, these results showed some improvement over those of Altman's (1968) since the correct rate of classification in Altman's model was 29% and 36% in year four and five before failure, it should be noted that some of the variables experienced some instability regarding the direction of the sign of their coefficient over time.

Blum, (1974) criticized the lack of theoretical basis in the selection of variables for the discriminant models developed up to then. He based his choice of variable on the Failing Company Doctrine (Blum, 1969) . The variables included :

- Liquidity

  X_1 quick flow ratio

  X_2 net quick assets to inventory

  X_3 cash flow to total liabilities

  X_4 net worth at fair market value to total liabilities

  X_5 net worth at book value to total liabilities

- Profitability:

  X_6 rate of return to common stockholders who invest for a minimum of three years.

- Variability:

  X_7 standard deviation of net income

  X_8 trend breaks for net income

  X_9 slope for net income

  X_{10} - X_{12} same as X_7 to X_9 but for the net quick asset to inventory ratio.

Blum's Failing Company Model distinguished failing from non failing firms with an accuracy of ninety four percent one year prior to failure, eighty percent, two years prior to failure and seventy percent in years three four and five before failure. Although the Failing Company Model did not lead to increase in the percentage of correct classifications. Blum argued that it was more reliable than most of the older multi-variate models of business failure. The instability of some of the variable coefficient signs over time question the validity of such a statement. The use of discriminant analysis in regard to the analysis of company failure was much more recent (Taffler,1976, 1982; Betts and Belhoul, 1982a) in the U.K.

Taffler, first, developed his discriminant model in 1976 for U.K. based companies. Its study included twenty three failed companies and forty five going concerns. The initial set of seventy eight variables including trend measures was reduced to five by the use of a stepwise selection of variables. A factor analysis of the financial ratios was performed in order to get a better understanding of their inter-relationships and to avoid selecting variables too closely related. The final discriminant function included the following variables:

- Earnings before interest and taxes to opening balance sheet total assets.
- Total liabilities to net capital employed.
- Quick assets to total assets.
- Working capital to net worth.
- Sales over coverage inventories.

Taffler's model correctly classified 98.5% of the samples. However, when tested on thirty three companies that failed, between 31.12.73 and 31.12.76, four companies were mis-classified revealing that the model discriminatory ability decreased when used on companies different from those from which it was derived.

Betts and Belhoul (1982 a) used the discriminant analysis approach on a more recent set of companies. The samples comprised twenty six failed and one hundred and thirty one continuing companies. However, the sample of going concerns was selected on a purely random basis unlike most of the previous studies that matched the sample of going companies to the sample of failed firms. The only other exception was Taffler (1976, 1982) but his sample of going companies was selected among financially sound companies only. Therefore the problem of unrepresentative samples of the entire population of companies arises which is a frequent criticism of discriminant analysis applications.

Betts and Belhoul's best discriminant function was arrived at by selecting five financial ratios out of an initial set of twenty six. The five discriminatory variables were:

- Earnings before tax and interest over total assets
- Quick assets over current assets
- Current assets over net capital employed
- Working capital over net worth
- Days creditors

Although, the variables selected are different from those of Taffler's model, they are associated with the same financial dimensions, namely, profitability, quick asset position, financial leverage, working capital position and level of activity according to Taffler's (1982) financial classification framework. It would then seem that if discriminant models for the prediction of company failure need re-adjustments over time this should be done relative to the importance of each variable in the discriminant function rather than relative to the financial dimensions involved. The accuracy of Betts and Belhoul's model was nearly ninety seven percent. These results are comparable to the results of previous similar researches but no test to identify companies two and more years prior to failure was attempted.

In order to increase the performance of the discriminant function in years two, three, four and five before failure, Altman et al (1977) considered new types of financial variables besides financial ratios, namely, stability of earnings which was already taken into account by Blum (1974). However, the data base used was different from that of Blum since the variables were selected empirically. The study resulted in seven variables being selected:

X_1 : Return on assets: earning before interest and taxes to total assets.

X_2 : Stability of earning: normalised measure of the standard error of estimate around a ten year trend in X_1.

X_3 : Debt service: earnings before interest and taxes to total interest payments.

X_4 : Cumulative profitability: retained earnings to total assets

X_5 : Liquidity: current assets to current liabilities

X_6 : Capitalization: equity to total capital

X_7 : Measure of size: total assets

This newer "Zeta" model predicted better than Altman's first model. The correct classification five years prior to bankruptcy was 69.8 percent compared to 36 percent using Altman's earlier model.

This improvement in the classification ability of discriminant models was pushed forward by Dambolena and Khoury (1980) when they generalized the concept of ratio stability to the whole set of financial ratios they employed. The nineteen financial ratios used in their study covered the following dimensions:

Profitability

Activity and turnover

Liquidity

Indebtness

Four different methods were employed to calculate the stability of the financial ratios:

1) standard deviation of the ratio over three year periods.
2) standard deviation over four periods.
3) standard error of estimate around a four year trend and
4) coefficient of variation over four year periods.

Their best discriminant function five years prior to failure included four financial ratios and two measures of stability. The measure of stability leading to the best results were calculated according to method 2, although method 1 gave very similar results. Methods 3 and 4 gave inferior results. The accuracy of the discriminant function was 82.6% five years prior to bankruptcy which is a relatively large increase compared to the performance of the discriminant models previously developed. The only study that revealed comparable results was that of Deakin (1972). However, as noted earlier, the discriminant function, he derived indicated instability in the signs of the coefficients of the variables questioning to some extent the validity of his results. Dambolena and Khoury's discriminant function contained the following variables:

- financial ratios:

X_1 : net profit to sales

X_2 : net profit to total assets

X_3 : fixed assets to net worth

X_4 : funded debt to net working capital

X_5 : total debt to total assets

- stability measures:

X_6 : inventory to net working capital

X_7 : fixed asset to net worth.

The study by Betts and Belhoul (1982b) was carried out on U.K. data to further examine the concept of financial ratio stability. The idea was to investigate whether the inclusion of financial ratio stability measures would lead to comparatively better results as they render the utilization of the discriminant model more complicated and require more computations. As a consequence a larger set of financial ratios (twenty nine) than that used by Dambolena and Khoury (1980) was utilized. Other financial variables such as trend in assets, sales and total number of employees were also included in the study together with measures of size. The trend and size measures did not appear to make any significant contribution. Although the analysis was carried out only as far back as three years before failure due to the unavailability of data, the inclusion of the stability measures proved to be very significant showing the relevance of the stability of performance concept to the problem of identifying failing companies. Betts and Belhoul's best discriminant function included the following variables:

- financial ratios:

X_1 : earnings before taxes and interest to total assets

X_2 : quick assets to net worth

X_3 : current liabilities to total assets

- stability measures:

X_4 : earning before taxes and interest to total assets

X_5 : net worth to total liabilities

X_6 : quick assets to current assets

X_7 : days creditors

The stability measures were the standard deviation of the ratios over a three year period. The accuracy of the function three years prior to failure was 92.3%.

Another problem addressed by Norton and Smith (1979) in relation to the prediction of bankruptcy was the effects of inflation on the predictive ability of discriminant models. Their samples were composed of thirty firms each. The period of the analysis covered the years from 1968 to 1975 which were characterised by high rates of inflation. Norton and Smith calculated a set of thirty two financial ratios from historical cost (HC) financial statements and from general price level (GPL) adjusted financial statements. They used a different procedure for the selection of the variables in order to test whether any improvement from using GPL data was due to different variables being chosen or to the adjustment being made on HC data. They concluded that both GPL and HC financial ratios revealed some ability in predicting company failure and that .

" In spite of the sizable differences in magnitude that existed between GPL and HC financial statements little difference was found in the bankruptcy predictions."

Therefore, they argued that GPL financial statements which are more costly and incur inconvenience could not be recommended for the prediction of company failure.

Other studies predicting bankruptcy were concerned with more specific corporate organisations.

- Banks (Meyer and Pifer, 1971; Sinkey 1975)
- Railroads (Altman, 1973)
- Insurance Companies (Pinches and Trieschmann, 1977)

2.7.2 DISCRIMINANT ANALYSIS AND COMMON SHARE ANALYSIS.

Common share analysis is the area of financial analysis where studies using discriminant analysis firstly appeared (Walter, 1959; Smith, 1965). According to Altman (1981) these types of studies can be classified into four categories:

- 1. Common Stock investment
- 2. Price-earnings (P.E.) ratio
- 3. Information content
- 4. Capital structure

In the first category, Smith (1965) used discriminant analysis to classify common stocks into five brokerage-firm determined investment categories, namely ; growth, stability, quality, income and speculative. The study was based on 1962 data covering fifty shares. A hold out sample of one hundred shares was used to test the accuracy of the model. Smith's best discriminant function included the following variables:

- dividend yield
- payout
- current ratio
- earnings growth
- asset growth
- P.E. ratio
- share turnover

The initial set of variables included fourteen variables. Several techniques were employed for selecting the variables.

The model had an accuracy of 72 percent which is a high score for a more than two group discriminant analysis. However, when tested on the hold out sample the accuracy dropped to 56 percent.

White (1975) used more recent data in classifying companies according to Standard and Poor's share grouping. Three classes were investigated (A,B+, B-). The initial list of variables comprising of twenty four variables was reduced to six. Factor analysis was the technique of selection utilized to reduce the dimensionality of the data. The explanatory variables of White's model were:

- consecutive dividend years
- volatility of price
- dividend yields
- two measures of return on assets
- asset growth

The accuracy shown by the model was of 84 percent on the original samples and 68 percent on a hold out sample. Although this study gave better results than Smith's analysis, it should be noted that the number of classes was smaller and that the hierarchy of the ratings was not implicitly considered.

In the price earnings ratio category, three studies are worth mentioning. Two have attempted to discriminate between high and low P.E. ratio firms using ex-post financial indicators. The third was concerned with price volatility classification.

Walter (1959) selected from a sample of five hundred companies the highest and the lowest fifty E.P. ratio firms (note that in this case the inverse of P.E. ratio was considered). He then analysed the characteristics specific to each of these groups using discriminant analysis. The six explanatory variables used by Walter were:

- dividend payout
- price stability
- change in return on assets
- total assets to total debt
- interest coverage
- growth in sales

His model correctly classified 87 percent of the original samples and 80 percent of a hold out sample. However, when the same variables were entered in another discriminant analysis on the same samples but different periods, the signs of some of the variables changed and the weights of some of the coefficients experienced a great deal of variation bringing some suspicion regarding the reliability of Walter's discriminant model.

Schick and Verbrugge (1975) addressed the same problem but in a more specific setting since they were interested in discriminating between low and high P.E. ratio banks. The sample of high P.E. ratio banks was composed of those having a ratio greater than o.5 standard deviation above the mean while the low P.E. banks were defined as having a ratio smaller than o.5 standard deviation below the mean. Using stepwise descriminant analysis, an original list of forty-one variables was reduced to six including:

- logarithm of outstanding shares.
- stability of earnings.
- five year growth in net income
- return on security portfolio
- loans to deposit ratio
- one year growth in state income

The final discriminant function correctly classified 83 percent of the original sample and 65 to 77 percent of a hold out sample.

The study concerned with price volatility classification was by Klemkowsky and Petty (1973). From a random sample of one hundred and sixty shares, they analysed the lowest and highest quartiles. Rejecting colinear variables and using stepwise discriminant analysis, Klemkowsky and Petty selected eleven variables to enter their discriminant function of which two:

- share turnover
- average price

explained most of the difference in price variability. The final discriminant function revealed more accuracy in classifying hold out samples (86 percent correct classification) than in classifying the original samples (80 percent).

The major criticism concerning the three above studies is about their sample selection which represented only a portion of the total population. The use of any of these discriminant models could result in business concerns being classified into an extreme group when they might have come from the portion of the population which was not represented in the analyses.

Regarding the effects of accounting information on share performance, two studies used discriminant analysis to test these effects before the accounts are published (Gonedes, 1974) and after they have been made available to the public (Altman and Brenner, 1981).

Gonedes (1971) measured the performance of shares as their cumulative average error (CAE) from the two parameter asset pricing model (Markowitz, 1959; Sharpe, 1964; Litner, 1965; Black 1972). Companies were divided into positive CAE and negative CAE on the basis of their last twelve months prior to the announcement date. Then, the classification of these firms based on financial ratios calculated from the published statement was carried out on an univariate as well as a multivariate basis. The list of variables, he considered comprised the following seven financial ratios:

- working capital to total assets
- common equity to total assets
- operating income to total assets
- earnings per share
- total assets turnover
- net income to total assets
- cash flow to total debt

Using discriminant analysis, the seven variables correctly classified 62.3 percent of the original sample and 53.6 percent of a hold out sample used to cross validate the results. However, as Gonedes pointed out, similar classification results could have been obtained by using the earnings per share variable only. Gonedes' conclusion indicated that the account numbers taken jointly do provide pertinent information.

Altman and Brenner's study (1981) was differently orientated. Discriminant analysis was ulilised to identify firms that had a bankruptcy profile during the years 1960 to 1963. The discriminant model developed by Altman (1968) was used to identify ninety two such companies in the above mentioned period. Then the cumulative average errors (CAE) for every one of the ninety two companies were calculated for a period of eighteen months following the availability of the accounts. The null hypothesis was that the CAE's would not be very different from zero if the information released by the companies did not have any effect on shares' performance. If the contrary was true, the CAE's should take negative values. Altman and Brenner tested three models: 1) the two factor market model, 2) the single factor market model, and 3) the two parameter market model.

Results from models 1) and 3) indicated a downward trend resulting in significant negative CAE's and that the market's realisation of the firm's financial difficulties persisted for at least twelve months. Results from model 2, although revealing a downward trend, did not prove to be significant. Therefore, this information was not new or the market reacted instantaneously.

The last category of studies was concerned with capital structure and classification problems. The first study presented below, analyses the characteristics of debt versus equity issuing firms for predictive aims. Martin and Scott (1974) classified one hundred and twelve firms into sixty two industrial debt issuers and fifty industrial equity issuers. Using stepwise discriminant analysis, they reduced a list of twenty three variables to six, including:

- Debt to total assets
- Dividend payout
- P - E ratio
- Investment
- Current assets to total assets
- Cash flow to net worth

Their discriminant model had a 75 percent and 78 percent accuracy in classifying the original and hold out samples respectively. However, as Altman (1981) pointed out, Martin and Scott's study suffered from the fact that the majority of the population of companies was not taken into consideration. These were the firms which financed their operations neither with new debt nor new equity. Furthermore, some companies might have been both equity and debt issuers.

Another study by Frank and Weigandt (1971) was concerned with a slightly different topic in that it analysed convertible debt characteristics. The initial samples were classified according to whether or not debt conversion into equity occurred over a period of twelve months. On data from the year 1963, twenty six companies were included in the converted bond group and ninety eight in the non converted bond group. An original set of eight variables was subjected to stepwise discriminant analysis. Only one variable entered the final discriminant function; the conversion value over call price ratio. Frank and Weigandt's analysis indicated a high classification accuracy since 92 percent of the original observations were correctly assigned, and 90 percent of the hold out sample was accurately classified.

Norgaard and Norgaard (1974) applied discriminant analysis to the problem of share repurchase. This has been an area of controversy in the financial literature where some authors argue that the phenomenon finds its justification as an alternative to other uses of funds. Norgaard and Norgaard tried, using discriminant analysis to identify the important characteristics of repurchasers. Their criteria for inclusion in large share repurchaser and small repurchaser groups were that a firm should hold at least 8 percent of the issued shares and at most 0.1 percent respectively. Their samples comprised sixty large repurchasers and sixty small repurchasers from various industries. Fifteen variables were selected by the authors. Five were price related measures, one a size measure and nine, financial statement ratios. The variables were not subjected to any selection procedure. It should be pointed out, however, that discriminant analysis was used in order to find out which were the main characteristics of large repurchasers, rather than for predictive purposes. Norgaard and Norgaard concluded that large repurchasers are characterised by depressed share prices, inferior operating results, lower growth (sales and earnings) and smaller dividend payments. In the year of their analysis, 1973, they noticed that poor performers had a tendency to repurchase more.

The above analysis was complemented by Spero (1975) when he observed that repurchasers can be divided into two distinct groups.

1) Repurchaser non reissuers group composed of companies that hold the shares in their treasury for a considerable length of time of repurchase.
2) Repurchaser- issuer group comprising firms that reissue these shares for different strategic reasons.

Discrimination between these two groups gave excellent classification results for the classification of the reissuer group but much poorer accuracy regarding the non-reissuer group. Spero's general conclusions were that reissuing firms appeared to be healthier than non reissuing companies and that this was reflected in their stronger share price.

2.7.3. DISCRIMINANT ANALYSIS AND THE RATING OF BONDS

Bond ratings are particularly important in the U.S.A. since most of the investors rely on them. Several private agencies ascribe ratings to a certain number of bonds issued that year. The most famous are Moody's and Standard and Poor's.

Bond ratings are partly based on the financial condition of the bond issuer measured by the usual financial variables derived from available information and partly on the evaluation of the rater regarding the future ability of a firm to meet its interest and principal payments. Because of this value judgment - the non quantifiable factors - rating agencies claim that a predictive model based on financial variables can not come up with the ratings. However several analysts have attempted to reproduce the agencies bond ratings, using multivariate methods. Although the first studies employed multiple regression analysis as the base for their predictive model (Horrigan, 1965, Pogue and Soldofsky, 1969, West, 1970), Pinches and Mingo (1973 and 1975) found multiple discriminant analysis more appropriate to tackle this problem since a classification process is investigated.

Their study was based on a sample of one hundred and eighty bonds rated by Moody's and issued between 1st January,1967 and 31st December, 1968. Forty eight of these bonds were removed from the original sample to form a hold out sample in order to cross validate the results. Five ratings were considered - Aa, A, Baa, Ba, B.

An initial list of thiry five variables was factor analysed in order to reduce the dimensionability of the data. Seven factors emerged, namely:

- 1) Size
- 2) Financial leverage
- 3) Long term capital intensiveness
- 4) Return on investment
- 5) Short term capital intensiveness
- 6) Earnings stability
- 7) Debt and debt coverage stability

By allowing only one variable from each dimension to be selected, the final discriminant function contained variables related to only five dimensions. They were:

- Years of consecutive dividends
- Issue size
- Interest coverage
- Long term debts to total assets
- Net income to total assets

which were associated with factor 6,1,7,2 and 5 respectively. Another variable which was not incorporated in the factor analysis was also selected by the multiple discriminant analysis.This variable was subordination which is represented by a dichotomous variable (0,1).

The discriminant function correctly classified 69.7 percent of the original sample and 64.6 percent of the hold out sample, which was not an improvement upon the earlier study of Horrigan (1965), Pogue and Soldofsky (1969) and West (1970). However, most of the inaccuracy of the model was in classifying Baa ratings since only 16 percent of them were correctly classified. This inability of the model to assign satisfactorily certain bonds to the Baa ratings was also noticed when the model was applied to the hold out sample.

In order to improve the prediction of the Baa ratings, Pinches and Mingo (1975), developed two alternative models to their first model presented above.

Their first alternative was to fit a quadratic discriminant model since the dispersion matrices of the groups were not equal. The classification results indicated a slight drop in the rate of correct classification to 64.6 percent - although some additional Baa bonds were accurately predicted.

The second alternative was to recognise the existance of two bond populations: the non-subordinated population and the subordinated population, and to consider these two populations separately. Since the dispersion matrices were found to be unequal, quadratic rules were applied. The results of the second alternative model revealed an increase in the correct rate of classification to 75 percent, accompanied by a much improved rate of correct classification regarding the Baa ratings (48 percent).

The main criticism concerning the approach of Pinches and Mingo as well as that of the other researchers mentioned above is the non-recognition of the implicit hierarchy of the ratings. However, attempt to take this factor into account by using logit analysis has not ended in an improvement in classification rate. (Kaplan and Urwitz, 1979).

Another study worth mentioning, although not being directly related to the categories defined above is Hoshino's (1982) analysis of corporate mergers in Japan. Using both univariate and multivariate statistical analysis, he examined the performance of merging firms before and after the merger actually took place. Hoshino used five variables in two discriminant runs:

X_1: Net worth to total assets.

X_2: Current ratio.

X_3: Debt to equity.

X_4: Turnover ratio.

X_5: Net profit to total assets.

His first comparison covered five periods.
The Companies characteristics are compared one year before and one year after the merger, two years before and two years after the merger and so on until five years before and five years after the merger. The classification accuracy of the discriminant functions varied from 80 percent to 83.3 percent. However, to remove the possible external effects that could have biased the results, such as the Oil Crisis of 1973 , and the resulting high inflation period, the merging companies were compared to non-merging firms. The period investigated was 1967 to 1973. A discriminant function was derived from every half of a year. The accuracy of the discriminant functions dropped since at its lowest, 56.9 percent of the companies were correctly classified and at its highest this was equal to 76.8 percent. A discriminant run was performed on the aggregated data resulting in an overall accuracy of 59.8 percent. Hoshino concluded that financial performance of merging and non-merging firms could be distinguished and that mergers had negative effects on company efficiency.

This short review of the financial literature on the use of discriminant analysis was not meant to be totally exhaustive, but to present the most significant findings in this area. It indicates that discriminant analysis is a widely applied technique in the field of financial analysis. The nature of these findings and their wide acceptance in financial circles make discriminant analysis an appropriate technique for the purpose of this study.

CHAPTER 3

METHODOLOGY AND SAMPLE SELECTION

CHAPTER 3

3.1 Introduction

As outlined in the first chapter the aim of this study is to investigate whether companies that utilise more efficiently their resources present specific financial characteristics and whether on the basis of these differences they could be identified as well performing. The classification problem arises when a number of measurements on an individual or a group of individuals is made so that they can be classified into two or more groups. The statistical technique of discriminant analysis can be used provided there exists a combination of measurements that are significantly different between the groups. If the groups can be distinguished on the basis of a set of selected measurements, a discriminant function can be derived and further individuals can be classified in one of the groups with a certain degree of confidence.

The purpose of this chapter is twofold: to explain the technique of discriminant analysis and to present the methodology used in selecting the samples.

The nature and application of discriminant analysis together with the derivations of the mathematical formulae and the necessary assumptions are presented to provide a basis for a better understanding of the interpretation of the results. Then criteria for the inclusion of companies in the well performing and less well performing samples are discussed. (Performance in this chapter means efficiency with which resources are utilised). Then the reasons for choosing the data source are given.

3.2 METHODOLOGY

3.2.1 A Review of the Discriminant Technique

At the beginning the problem of discriminant analysis was not clearly defined and was seen as the problem of discriminating between two or more distributions. Fisher (1936) was the first to introduce the idea of linear discriminant function. In the mid-thirties he developed the technique known as the linear discriminant function to aid in the solution of taxonomic and classification problems in biology.

When a number of measurements are made on several individuals belonging to different groups and it is impossible to assign them to their respective group on the basis of any one measurement alone, then a method that could combine the characteristics of the individuals in order to make the correct classification decision would be suitable. The linear discriminant function was an answer to this problem.

Fisher's approach was based on the two group situation and was a multivariate extension of a rule he suggested for classifying observations into two different univariate populations.

The discriminant function is calculated so as to maximize the difference between the means of the groups relative to the variance of the groups. Using the analysis of variance terminology, one will refer to the ratio of the variance between groups to the variance within groups.

The linear discriminant function would then be of the form:

$$z = a_1x_1 + a_2x_2 + \ldots. + a_nx_n + u$$

$a_1 \ldots\ldots a_n$	=	discriminant coefficients
$x_1 \ldots\ldots x_n$	=	measurements made on the individuals
u	=	constant
z	=	index value

Measurements made on further individuals can be entered into the discriminant function and a 'z' index value estimated. By comparing the 'z' values with a break point known as the "cut off" point which divides the range of possible value of 'z' in two parts, a classification decision can be reached. Individuals scoring above the "cut off" point are assigned to one group while those scoring below are classified in the other.

The magnitudes of the 'z' values are not meaningful in themselves. The discriminant score is not a predicted value and is only comparable to other 'z' scores computed from the same linear discriminant function.

3.2.2. ADVANTAGES OF THE LINEAR DISCRIMINANT FUNCTION OVER OTHER CLASSIFICATION TECHNIQUES

Other classification techniques can be used to classify individuals: Two of the most important are:

1. the linear probability function: the probability of an individual belonging to a group can be estimated using regression analysis with a dichotomous (0-1) dependent variable (Ladd 1966)
2. the Contour technique whereby the probability of an individual lying that far from the centroid of a group is estimated. (Cooley & Lohnes 1971)

Although the linear probability approach is mathematically equivalent to the discriminant analysis technique, it suffers from two main limitations pointed out by Goldberger (1964). The variance of the error term varies with the values of the independent variables and the predicted probabilities can be outside the range 0 - 1.

On the other hand, the contour technique involves the multiplication of individuals' mean deviation characteristics by the inverse of the dispersion matrix in each group rendering the computation cumbersome. Besides the measurements must be distributed multivariately normal.

The discriminant analysis technique overcomes these difficulties as the only assumption is the equality of variance - covariance matrices in the two groups. The classification rule is optimal if the observations are distributed multivariately normal (Lachenbruch, 1975) but as Mardia et al (1979) point out the discriminant rule is still appropriate when the hypothesis of normality is not entirely satisfied in the two group case. Furthermore, the necessary computations to make the discriminant model practical are multiplications and additions and the comparison of the 'z' value with a break point, making it particularly simple to use. From its form as a linear function, a clear interpretation of the effect of each variable can be drawn.

3.2.3 Examples of Discriminant Analysis Applications

3.2.3.1 In Taxology and Biology

In his original paper Fisher (1936) used the dicriminant technique to classify two species of iris, on the basis of four characteristics: sepal length,sepal width, petal length and petal width. Later Rao (1948) classified individuals belonging to three populations of India (the Brahim caste, the Artisan caste, the Korwa caste) according to their stature, sitting height, nasal depth and nasal height. Other researchers used the technique to classify insects and small living creatures (Hoel 1964).

3.2.3.2 In Medicine

Lachenbruch (1975) mentions two studies. The first was concerned with the classification of patients as "normal" or "abnormal" on the basis of measurements devised from the reading of their electrocardiograms. The second evaluated the chances of a patient to survive a myocardial infraction on the basis of measurements obtained on his blood pressure, heart rate, stroke index and mean arterial pressure.

3.2.3.3 In Archeology and Geology

On measurements made on the remains of a skeleton, an archaeologist may want to know whether this individual belonged to a particular tribe. Discriminant analysis can be used to allocate him to the tribe he most resembles. In the same fashion, geologists have employed discriminant analysis to gain more knowledge of the origin of certain sediments.

3.2.3.4 In Reliability Engineering

Sayles (1980) assessed the reliability of seals using discriminant analysis.

3.2.3.5 In Social Sciences

This is a field where discriminant analysis has been widely applied. Classification problems arise very often in psychology and education. In order to advise students on a future course of study Porebski (1966) constructed a discriminant model that would classify prospective students as closely resembling successful graduates in engineering,building, art or commerce.

3.2.3.6 In Economics and Business

Discriminant analysis was used to classify loan users into "bad" ones and "good" ones. Farmers were also split into wheat farmers and cattle farmers using discriminant analysis. In marketing, discriminant analysis is used to classify buyers of certain types of products.

3.2.3.7 In Financial Analysis

As discussed in the preceding chapter the introduction of discriminant analysis to the field of finance is fairly recent. However, its analytical achievements have proved that it is a very powerful technique when used along side the more classical techniques of financial analysis especially in the areas of investment theory and bankruptcy analysis.

Apart from the above examples an exhaustive list of uses where discriminant analysis has been applied together with development of the theory can be found in Gupta (1973).

3.2.4 Computation of the Discriminant Function

In this section two approaches will be presented for the two group case. These two approaches lead to equivalent results and it will be shown that if the variables are distributed multivariately normal then the Fisher's approach is optimal. As most of the calculations involve matrix algebra, matrices and vectors will be distinguished from scalars by the use of capital letters for the former and small letters for the latter, this notation will be retained throughout the thesis.

3.2.4.1 Fisher's Linear Discriminant Function

This approach is based on matrix calculus; the linear combination is defined as follows:-

$$z = a_1x_1 + a_2x_2 + ... + a_kx_k \qquad (1)$$

where k represents the number of variables (individuals' characteristics)

The function (1) can be expressed as:-

$$z_{i1} = a_1x_{i11} + a_2x_{i21} + ... + a_kx_{ik1} \qquad (2)$$

an estimate of the value of the i^{th} individual in group I.

($i = 1,.....,n_1$; n_1 = number of individuals in group I)

For group II the function is:-

$$z_{i2} = a_1x_{i12} + a_2x_{i22} + ... + a_kx_{ik2} \qquad (3)$$

where $i = 1,..,n_2$; n_2 = number of individuals in group II

The values of the discriminant coefficients are estimated so that the separation between the two groups will be maximum. In the present case the separation between the two groups is seen as the difference between the means of the "z" values in each group.

If $\bar{z}_1$ and $\bar{z}_2$ represents the mean of the "z" values in group I and group II respectively then

$$\bar{z}_1 = \frac{\sum_{i=1}^{n_1} z_i}{n_1} = \frac{\sum_{i=1}^{n_1} (a\ x_{i11} + a_2 n_{i21} + \ldots + a_k x_{ik1})}{n_1}$$

$$= a_1\ \bar{x}_{11} + a_2\ \bar{x}_{21} + \ldots\ldots + a_k \bar{x}_{k1} \qquad (4)$$

and

$$\bar{z}_2 = \frac{\sum_{i=1}^{n_2} z_{i2}}{n_2} = \frac{\sum_{i=1}^{n_2} (a_1 x_{i12} + a_2 x_{i22} + \ldots + a_k x_{ik2})}{n_2}$$

$$= a_1 \bar{x}_{12} + a_2 \bar{x}_{22} + \ldots\ldots + a_k \bar{x}_{k2} \qquad (5)$$

Let $\bar{x}_i = \bar{x}_{j1} - \bar{x}_{j2}$ $(j = 1,\ldots,k)$ be the difference between the means of the j^{th} variables in group I and group II, the quantity to be maximized is then:-

$$D = A\bar{X} \qquad (6)$$

where

$$\bar{X} = \begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \\ \\ \\ \bar{n}_k \end{bmatrix} = \bar{X}_1 - \bar{X}_2 = \begin{bmatrix} \bar{x}_{11} \\ \bar{x}_{21} \\ \\ \\ \bar{x}_{k1} \end{bmatrix} - \begin{bmatrix} \bar{x}_{12} \\ \bar{x}_{22} \\ \\ \\ x_{k2} \end{bmatrix} \text{ and } A = \begin{bmatrix} a_1 \\ a_2 \\ \\ \\ a_k \end{bmatrix}$$

As Fisher pointed out D is a random variable influenced by the variance within their respective group of z_{i1} and z_{i2}. Hence D should accordingly be maximized relative to the group variation in the " z " values.

An expression of the variation within the group of z_{i1} is:-

$$\sum_{i=1}^{n_1} (z_{i1} - \bar{z}_1)^2 = a_1^2 \sum_{i=1}^{n_1} (x_{i11} - \bar{x}_{11})^2 + \ldots + a^2 \sum_{i=1}^{n_1} (x_{ik1}\ \bar{x}_{k1})^2$$

$$+ \ldots + 2a_1a_2 \sum_{i=1}^{n_1} (x_{i11} - \bar{x}_{11})(x_{i21} - \bar{x}_{21}) + \ldots\ldots$$

$$+ 2a\ \ {}_1a \sum_{i=1}^{n_1} (x_{i,k-1,1}\ \bar{x}_{k-1,1})(x_{ik1} - \bar{x}_{k1})$$

$$= a_1^2 w_{11}^{(1)} + \ldots + a_k^2\ w_{kk}^{(1)} + 2a_1a_2w_{12}^{(1)} + \ldots.$$

$$+\ 2a_{k-1,k}\ w^{(1)}{}_{k-1,k}$$

in which $w_{kl}^{(1)} = \sum_{i=1}^{n_1} (x_{ik1} - \bar{x}_{k1})\ (x_{il1} - \bar{x}_{l1})$

In matrix notation

$$\sum_{i=1}^{n_1} (z_{i1} - \bar{z}_1)^2 = A'\ \overset{(1)}{W}\ A \tag{7}$$

where

$$W^{(1)} = \begin{bmatrix} w_{11}^{(1)} & \ldots\ldots\ldots & w_{1k}^{(1)} \\ \cdot & & \cdot \\ \cdot & & \cdot \\ \cdot & & \cdot \\ \cdot & & \cdot \\ \cdot & & \cdot \\ \cdot & & \cdot \\ w_{k1}^{(1)} & \ldots\ldots\ldots & w_{kk}^{(1)} \end{bmatrix}$$

Similarly the variation of z_{i2} is:-

$$\sum_{i=1}^{n_2} (z_{i2} - \bar{z}_2)^2 \quad = \quad A' \, W^{(2)} \, A \tag{8}$$

Now if one lets:

$$W \quad = \quad W^{(1)} \quad + \quad W^{(2)} \tag{9}$$

the sum of $\sum_{i=1}^{n_1} (z_{i1}-\bar{z}_1)^2 + \sum_{i=1}^{n_2} (z_{i1}-z_2)^2$ can be written as:-

$$A' W^{(1)} A + A' W^{(2)} A \quad = \quad A' \; (W^{(1)} + W^{(2)}) A \quad = \quad A' WA \tag{10}$$

Having denoted both the separation of the groups and the variation within groups, the discriminant criterion as defined by Fisher is:-

$$\lambda \quad = \quad \frac{(A'\bar{X})^2}{A' WA} \tag{11}$$

the expression to be maximized. To find the vector A which maximizes λ , one takes the first derivative with respect to A and sets it equal to zero, giving:-

$$\frac{\partial\lambda}{\partial A} = \frac{A'WA\left(\frac{\partial(A'\bar{X})^2}{\partial A}\right) - (A'\bar{X})^2\frac{\partial A'WA}{\partial A}}{(A'WA)^2} = 0$$

$$= \frac{\frac{\partial(A'\bar{X})^2}{\partial A}}{A'WA} - \left(\frac{A\bar{X}}{A'WA}\right)^2 \cdot \frac{\partial A'WA}{\partial A} = 0 \qquad (12)$$

then

$$\frac{1}{A'WA} \cdot \frac{\partial(A'\bar{X})^2}{\partial A} = \left(\frac{A'\bar{X}}{A'WA}\right)^2 \cdot \frac{\partial A'WA}{\partial A} \qquad (13)$$

Re-writing the derivative on the left as:-

$$\frac{1}{A'WA} \cdot \frac{\partial(A'\bar{X})^2}{\partial(A'\bar{X})} \cdot \frac{\partial(A'\bar{X})}{\partial A} = \left(\frac{A'\bar{X}}{A'WA}\right)^2 \cdot \frac{\partial A'WA}{\partial A} \qquad (14)$$

then since

$$\frac{\partial(A'\bar{X})^2}{\partial(A'\bar{X})} = 2A'\bar{X} ,$$

$$\frac{\partial(A'\bar{X})}{\partial A} = \bar{X} \qquad \text{and}$$

$$\frac{\partial A'WA}{\partial A} = 2WA$$

as shown in appendix I (14) can be written as

$$\frac{2A'\bar{X}}{A'WA} \cdot \bar{X} = \frac{(A\bar{X})}{A'WA} \cdot 2WA \tag{15}$$

Dividing by 2 and multiplying by $\left(\frac{A'WA}{A'\bar{X}}\right)^2$ one gets:-

$$\frac{A'WA}{A'\bar{X}} \cdot \bar{X} = WA \tag{16}$$

Now if one assumes that W^{-1} exists (W^{-1} is the inverse of matrix W, see Appendix I). Then the solution of vector A can be found by pre-multiplying each side by W^{-1} giving:-

$$A = \frac{A'WA}{A'X} W^{-1}\bar{X} \tag{17}$$

Setting $\frac{A'WA}{A'X}$ equal to 1 since this will not affect the proportionality among the elements of vector A, we have:-

$$A = W^{-1}\bar{X} = W^{-1}(\bar{X}_1 - \bar{X}_2) \tag{18}$$

From equation (11) we notice that the vector A may be multiplied by any scalar without affecting the ratio $(A\bar{X})^2/A'WA$.

When the population parameters are not known and this is the most frequent situation, it is usual practice to replace them by their sample estimates. The discriminant function is then written as:-

$$z = X' W^{-1}_{(s)} \; (\overline{X}_{1(s)} - \overline{X}_{2(s)}) \qquad (19)$$

where the subscript(s) refers to sample estimates.

The classification procedure is to assign an individual to group I if his " z" value is closer to

$$\overline{z}_1 = \overline{X}'_{1(s)} \; W^{-1}_{(s)} \; (\overline{X}_{1(s)} - \overline{X}_{2(s)})$$

than to z_2 and to group 2 otherwise. The "cut off" point between $\overline{z}_1$ and $\overline{z}_2$ is

$$\frac{z_1 + z_2}{2} = \frac{\overline{X}'_{1(s)} \; W^{-1}_{(s)} \; (\overline{X}_{1(s)} - \overline{X}_{2(s)}) + \overline{X}'_{2(s)} \; W^{-1}_{(s)} \; (\overline{X}_{1(s)} - \overline{X}_{2(s)}}{2}$$

$$= \frac{(\overline{X}_{1(s)} + \overline{X}_{2(s)})' \; W^{-1}_{(s)} \; (X_{1(s)} - X_{2(s)})}{2}$$

z will be closer to z_2 if

$$|z - \overline{z}_2| > |z - \overline{z}_1|$$

which happens when $z - 1/2 \; (\overline{z}_1 + \overline{z}_2) > 0$ if we assume $\overline{z}_1$ to be greater than $\overline{z}_2$. The discriminant function can therefore be re-written as:-

$$z = X' \; W^{-1}_{(s)} \; (\overline{X}_{1(s)} - \overline{X}_{2(s)}) - \frac{1}{2} (\overline{X}_{2(s)} + \overline{X}_{1(s)})' \; W^{-1}_{(s)} \; (\overline{X}_{1(s)} - \overline{X}_{2(s)}) \qquad (20)$$

and the decision rule will be to allocate an individual to group 1 if his " z" value is greater than zero and to group 2 if it is smaller than zero assuming that $\bar{z}_1$ is greater than $\bar{z}_2$. It will be seen below that the use of zero as a "cut off" point can be improved upon if prior probabilities of an individual belonging to either group are known to be different.

3.2.4.1 The Bayes' Discriminant Rule Approach

This approach is different in nature from Fisher's approach in that we assume the distributions of the vector characteristics in two groups to be known and that the classification rule is based on the form of the distribution.

One possibility is to define a rule that minimizes the total probability of misclassification. Another would be to minimize the maximum probability of misclassification in the two groups. If the costs of misclassification are taken into account then the aim could be to minimize the total cost of misclassification.

In this section, we will restrict our discussion to the rule that minimizes the total probability of misclassification and present the implication of introducing costs of misclassification since this is the classification rule that will be used later in the study.

In the two group case, an individual will be classified as coming from either group depending on the vector of measurements $X' = (x_1, x_2, \ldots, x_k)$ made on him. A discriminant rule is defined such as:-

- assign an individual to group I if he is characterised by a set of values $x'_1, x'_2, \ldots x'_k$

- assign an individual to group II if his characteristics are different from $x'_1, x'_2, \ldots x'_k$

Representing the observed individual as a point in the p - dimensional space R and dividing R into two regions R_1 and R_2, the individual will then be allocated to group I if X is in region R_1 and to group II if X falls in region R_2. R_1 and R_2 are considered to be mutually exclusive. Their union includes the entire p - dimensional space.

Two types of errors can be made if such a classification procedure is followed. The first, "type I error" is to assign and individual to group II when he is in fact from group I. The second, "type II error", is to assign him to group I when he comes from group II. Table 3.1 shows the type of possible mis-classifications.

TABLE 3.1

TYPE OF MISCLASSIFICATION ERROR

		Predicted Membership	
		Group I	Group II
Actual Membership	Group I		type I error
	Group II	type II error	

If we suppose that a priori probabilities of belonging to either group exist one can denote p_1 as the probability for an individual to come from group I and p_2 the probability that he is from group II. Now if one defines f_1 (X) as the density function of the vector of characteristics if X comes from group I and $f_2(X)$ if it is from group II, the probability of making a type I error is:-

$$p_1 \int_{R_2} f_1 (x) \, d X \qquad (1)$$

and the probability of making a type II error is:-

$$p_2 \int_{R_1} f_2 (x) \, dX \qquad (2)$$

Hence the total probability of misclassification is:-

$$p_1 \int_{R_2} f_1(X) \, dX + p_2 \int_{R_1} f_2 (X) d(X) \qquad (3)$$

the quantity to be minimized.

Using Bayes' theory one minimizes the risk of misclassification for a given observation by assigning it to the group with the largest posterior probability. Since the prior probability of being from group i is p_i $(i = 1,2)$ the posterior probability of belonging to group i is:-

$$\frac{p_i \, f_i \, (X)}{p_1 f_1(X) + p_2 f_2(X)} \qquad i = 1,2$$

We would assign X to group I if:-

$$\frac{p_1\ f_1(X)}{p_1\ f_1(X)\ +\ p_2\ f_2(X)} > \frac{p_2\ f_2(X)}{p_1\ f_1(X)\ +\ p_2\ f_2(X)}$$

otherwise one chooses group II. In doing so one minimizes the probability of misclassification at each point and hence over the whole space. The discriminant rule would be:-

$$\text{group I :} \qquad p_1\ f_1\ (X) > p_2\ f_2(X)$$

$$\text{group II :} \qquad p_1\ f_1\ (X) \leqslant p_2\ f_2(X)$$

and thus assign X to group I if

$$\frac{f_1\ (X)}{f_2\ (X)} > \frac{p_2}{p_1} \tag{4}$$

and to group II otherwise. The fact that X is classified in group II when $f_1\ (X)\ /\ f_2(X)\ =\ p_2/p_1$ is arbitrary and X may go in either group. Proof that this procedure is the best is given in Appendix II.

Taking into account costs of misclassification will affect the rule if the cost of making a type 1 error is different from the cost of making a type II error. Table 3.2 shows the cost of making either error.

TABLE 3.2 COST OF MISCLASSIFICATION

		Predicted Membership	
		Group I	Group II
Actual Membership	Group I	0	C_1
	Group II	C_2	0

What one wishes to minimize is the expected cost of making an error. Therefore (3) should be modified to account for cost of misclassification and re-written as:-

$$c_1 p_1 \int_{R_2} f_1(X)\, d(X) + c_2 p_2 \int_{R_1} f(X)\, d(X) \qquad (5)$$

which is the total cost of misclassification. One then chooses R_1 and R_2 so that X is assigned to

group I if $c_1\, p_1\, f_1\, (X) > c_2\, p_2\, f_2\, (X)$

group II if $c_1\, p_1\, f_1\, (X) \leq c_2\, p_2\, f_2\, (X)$

The discriminant rule may be re-written in the form if

$$\frac{f_1(X)}{f_2(X)} > \frac{c_2 p_2}{c_1 p_1} \qquad (6)$$

X belongs to group I and to group II otherwise. Here again X could be assigned to either group when $f_1(X) / f_2(X) = c_2 p_2 / c_1 p_1$. For a thorough discussion on the inclusion of cost in the discriminant rule see Anderson (1958).

A special case of the application of the rule defined above is when group I and group II have multivariate normal populations with common variance co-variance matrix. This case is particularly important in financial analysis since the assumption that financial ratios do not deviate strongly from multivariate normality is commonly held among financial analysts and researchers [Taffler (1976), Pinches et al (1973, 1975), Altman (1968), Dambolena and Khoury (1980), Betts and Belhoul (1982)].

Population in group I will be distributed as $N(\mu_1, \Sigma)$ and that of group II as $N(\mu_2, \Sigma)$ where $N(\mu_i, \Sigma)$ defines a multivariate normal population with vector of means $\mu_i' = (\mu_{1i}, \mu_{2i}, \ldots, \mu_{ki})$ in the i^{th} population (i=1,2) and variance co-variance matrix Σ (definition of the multivariate normal distribution is given in Appendix III).

Thus

$$f_i(X) = (2\pi)^{-\frac{1}{2}k}(\det \Sigma)^{-\frac{1}{2}}\exp(-\tfrac{1}{2}(X-\mu_i)'\Sigma^{-1}(X-\mu_i)) \qquad (7)$$

represents the density function of (X) in group i (i = 1, 2)

Following the procedure described above the density ratio is:-

$$\frac{f_1(X)}{f_2(X)} = \frac{\exp\ (-\frac{1}{2}(X-\mu_1)'\ \Sigma^{-1}\ (X-\mu_1)}{\exp\ (-\frac{1}{2}(X-\mu_2)'\ \Sigma^{-1}\ (X-\mu_2)}$$

$$= \exp\ \{-\tfrac{1}{2}\ [(X-\mu_1)'\Sigma^{-1}(X-\mu_1)-(X-\mu_2)'\Sigma^{-1}(X-\mu_2)]\}\ (8)$$

The Bayes discriminant rule against a priori probabilities p_1 and p_2 when the costs of misclassification are equal is to assign X to group I when (8) is greater than p_2/p_1 and to group II otherwise.

Taking the logarithm we have:-

$$-\frac{1}{2}\ [(X-\mu_1)'\Sigma^{-1}(X-\mu_1)-(X-\mu_2)'\Sigma^{-1}(X-\mu_2)] > \log\frac{p_2}{p_1} \qquad (9)$$

$$-\frac{1}{2}\ [X'\ \Sigma^{-1}\ X - X'\Sigma^{-1}\mu_1 - \mu_1'\ \Sigma^{-1}\ X + \mu_1'\Sigma^{-1}\ \mu_1$$

$$- X'\ \Sigma^{-1}\ X + X'\ \Sigma^{-1}\mu_2 + \mu_2'\ \Sigma^{-1}X - \mu_2'\ \Sigma^{-1}\mu_2] > \log\frac{p_2}{p_1} \quad (10)$$

$$X'\ \Sigma^{-1}\ (\mu_1 - \mu_2) - \tfrac{1}{2}\ (\mu_1+\mu_2)'\Sigma^{-1}(\mu_1 - \mu_2) > \log\frac{p_2}{p_1} \quad (11)$$

From this approach the discriminant function is

$$z = X'\ \Sigma^{-1}(\mu_1 - \mu_2) - \tfrac{1}{2}(\mu_1 + \mu_2)'\Sigma^{-1}(\mu_1 - \mu_2) \qquad (12)$$

with a "cut off" point $k = \log (p_2/p_1)$. This value of k can be modified to take into account the costs of misclassification if they are different giving $k = \log (c_2p_2/c_1p_1)$.

Up to this stage one has assumed that the population parameters are known. However, this is rarely the case. Samples estimates of μ_1, μ_2 and $\sum$ are thus substituted in the discriminant function. The sample anologue to (12) is:-

$$z = X' S^{-1} (\bar{X}_1 - \bar{X}_2) - \tfrac{1}{2}(\bar{X}_1 + \bar{X}_2)' S^{-1}(X_1 - X_2) \qquad (13)$$

where S is the pooled variance co-variance matrix and is equal to $\frac{n_1 S^{(1)} + n_2 S^{(2)}}{n_1 + n_2 - 2}$ $S^{(1)}$ and $S^{(2)}$ are variance co-variance matrices of group I and group II respectively, n_1 and n_2 are the number of individuals in each group.

The allocation rule given by (13) is exactly the same as the one derived in the preceding section proving that Fisher's discriminant rule is optimal if the populations in the two groups are distributed multivariately normal.

3.2.5 Testing the Ability of the Discriminant Function

Once the discriminant function has been evaluated, the next step would be to test its ability. Generally this is done by questioning three major aspects of discriminant analysis, namely:

- Separation between the groups.
- Number of variables included in the function.
- The ability of the function to classify further observations.

3.2.5.1 Testing the Separation between Groups

By testing the separation between groups one may ask: is the observed difference between the group means statistically significant? Accordingly one determines if the observations from which the discriminant function is derived can be correctly classified and hence if classifications of further observations given measurements on the variables considered can be made.

From the preceding section a measure of the distance between the two groups can be calculated:-

$$\bar{z}_1 - \bar{z}_2 = \bar{X}_1' S^{-1}(\bar{X}_1 - \bar{X}_2) - \bar{X}_2' S^{-1}(\bar{X}_1 - \bar{X}_2)$$

$$= (X_1 - X_2)' S^{-1}(X_1 - X_2) \qquad (1)$$

which is the Mahalanobis's D^2. D^2 can be modified to follow an F distribution and thus used to test the significance of the difference between the two groups. The statistic

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

follows an F distribution with p and $n_1 + n_2 - p - 1$ degrees of freedom. n_1 and n_2 are the number of observations in group I and group II respectively. p is the number of measurements made on each individual.

This test of difference between groups is equivalent to Hotteling's T^2 test which is a generalisation of the univariate student's t test to the multivariate case.

A similar result would be reached by using the multivariate analysis of variance technique tests. A description of the MANOVA technique is given in Appendix IV.

Wilks' lambda is defined as:-

$$\Lambda = \frac{\det (W)}{\det (T)} \tag{3}$$

where W is the within group sum of square and product matrix and T the total sum of square and product matrix. The elements of W and T are:-

$$w_{ij} = \sum_{k=1}^{g} \sum_{n=1}^{n_i} (x_{ikn} - \bar{x}_{ik})(x_{jkn} - \bar{x}_{jk})$$

$$t_{ij} = \sum_{n=1}^{n_1+n_2} (x_{in} - \bar{x}_i)(x_{jn} - \bar{x}_j)$$

g is the number of group, in our case g equals 2. n_1 and n_2 are as defined above in (2). i and j take the values from 1 to p, p being the number of variables. Then

$$F = \frac{1 - \Lambda}{\Lambda} \frac{(n_1 + n_2 - p - 1)}{p} \tag{4}$$

follows an F distribution with p and $n_1 + n_2 - p - 1$ degrees of freedom. This F statistic is equivalent to (2). Thus for a given level of significance it will be easy to check if the means of the two groups are different. The value obtained from (2) or (4) is compared to the value of an F - table with p and $n_1 - n_2 - p - 1$ degrees of freedom with α level of significance. A value of (2) or (4) higher than the F table means that the separation between the two groups is significant. The higher the value the greater confidence one has in ascertaining the difference between the groups.

3.2.5.2 Is Any Variable or Subset of Variables Included in the Discriminant Function Redundant ?

Once a significant difference between the two groups is established it is of interest to determine whether all the variables included in the discriminant function are needed. In other words, one tries to assess if a subset p_1 of p variables would do as well as the whole set. One tests if the $p - p_1$ remaining variables are adding any more information to the discriminant function. Rao (1973) proposes a test of the hypothesis H_o: $D^2p = D^2p_1$ where D^2p and D^2p_1 are the Mahalanobis distances based on the whole set of variables and on the subset p_1. He derives the statistics

$$F = \frac{m - p + 1}{p - p_1} \cdot \frac{C^2(D_p^2 - D_{p1}^2)}{m + C^2D^2_{p1}} \tag{1}$$

where $C^2 = n_1 n_2/(n_1 + n_2)$ and $m = n_1 + n_2 - 2$, which follows under the null hypothesis an F distribution with $p - p_1$ and $n_1 + n_2 - p - 1$ degrees of freedom. An important application of this test is when $p_1 = p - 1$ where one is testing the importance of one particular variable once all the others have been taken into account. Then one has

$$F = \frac{m - p + 1}{1} \cdot \frac{C^2(D^2 - D_p^2 - 1)}{(m + C^2 D_p - 1)} \tag{2}$$

with 1 and $n_1 + n_2 - p - 1$ degrees of freedom which follow an F distribution. Mardia et al (1979) give a simplified F statistic based on the total sum of square and product matrix.

This can be used to test all the variables. Then provided that the performance of the discriminant function is not affected the variable to which the highest F value corresponds is discarded. The whole procedure can be repeated with the $p - 1$ variables and so on until eliminating any more variable would strongly affect the discriminating power of the function. This procedure is known by the users of statistical computer package as the backward selection of variables. Further procedures concerning the selection of variables will be presented in chapter 5.

3.2.5.3 Estimating the Probability of Misclassification

One of the most important uses of a discriminant function is in classifying further individuals on the basis of measurements made on them. Potential users of the discriminant function would then wish to have an idea of the proportion of cases that could be misclassified. The percentage of cases misclassified is regarded by statisticians as the evaluation of the function performance.

From section 4, paragraph 2 of this chapter, one has seen that when the parameters of the populations are known the discriminant function is:-

$$z = X' \Sigma^{-1}(\mu_1 - \mu_2) - \tfrac{1}{2}(\mu_1 + \mu_2)' \Sigma^{-1}(\mu_1 - \mu_2)$$

If one knew the distribution of z one could derive the probabilities of misclassification. z being a linear transformation of the vector X of characteristics and X being multivariate normal z is normally distributed.

When X is distributed according to $N(\mu_1 , \Sigma)$ the mean z is:-

$$E\,(z/\text{group I}) = \mu_1'\textstyle\sum^{-1}(\mu_1 - \mu_2) - \tfrac{1}{2}\,(\mu_1 + \mu_2)'\textstyle\sum^{-1}(\mu_1 - \mu_2) \tag{1}$$

$$= \tfrac{1}{2}\,(\mu_1 - \mu_2)'\textstyle\sum^{-1}(\mu_1 - \mu_2)$$

$$= \tfrac{1}{2}\,\delta^2$$

δ^2 is the Mahalanobis distance when the population parameters are known. In group II the mean of z is:-

$$E\,(z/\text{group II}) = \mu_2'\textstyle\sum^{-1}\,(\mu_1 - \mu_2) - \tfrac{1}{2}\,(\mu_1 + \mu_2)'\textstyle\sum^{-1}(\mu_1 - \mu_2)$$

$$= -\tfrac{1}{2}\,(\mu_1 - \mu_2)'\textstyle\sum^{-1}(\mu_1 - \mu_2) \tag{2}$$

$$= -\tfrac{1}{2}\,\delta^2$$

the variance of z in either group is:-

$$V(Z) = E\left[(X - \mu_i)'\textstyle\sum^{-1}(\mu_1 - \mu_2)\right]^2$$

$$= E\left[(\mu_1 - \mu_2)'\textstyle\sum^{-1}(X - \mu_i)(X - \mu_i)'\textstyle\sum^{-1}(\mu_1 - \mu_2)\right]$$

$$= (\mu_1 - \mu_2)'\textstyle\sum^{-1}E\left[(X - \mu_i)'(X - \mu_i)\right]\textstyle\sum^{-1}(\mu_1 - \mu_2) \tag{3}$$

$$\doteq (\mu_1 - \mu_2)'\textstyle\sum^{-1}\textstyle\sum\textstyle\sum^{-1}(\mu_1 - \mu_2)$$

$$= (\mu_1 - \mu_2)'\textstyle\sum^{-1}(\mu_1 - \mu_2)$$

$$= \delta^2$$

The probability of misclassification are for Group I:

$$p_1 = \int_{-\infty}^{c} (2\pi\ \delta^2)^{-\frac{1}{2}} \exp\left\{-\tfrac{1}{2}\ \frac{(z-\frac{1}{2}\delta^2)^2}{\delta^2}\right\}dz = \Phi\left(\frac{c-\frac{1}{2}\delta^2}{\delta}\right) \tag{4}$$

and for group II:

$$p_2 = \int_{c}^{+\infty} (2\pi\delta^2)^{-\frac{1}{2}} \exp\left\{-\tfrac{1}{2}\ \frac{(z+\frac{1}{2}\delta^2)^2}{\delta^2}\right\}dz = \Phi\left(-\frac{c+\frac{1}{2}\delta^2}{\delta}\right) \tag{5}$$

where Φ is the cumulative density function of the normal distribution and $c = \log \dfrac{c_2 p_2}{c_1 p_1}$, the cut off point. When the costs of misclassification and the priori probabilities are equal $c = o$ and

$$p_1 = p_2 = \Phi\left(-\tfrac{1}{2}\ \delta\right) \tag{6}$$

As the parameters $\mu_{(1)}, \mu_{(2)}$ and Σ^{-1} are often not known, several methods have been developed to estimate error rates.

Method 1: Estimates from the samples are substituted and $D^2 = (\bar{X}_1 - \bar{X}_1)'S^{-1}(\bar{X}_1 - \bar{X}_2)$ is the estimate of δ^2 but as Giri (1977) points out

$$E\,(D^2) = \frac{n_1 + n_2 - 2}{n_1 + n_2 - p + 1}\,\delta^2 + \frac{p\,n_1 n_2}{n_1 + n_2}$$

Thus $\Phi(-\frac{1}{2}D)$ is underestimating $\Phi(-\frac{1}{2}\delta)$. The use of an unbiased estimated of δ^2 given by

$$\tilde{D}^2 = \frac{n_1 + n_2 - p + 1}{n_1 + n_2 - 2}\,D^2 - \frac{p\,n_1\,n_2}{n_1 + n_2}$$

would improve the estimation of the probabilities of misclassification.

Method 2: Smith (1947) proposed a method based on the samples used to construct the discriminant function. Each of the $n_1 + n_2$ individuals is in turn classified using the discriminant function and the proportions of misclassifications are taken as the estimate of p_1 and p_2. Unfortunately this approach, known as the re-substitution method, is very crude and tends to be over optimistic.

Method 3: This method known as the jack-knife or hold out method proposed by Lachenbruch (1967) is described below. Let $X_{n,i}$; $n = 1, \ldots, n_i$ $(i=1, 2)$ be samples of size n_1 and n_2 from group I and II. The discriminant function is estimated by leaving out one individual from either sample. The omitted individual whom one correctly knows as coming from group I or group II is then classified using the discriminant function and one notes whether he is correctly or incorrectly assigned. Repeating the procedure for all the individuals of group I will give the number of misclassifications. By dividing it by n_1 one will obtain an estimate p_1. Using the same procedure with respect to the n_2 individuals of group II one will estimate p_2.

Method 4: This method was presented by Lachenbruch and Mickey (1968). $z_{n,i}$ is the value of z obtained by omitting the n^{th} individual in group i $(i = 1,2)$ as in Method 3 and

$$u_1 = \frac{1}{n_1} \sum_{n=1}^{n_1} z_{n,1} \quad , \quad u_2 = \frac{1}{n_2} \sum_{n=1}^{n_2} z_{n,2}$$

$$s_1^2 = \frac{\sum_{n=1}^{n_1} (z_{n,1} - u_1)^2}{n_1 - 1} \quad , \quad s_2^2 = \frac{\sum_{n=1}^{n_2} (z_{n2} - u_2)^2}{n_2 - 1}$$

are calculated. p_1 and p_2 are then estimated by $\Phi(-\frac{u_1}{s_1})$ and $\Phi(\frac{u_2}{s_2})$ respectively. Since z has the same variance regardless of the groups. A better estimate of s_1^2 and s_2^2 is:-

$$s^2 = \frac{(n_1 - 1)\, s_1^2 + (n_2 - 1)\, s_2^2}{n_1 + n_2 - 2}$$

Method 5: This method is based on the asymptic distribution of z. Wald (1944) showed that if $\overline{X}_i$ is the estimate of μ_i based on a sample of n_i independent observations from $N(\mu_i , \Sigma)$ then

$$p \lim_{n_i \to \infty} \overline{X}_i \to \mu_i \qquad (i = 1,2)$$

similarly

$$\underset{n_1, n_2 \to \infty}{\text{p lim}} \; S \to \Sigma$$

and $S^{-1}(\overline{X}_1 - \overline{X}_2)$ converges to $\Sigma^{-1}(\mu_1 - \mu_2)$ and $(\overline{X}_1 + X_2)' S^{-1} (\overline{X}_1 - \overline{X}_2)$ to $(\mu_1 + \mu_2)' \Sigma^{-1} (\mu_1 - \mu_2)$ in probability as n_1 and n_2 tend towards infinity.

Hence the limiting distribution the sample based z (s) is normal with

E (z(s)/group I) $= \frac{1}{2}\,\delta^2$, E(z(s)/group II) $= -\frac{1}{2}\,\delta^2$ and V(z(s)) $= \delta^2$

If the number of discriminators is small and the sample sizes large enough this method will yield satisfactory results. A manner of improving the probability of misclassification estimates using the asymptotic expansion method is suggested by Okamoto (1963,1968).

Using Monte Carlo sampling experiments Lachenbruch and Mickey (1968) concluded that assuming approximate normality, method 1 and 2 were the poorest, method 5 gave the best results followed by Method 3 and 4 not far behind.
Method 6. Another method, which was not included in Lachenbruch and Mickey's comparative study, is to divide the samples into two sets, to use one set to derive the discriminant function and to evaluate its classification ability using the other set. This method is attractive and should give good estimate of the probabilities of misclassification. However, it requires large samples and is wasteful of data.

Furthermore, as Pinches (1980) points out the estimated probabilities of misclassification are based on sub-samples and may differ from those based on the whole samples.

3.2.6 ROBUSTNESS OF THE DISCRIMINANT FUNCTION

The discriminant function as an optimum classification rule is based on three assumptions:-

i) the populations in group I and group II are multivariate normal.

ii) the group variance co-variance matrices are equal.

iii) all the individuals used to construct the discriminant function are correctly classified.

In practice departure from one or more assumptions may occur. It would be of interest to evaluate how much the performance of the discriminant function are affected when this happens.

1) Departure from normality.

Although Fisher's discriminant rule approach is distribution free it was shown not to be optimum if the group populations are not multivariate normal. Lachenbruch et al (1973) found that even though non-multivariate normality affects the error rate of classification rule, the discriminant function performs well when the observations are transformed to approximate normality.

2) Unequal variance co-variance matrices.

When the variance co-variance matrices are not equal the optimal rule is arrived at by the fitting of a quadratic discriminant function.

The form of a quadratic discriminant function for the two variable case is:-

$$z = a_1 x_1 + a_2 x_2 + a_3 x_1^2 + a_4 x_2^2 + a_5 x_1 x_2 + a_0$$

which has more terms than the linear discriminant function. In the five variable case the quadratic discriminant function has twenty one terms making it less convenient to be used by individuals with an unsophisticated knowledge of mathematics. Furthermore, the interpretation of the contribution of the different variables to the discriminatory power of the function is less readily possible.

The use of quadratic discriminant functions appears to be less convenient. Hence potential users of a discriminant function would like to know if the improvements regarding misclassifications due to the fitting of a quadratic function overcome the inconvenience of its use. Lachenbruch (1975) reviewed the work done by other researchers in comparing the impact on performance of fitting a linear or a quadratic function when the variance-covariance matrices are unequal. He concluded that if the variance-covariance matrices are not too different the linear discriminant function performs satisfactorily and pointed out that the quadratic discriminant function is badly affected if normality does not hold.

Furthermore, Marks and Dunn (1974), Wahl and Kronmal (1977) and Van Ness and Simpson (1976) noted that the improvements gained by fitting a quadratic function relative to a linear function decrease as the number of variables increases.

3) Misclassification in the samples.

Many situations may arise where some individuals have initially been wrongly assigned. Such situations mean that the function is derived from incorrect information since some individuals do not belong to their true group. If such initial misclassifications occur at random the effect on the linear discriminant function is not drastic (Lachenbruch (1966), McLachlan (1972)). Neill's paper (1978) where it is suggested to utilize all the unclassified data with the classified data reinforces these points. However, as Lachenbruch (1974) stated non random initial misclassifications affect severely the error rates resulting in highly biased estimates.

3.3 SAMPLE SELECTION

Having presented the methodology to be used the next task is to select the two samples. For the best statistical accuracy the samples should be

1) as large as possible.
2) correctly classified.
3) above all randomly selected so that they are representative of their underlying population, namely the well performing company population and the less well performing company population.

In order to achieve this, criteria to be met by the firms in order to enter the analysis should be defined. Then as many companies as the data availability allows should be considered. Finally, on the basis of another set of criteria, the companies are assigned to their respective group.

3.3.1 THE SOURCE OF THE DATA

The source of the data is the Exstat tape provided by Extell Company Limited. More than two thousand companies are listed on the tape. One thousand three hundred are U.K. based. About two hundred pieces of information are available for a period of seven years for most of the companies. The data includes detailed Balance Sheet and Profit and Loss Account allowing the computation of a large number of financial ratios. Data on other characteristics of the firms such as industrial classification, number of employees, etc., are also provided.

The reasons for choosing the Exstat tape as a source of data can be divided in three broad categories: Comparability of the data, availability of a large amount of data and easy access by use of computer.

1 Comparability of the data

This is a very important aspect of the study, as the analytical tools to be used are statistics and financial ratios. If any consistency is to be found in the results, then the different items included in the data should be presented in the same manner and the use of the same unit of measurement should be insured. Mulondo(1981) underlined the inconsistency with which companies present their accounts.

2. Availability of a large amount of data

As mentioned earlier the larger the sample the more consistent the analysis. The Exstat tape provides information on 1380 U.K. based firms which is a large sample by any means.

3. Easy access

The use of published accounts would have meant the collection of data and their transfer to computer file. This would have demanded a lot of energy and time and would have certainly resulted in the selection of small samples. Being computer readable the Exstat tape can be accessed rapidly and easily and hence the totality of the data listed on the tape can be entered into the analysis.

3.3.2 CRITERIA FOR THE INCLUSION IN THE ANALYSIS

The companies included in the analysis were selected according to the following criteria:

1. Definition of a Company.

A Company was defined in its broadest sense. A complete legal entity involved in any commercial or industrial activities was considered as a company. Therefore firms that are part of a larger organisation are not eligible unless they have a separate legal status.

2. No restriction was made regarding the type of ownership. In many financial studies the samples are constituted of public companies only . Mulondo(1981) and Taffler (1976) among others, put forward the arguments of availability and uniformity of the data as reasons for their favouring such

a practice. Public companies are required by law (Company Act 1967) to publish information about their trading activities and to submit annually their accounts to the Department of Trade. These requirements make data about public companies more uniform and readily available than those of private companies and partnerships. In this study, by the use of the Exstat tape, these problems are overcome, since, as mentioned earlier, the presentation of the data for each company is uniform and more than one thousand three hundred companies are listed on the tape.

3. The companies should be U.K. based. Although companies from the U.S.A., France, Germany, Australia and Japan among other countries are included in the Exstat tape, it was decided to work only on British companies for the sake of comparability. Accounting practice and company laws differ widely from country to country rendering the comparison of the data almost impossible.[1] Besides the number of overseas companies available on the tape is too small to achieve any meaningful analysis.

4. The companies need not be quoted on the stock exchange. Some researchers have restricted their analysis to companies quoted on the stock exchange (Taffler (1977), Mulondo (1981)) but no reason appears to validate this approach, as many studies related to comparison of performance have been carried out on mixtures of quoted and unquoted companies (Centre for Inter-firm Comparison (1977, 1981), Roosta (1979), Pohlman and Hollinger (1981)).

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1 Goodrich (1980) using factor analysis revealed that countries can be grouped according to their accounting characteristics.

5. The companies should be listed on the Exstat tape for at least seven years as this is the minimum period of time on which the analysis is performed and should not have any missing observations during their last seven years of listing.

6. The companies should not have undertaken any exceptional change during the period of analysis. Companies that have undergone a significant change in activities or a large increase in size through merger oracquisition were removed from the samples. Total assets was chosen as the measure of size and increases in total assets were calculated for each company and for each year.

In all eight hundred and twenty one companies satisfied the general criteria.

3.3.3 SPECIFIC CRITERIA FOR INCLUSION IN THE SAMPLES

In chapter 2 our discussion showed that the concept of performance touches all aspects of a company. Many factors affect the performance of companies and their influence may be different in each case. In this section we shall try to define a measure of the efficiency with which companies resources are utilized that could be acceptable by both the parties that are directly involved in the life of business concerns and a governmental department that would be monitoring the health of the economy.

3.3.3.1 The Concept of Performance

The objectives of a company change following the different stages of its life cycle. When a company is set up, its primary objective would seem to be its survival. Distributions of company bankruptcies against time show that the younger a company is, the higher its probability to fail (Altman (1971), Bradstreet (1977), Roosta (1978)). Failure in a general fashion can be viewed as the incapacity of a company to meet its financial obligations. In order to avoid bankruptcy, companies should maintain their financial reservoir above a certain level through efficient planning and control. The management must therefore balance a certain degree of liquidity with the cost of financing it measured by the interest paid.

Once the company has established itself, its survival might not appear to be its primary goal anymore as this is taken for granted. Its aim would then be to maximise the use of its resources (Antony (1960)). Companies often see it as a completely different goal, although efficiency and survival are closely interrelated, since if a company is not utilizing its resources efficiently then financial troubles are bound to occur, and its viability put into question.

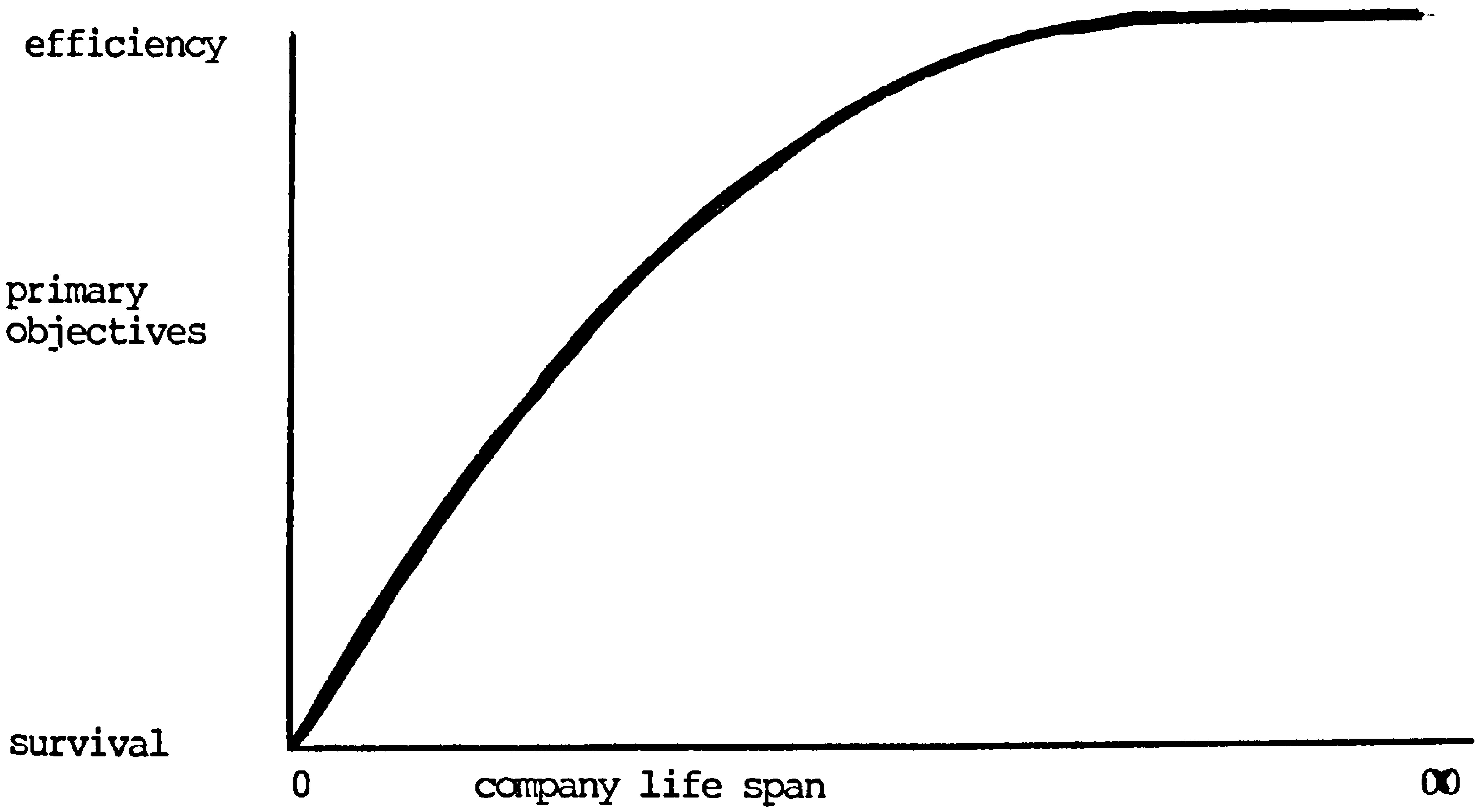


Fig.3.1 Primary Objectives of a Firm

The resources of a company have often been associated with its capital only. However, more and more financial analysts are including the human factor in the resources of a company and classify these resources in two categories.

a) Human Resources. These are the employees of the firm from the workers on the production line to management.

b) The Capital Resources. These are the equipment and goods a firm uses in order to provide its customers with goods and services. These include, land, buildings, machinery, stocks, cash etc.

A measure of success would then evaluate the company's capability to achieve its objective.

3.3.3.2 Measures of Company Efficiency

Taking into account the viewpoint of a government department as well as that of management, a measure of success should evaluate the efficiency with which resources are utilized at company level as well as at economy level. Since the economic network of a nation is composed of thousands of companies, the optimization of resources at company level would, for all companies, result if not in optimal use of the entire national resources, at least in their less wasteful utilization. This implies that a measure of efficiency at company level would be acceptable for a government department monitoring the health of the economy.

In order to find such a measure one must firstly give a measure of the achievements of a company and at a second stage relate it to inputs.

1. Earnings before Interest and Taxes

Profit is often taken as a measure of company achievement mainly because it is the expression of the final result of a company and shows the company capability to generate a surplus. For comparability and uniformity profit is generally considered:

a) Before interest since the level of interest paid indicates the magnitude of capital borrowed to shareholders' fund. A company with a larger amount of borrowed capital would be seen as realising less profit than a company relying on more owned capital even though their efficiency is the same if profit is estimated after deduction of interest payments. Besides, some firms may extensively use their creditors to finance part of their assets.

b) Before taxes since the companies have no power control over the rates of taxation . A high level of taxation would reduce considerably the amount of profit achieved. Furthermore, taxation rates vary from year to year and economic sector to economic sector.

c) Free of items which could distort the comparison of the current year operating profit with that of the previous years. Such items include, tax adjustments, redundancy payments, special pension provisions, profits and losses on the sale of assets, profits and losses on the sale of an investment not acquired with the intention of resale etc. (Extat User Manual gives an exhaustive list of discarded items, p.24, 25, note 32 and 33; (1979)).

Profit as defined above will be termed Earnings before Interest and Tax (EBIT) hereafter.

2. Value Added

Another typical measure of the achievement of a firm is value added. It is defined as the net output of the company

Beattie (1970) measures it

> "either by deducting from sales the costs of goods and services purchased from outside the firm or by adding together the firm's labour costs (wages and salaries, etc.) operating profit and depreciation charges"

Value added is preferred by some researchers to EBIT. They argue that value added is a better measure of achievement since it estimates the value that has been added by the company through the transformation process to the products or services offered to customers. However, using such a measure does have some limitations. Value added is not directly related to profit which is the ultimate test if a company is to survive in a capitalist type market. Moreover, if a firm turns towards financial institutions for more financial resources, potential profits will be amongst the decisive factors which will enhance its application.

3.3.3.2.1 Return on Capital Ratios

These ratios are often referred to as return on investment in the financial literature. Some ratios, such as return on net capital employed or return on net worth may be used in order to assess success but according to our aim that is to measure the efficiency with which all the resources are utilized, return on assets was preferred since company assets include all the firm's capital resources. The computational formula is therefore:

$$\frac{\text{EBIT}}{\text{Total assets}} \times 100$$

Total assets are taken gross. Some researchers have favoured the use of net total assets. They deduct the current liabilities from the total assets. Such a practice was not followed in order to improve comparability. In effect, companies choose different sources from which to finance their total assets. Some may take extended credits or long-term borrowings while others may go for short - term borrowings or simply use the creditors as a means to finance part of their total assets. If current liabilities were deducted from total assets, companies using extensively short term borrowings or creditors to finance their assets would achieve a better return on assets than those depending on long term borrowings. Thus the rate of return on assets would be affected by the way assets are financed, making comparison difficult.

The return on asset ratio is regarded by many financial analysts as an adequate measure of overall efficiency. This view has been shared in many studies, among others,Harrington and others (Centre for Inter-firm Comparison 1977, 1981), Fadel (1977), Urrea (1981). However, other measures of overall efficiency have been opposed to EBIT / total assets ratio on the ground that it only evaluates the contribution of capital resources.

3.3.3.2.2 Labour Productivity Measures

These measures are ratios where the denominator is either the total number of employees or the total wages and salaries paid by the company. Hence profit can be expressed per employee or per £ of wages and salaries. Other labour productivity measures are, sale per employee and sale per £ of wages and salaries or value added per employee and value added per £ of wages and salaries or units of products per employee. Total wages and salaries were introduced in the labour productivity measures in response to some of the criticism directed towards the use of total number of employees as denominator of these ratios. It has been argued that total number of employees does not reflect the qualifications of the personnel employed by a company. A managing director is supposed to contribute more to a firm's achievements than an unqualified worker. This is reflected in the salaries and wages paid.

However important these measures are in assessing the contribution of an important factor, namely labour, they are not sufficient in themselves for the following reasons:-

i) Only labour is taken into consideration.

ii) If sale or value added are the numerator of the ratios then these measures will not indicate to what extent the objectives of the enterprise are met since profit is for a private sector company a must in order to survive. Companies can experience growing sale or value added per employee and declining profitability at the same time.

iii) Including profit in the labour productivity ratios would still lead to problems. These ratios are reflecting the way the enterprises are managed rather than overall efficiency. A firm which relies heavily on capital would show a greater return per employee or per £ of wages and salaries than another firm which is highly labour intensive and that does not indicate whether the profit realised is sufficient to finance the capital requirements.

3.3.3.2.3 Measure of Total Productivity

As shown above although of valuable assistance in analysing efficiency, labour productivity ratios fail to include all the aspects of company productivity. To overcome these limitations, indices have been developed to take into account all the input factors. These ratios relate output to both labour and capital inputs. A typical total productivity measure is:-

$$\frac{\text{value added}}{\text{cost of labour} + \text{cost of capital}} \times 100$$

where

1) value added is as defined above.
2) cost of labour comprises wages and salaries plus the contributions paid by the company in respect to all the employees such as national insurance and pensions.
3) cost of capital is the depreciation of fixed assets during the period considered plus the national interest on the total capital employed.

For a thorough discussion of the total production indices see Beattie (1970).

3.3.3.2.4 EBIT over Total Assets: More than a Measure of Capital Utilization?

1) Arguments in favour of total productivity indices.

The main advantages of using an index of total productivity such as the index defined above over EBIT to total assets in measuring overall efficiency are that:

i) Inputs are directly related to outputs. A goal that EBIT over total assets is said not to fulfil.
ii) EBIT over total assets presents the same inconvenience as labour productivity measures i.e. it takes into account only one factor in this case capital.

iii) Value added is a better measure of achievement than EBIT since it is an estimation of the value added, through the transformation process, to the materials and services obtained from outside the firm in arriving at the final products. Thus value added expressed as a percentage of the cost of utilising the enterprise's resources results in an efficiency criterion in money terms.

iv) The total productivity indices are not affected by the capital-labour structure of the companies. Companies which are highly capital intensive will not be disadvantaged against firms that are highly labour intensive and vice-versa.

2) Can EBIT over total assets be chosen as a measure of overall efficiency ?

From the four arguments presented above total productivity indices would appear to be more appropriate for our type of analysis. However, the benefits of using such measures do not make up for the lack of their understanding and familiarity and do not come up strongly against the advantages inherent to the use of EBIT over total assets.

The return on asset ratio is in fact a measure that relates inputs to outputs since profit is arrived at by differentiating between these two flows.

EBIT over total assets takes into account the contribution of other factors besides capital. The cost of labour is deducted before the final profit is estimated and so is the cost of materials and services purchased from outside the firm. Hence a more labour intensive firm will see its profit reduced by a higher wage bill. This will be translated by a smaller return of assets than if the same efficiency was achieved with a less numerous or qualified workforce. In the same manner high capital intensive firms will have smaller return on assets since although their wage bill will be smaller, the denominator of the ratios will be higher. These examples illustrate the fact that return on asset ratio is very sensitive to changes in inputs and outputs of a firm.

Furthermore, studies have shown that the differences that arise in using a total productivity index and the return on asset ratio are very slight. In his work on one hundred and thirty five companies, Dunning (1969) found much similarities in the ways the companies were ranked according to the two measures. He concluded that because of the very close statistical association between the two measures the return on asset ratio was a good estimate of overall efficiency. Beattie (1970) reached the same conclusion. He ranked companies from five different industrial sectors according to the measure of total productivity defined in section 3.3.3.2.3 above and to a return on capital ratio. In this study the association was found to be very close again with coefficients of correlation ranging from 0.85 to 0.99 according to industrial sectors.

On the consideration of the above points, EBIT over total assets seems to be a preferable measure mainly for intrinsic reasons and partly due to availability of data reasons listed below.

Firstly, EBIT over total assets is a ratio that most of the managers use in appraising their firm's efficiency. Forty two firms out of forty four firms were reported by the National Association of Accountants in 1959 (Fadel 1977) to use it. The Centre for Interfirm Comparison (1973) reported that most of the firms included in its study -

> "agree that the EBIT over total asset ratio is an important indicator of the effective use of available resources".

This shows that EBIT/Total assets is a ratio that managers thoroughly comprehend.

Secondly, as pointed out before potential profit is the most important factor in the view of financial institutions when they are approached by firms. A reasonable return on assets would increase the chances of companies having temporary financial troubles of seeing their application through.

Thirdly, although growth often appears as an independent objective, profit has a marked effect on it. A company growth can be financed mainly by ploughing back profit or seeking funds on the capital market. In both cases profits are equally important since the capital market will base its decision to invest money into a firm upon its capability to yield a good return in the future.

Fourthly, EBIT over total assets gives more weight to the actions of management regarding the purchase of materials and services from outside the company. The skills deployed by the management in acquiring goods and services and in controlling inventories are directly reflected in the level of profit.

Fifthly, the breakdown of EBIT over total assets includes all the aspects of a firm regarding the use of resources. Pyramids of ratios based on the "Du Pont system" as will be illustrated indicate why the firm's performances have changed over time, why they are better or worse and pin point which areas have been affected.

Sixthly, not all the companies listed on the Exstat tape disclosed information about the number of employees and their wages and salaries. The use of a total productivity index would have considerably reduced the size of the samples, making the analysis less consistent.

In view of the above considerations and to make the most use of the Exstat tape, EBIT over total assets was retained as the measure of overall efficiency. One shall now describe the main components of the return on assets ratio.

3.3.3.3 The Pyramid of Ratios

The pyramid of ratio analysis was pioneered by the Du Pont Company and is still a widely used management tool. Figure 3.2

sets out a typical ratio pyramid. Return on assets comes at the top. Then the pyramid is divided into two branches. One presents the various asset turnovers while the other related profit to the different expenses. The first is topped by the asset turnover ratio and the second by the profit margin ratio.

The asset utilization or asset turnover ratio represents the amount of sale generated by unit value of capital invested in the total assets. The computational formula is:

$$\text{asset turnover ratio} = \frac{\text{Sales}}{\text{Total Assets}}$$

The higher the value of the ratio the more efficiently total assets are utilized. If two firms A and B are generating similar levels of sales but with different amounts of total assets the firm, say A, with the smaller amount of total assets is viewed as more efficient as far as total assets are concerned. This however does not prove that A has a better overall efficiency than B since one does not know what levels of profit are generated.

The profit margin ratio:

$$\frac{\text{EBIT}}{\text{SALES}} \times 100$$

expresses the cost/price relationship of the activities of a firm.

FIGURE 3.2. THE PYRAMID OF RATIOS

A rising profit margin suggests that a firm has managed to reduce the expenses related to production or increase the selling price or both of them. However, here again, this does not mean that the firm's overall efficiency is improving. The increase in profit margin could be achieved to the detriment of asset turnover.

These two ratios are indicators of different activities of the firm and cannot be taken individually to measure overall efficiency because of the shortcomings outlined above. They are the primary determinates of the return on asset ratio. Hence any change in EBIT over total assets is directly related to a change in one of these ratios or even to a change in both of them. Rapid increase in sales accompanied by falling profits indicate a fall in profit margin. This implies that the problem is with the relationship between price and cost. On the other hand, falling profit accompanied by a decrease in the volume of sales indicates a problem of asset management if the profit margin is kept constant. Going down the pyramid helps point out the specific factors influencing the variation in profit margin or asset utilization.

Effects of profit margin and asset turnover on EBIT over total assets

EBIT/Total Assets		Profit Margin		Asset Turnover
10%	=	5%	x	2
15%	=	5%	x	3
15%	=	7 .5%	x	2

This table outlines some examples of the incidence of varying profit margin and asset turnover on the return on asset ratio.

3.3.4 CONCLUSION OF SECTION 3.3.3

The preference of the return on asset ratio as the measure of overall efficiency of companies stems from the goal of the study. That is to find an acceptable measure of overall performance for both:

i) Managements who will have to ensure that the capital invested in the total assets yields profit in sufficient amount for their firm to survive in a capitalist type environment.

ii) A government department that would have the task of monitoring the economy at large in order to obtain the most efficient utilization of the national resources.

Besides although it is recognised that other parties involved directly or indirectly in the activities of a particular firm may feel the need to assess its efficiency and may choose different and often contradicting yardsticks, the author feels that the return on asset ratio is one of the most widely accepted measures of overall efficiency by the parties that are likely of having a direct influence on the company activities.

Having decided on a criterion of success one must turn to the selection of the two samples.

3.3.5 THE WELL PERFORMING COMPANY GROUP

The companies included in this sample were selected on the basis of their efficiency measured by their return on assets as defined above. Two requirements were made, the first concerning the minimum level of return on assets and the second regarding the minimum period of time during which the first requirement should be satisfied.

The second requirement proceeds from the view that a company to be considered as well performing should not only be successful but should be so over a period of time long enough to cast off the influence of any speculative or temporal favourable market conditions.

Such a requirement was enforced because it was felt that if resources are to be efficiently utilized this should be done not only over one year but over the longest possible period of time. In effect it is preferable to have a sustained rather than ephemeral efficient utilization of resources. Thus a company showing a very high but short-lived return on assets would be discarded for a company that may have a lower but sustained return on assets. Therefore the procedure followed in selecting the companies for inclusion in the high performance sample was to define a level of return of assets above which a company was considered as highly successful and then to ensure that the company has been maintaining such a level of efficiency over three years.

This three year period was retained because the companies were listed for a maximum of seven years and their first four year period of listing was reserved for the analysis on the potential high performers. Furthermore, it was thought that favourable and speculative market conditions would not last for such a length of time.

Concerning the minimum level of return on assets, no study has to the author's knowledge set a precise demarcation line between high performance and normal performance companies. Confronted with such a lack of information it was decided to base one's decision on the samples of companies available from the tape.

The average of the EBIT to total assets ratio over the years 1978, 1977, 1976 was calculated for each company. The companies were then ranked according to their mean value on the EBIT to total assets ratio on this three year period and the top half selected as the well performing company sample.

This practice of averaging the performance criteria over the period of time analysed is common practice in related studies. The Centre for Interfirm Comparison (Harrington and others, 1977, 1981) averaged a return on capital ratio over a period of four years while Child (1974) averaged its data over a five year period.

3.3.6 THE LESS WELL PERFORMING COMPANY GROUP

This sample contains all the companies that were not included in the well performing company sample i.e. the bottom half of the total sample of companies.

Considering the entire sample of companies rather than basing the analysis on the best and worst performing firms was done in order to avoid samples representing only a portion of the parent population. A criticism often levelled against discriminant analysis studies as discussed in chapter 2.

3.3.7 MATCHING OF THE SAMPLES

Past financial researchers favoured the matching of samples when the analysis was carried out on two or more groups. The practice is to select a sample and then to match each of the companies with the ones to be included in the other sample. In our case the idea would be once the sample of well performing companies has been established to match each of its constituents with a less well performing company to size, industry and financial years.

The problem of matching by financial years was not crucial since the companies in both samples were analysed for the same year. When used in the text year 1978 referred in fact to a period of time comprised between the 1st of April 1977 and the 31st March 1978. Similarly, year 1977 referred to the period of time starting on the 1st of April 1976 and ending on the 31st of March 1977 and so on for 1976, 1975, 1974, 1973, 1972.

The pairing of the sample according to size and industry was not attempted for the following four main reasons.

i) A reduction in sample size.

The statistical technique of discriminant analysis makes no assumption regarding the pairing of the samples. Matching the less performing set of companies to that of the well performing would reduce the number of companies considered by about six hundred leading to a formidable loss of information.

ii) The assumption regarding randomness of the samples.

Samples should be representative of their underlying populations. Matching samples would mean that both populations have identical structure as far as size and industry classification are concerned. This is not always true. In their study, Altman et al (1977) selected size measured by the firm's total assets as a variable entering their discriminant function. Thus size proved to be an important factor explaining failure. Matching by size would have in this case hidden an important explanatory factor of corporate failure.

On the problem of matching by industrial sectors, companies belonging to certain industrial sectors may prove to be slightly better performing leading to their over-presentation in the less well performing group and thus leading to a distortion of the real distribution of the less well performing sample according to industrial sector classification.

iii) The effect of size and industry characteristics are not clearly determined.

Although it is argued that inter-industry differences exist among some financial ratios (Gupta and Huefner, 1978; Brown and Ball, 1967; Lev, 1969), it is not clear whether all the ratios are affected in the same direction by industrial characteristics and whether this influence is consistent over all the financial dimensions of companies. Gupta and Huefner (1972) pointed out that, using a list of seven ratios, inter-industry differences were not visible when more aggregate ratios were used (total asset turnover and current asset turnover). Furthermore, their analysis based on clustering did not arrive at the same groupings when the ratios studied were different. Although in some cases the difference in grouping were slight, in others they were more pronounced making the homogeneity of the industrial classes not so obvious. It can be assumed that the larger the set of ratios selected the less representative the groupings would be.

The variations within the industrial classifications are not the same adding more controversy to the problem of the homogeneity of the groupings. Many companies belonging to an industry may have score on financial ratios that would be so far apart from their industry mean that they more closely resemble firms from other industrial sectors. This problem was encountered by Bass et al (1978) when basing their industrial groupings on the Standard Industrial Code, they found out that biscuit companies were more similar to cereal companies than to bakeries to which Industrial Standard Code group they belong.

Besides, bearing in mind that financial ratios can be grouped such as to represent particular financial dimensions (Pinches et al, 1973, 1975) and that any one of the ratios belonging to one of the group can be used to represent that particular dimension without too much loss of information, the ratios which are the less industry responsive can be selected for further use in the analysis. An example drawn from the study of Gupta and Huefner (1972) would be to reject the fixed asset turnover ratio which is industry affected in favour of the total asset turnover ratio which is a more aggregate ratio and which is not industry affected since both of them represent the "capital turnover" dimension. The same procedure can be extended to the other financial dimensions leading to the selection of more aggregate ratios that would offset possible industry differences.

The effects of size on the financial structure of firms is answered by the aim of financial ratios itself. They have been introduced in the field of financial analysis to allow comparison between firms of different sizes and are thought by financial analysts to take out the enterprise size dimension. This viewpoint has been widely reinforced by empirical evidence. Horrigan (1965) showed that financial ratios are uncorrelated to size. The same conclusions were later reached by Beaver (1967), Singh and Whettington (1968).

iv) Problems encountered in matching samples.

In most of the related studies where matching of the samples was attempted, this was carried out with the aim of finding pairs of companies which possessed as many common characteristics as possible. Pairs of companies should be drawn from the same industrial sector, have the same size and come from the same financial year. Although finding a significant number of ideally paired companies is not impossible, the work involved is tremendous and the cost is often unbearable. Edminster (1972) had to scan about 110,000 companies before he could find 21 pairs. This has often caused researchers to define vague pairing criteria leading to much ambiguity and criticism surrounding this aspect.

To underline the difficulties facing researchers when matching is attempted few examples concerning areas of controversy will be exposed.

Companies are not very well defined entities. Their activities often spread to more than one industrial sector rendering their industrial classification very difficult. We have seen in recent years more and more concerns diversifying their activities in order to reduce risk.

When it comes to size more problems are encountered since size can be defined as sales, total assets, number of employees, market capitalisation etc. Ideally a pair of companies should be matched on all the size aspects. They should have the same level of sales, amount of total assets, market value and number of employees. The probability of such an event occurring is very minute and the usage is to select one of the aspects of size as criterion. If total number of employees is taken then the problem is quite clear but if any of the other items is selected problems of interpretation will arise. For example, in the case of sales, should they be taken gross or net of value added tax ?

Other areas of controversy are ownership of assets and capital. Mulondo (1981) gives a good account of the problems related to these aspects.

From the four arguments raised above it is clear that a strict matching of the samples is not necessary and that if attempted it would create more problems than it solves.

3.4 CONCLUSION

Bearing in mind the aim of the study, the present chapter was divided into two broad parts. The first outlined the methodology to be used in investigating whether companies that have sustained a high level of efficiency in their resource utilisation over a certain period of time, present significant differences in their financial profile and if so whether on the basis of financial measurements those companies could be identified. The discriminant analysis technique was found most appropriate, since it has proved a very powerful technique in the field of company classification and is very simple to use, especially by people with an unsophisticated knowledge of mathematics. The derivations of the linear discriminant function were presented and it was shown that the test used to measure the discriminatory power of the discriminant function was the same as the test of differences between two groups. Hence the discriminant analysis was the statistical technique most appropriate to assist us in finding an answer to our investigation.

The second part was concerned with the selection of the samples. The measure of efficiency was defined as EBIT over total assets and the reasons for this choice were put forward. Then companies that satisfied the general criteria were allocated to the less well performing and well performing samples on the basis of their success measured by the return on asset ratio averaged over a three year period.

CHAPTER 4

SELECTION AND CLASSIFICATION OF VARIABLES

CHAPTER 4

4.1. INTRODUCTION

The analysis of balance sheets and financial accounts may vary with the purposes of those examining financial statements. The aim of this study is to investigate whether well performing companies and less well performing companies present significant differences in their financial characteristics. Generally, financial profiles of companies have been represented by financial ratios and financial statement classifications. However, more measures have been introduced in analysing the data available from published accounts. Measures of trend and change over the previous year were used in a study by Taffler (1976). More recently Dambolena and Khoury (1980) generalised the use of stability measures to the entire set of ratios employed in representing company financial profile. Measures of asset decomposition associated with structural changes were used by Lev (1971) to predict bankruptcy.

From the few studies listed above we can deduce that even though ratio analysis remains the backbone of any financial analysis, other measures can complement and reinforce it.

The financial variables utilized later in the study are described in this Chapter together with their characteristics. Then, in an attempt to facilitate the identification of the financial dimensions represented by the variable entering the linear discriminant function a classification framework is developed.

4.2 THE VARIABLES

4.2.1 FINANCIAL RATIOS

The need for a more thorough analysis of financial statement data in assessing the financial position of firms emerged with the industrial revolution and the more predominant role of the financial institutions in the ecomony. By the end of the nineteenth century commercial banks started requesting financial statements to "borrowers of money" (Foulke 1961).

However, the raw data from published accounts are not, in themselves, very indicative of companies financial characteristics but for the size. This is due to the fact that financial statement items are expressed in absolute values. To overcome such limits, financial analysts felt the necessity to classify those items into current and non current assets or liabilities, to compare them to each other and to scrutinize their relationships. Then around the beginning of the twentieth century the comparison of the current assets of firms to their current liabilities became a widespread practice. Foulke (1961) states that a current ratio of 2.5 to 1 was considered to be a reasonable margin of protection in those times. Although, shortly later other ratios were introduced, the impact of the current ratio was so important and long lasting that :

> "the usage of ratios in financial statement analysis can be said to have begun with the advent of the current ratio." Horrigan (1968)

4.2.1.1. Financial Ratio Analysis as an Analytical Technique

The main objective of financial ratio analysis, is to reduce the mass of financial statements information to a more manageable set of measures thence to facilitate the interpretation of financial statements.

The twentieth century has seen the formation of a great number of different ratios. (Taffler and Sudarsanam (1980) used 80 ratios in their study.) Regarding this aspect, it is generally argued in the financial literature that items in the numerator and denominators should be logically related.

Lev (1974) reviewed three kinds of logical relationships:

i. Economic relationship between the two values. e.g. profit to capital.

ii. Use of items based on common value. e.g. inventories should be related to cost of sales since they are valued at cost.

iii. Functional relationships e.g. the ratio components should vary in the same fashion. The use of net profit to sale was questioned since fixed expenses do not vary with sales.

However, he found these criteria inadequate since

- an economical relationship is self-evident.
- ratios with components valued differently have proved to be powerful e.g. sales to inventories.
- the relationship to be investigated is not only between the numerator and denominator of the ratio but between the ratio and some other economic indicator.

Financial ratios by themselves are difficult to interpret. At first it was usual practice to divide financial items into two categories : assets, equities and revenues, and liabilities and expenses, to relate items from the first category to those of the second and to regard high value for these ratios as desirable. This procedure presented some limitations as (i) ratios may be formed of items coming from the same category (e.g. profit to total asset or sales to inventories) and as (ii) a too high ratio value may sometimes not be optimal. A high current ratio can show an under utilization of resources and a high sale to inventory ratio is often indicative of a too low level of stock resulting in disruption and losses of revenues.

To overcome these limitations financial analysts resorted to the use of standards against which the ratio values would be compared. Values of two on the current ratio and of at least one on the equity to total liabilities and equity to fixed assets have been for a long time accepted as values around which companies should score in order to be considered healthy.

The utilization of standards in ratio analysis shifted the emphasis towards the comparison of ratios. Nowadays the two main types of comparison are: intra company comparison and inter company comparison.

In the intra company comparison, ratios for several successive years are compiled and their trend analysed. Any change in the ratio value would be judged and give valuable information as to whether the financial performance of the company has deteriorated or improved.

On the other hand inter company comparison would give more information on the firm performance relative to other firms which could be in the same industrial sector or which could be its main competitors. But problems that were discussed in Chapter Two regarding the selection of samples impede the adequacy of industry standards as criteria for comparison.

Furthermore, the use of financial ratios on an univariate basis presents some shortcomings. The inter-relation between the different ratios is not taken into account and they may release conflicting signals (Lev, 1974). The use of multivariate analysis offers a solution to these problems in that several weighted ratios are combined. Several indices for evaluating performance were proposed (Wall and Dunning,1928; Tamri,1966; Burch,1972; Sashua and Goldsmith,1974) but most of them suffered from the quite arbitrary manner in which the weights and/or the variables were chosen.

From the points mentioned above, there is considerable evidence that ratio analysis is widely used in assessing the financial position of firms from data drawn from their financial statements and published accounts. Such a view is reinforced by the now established practice by government departments and security analyst firms to go ahead and publish listings of detailed annual information about companies in ratio form. In the United Kingdom, a few examples are the National Economic Development Committee, the Department of Industry for the government departments and the Extel Statistical Services Limited, the Centre for Interfirm Comparison, the Jordan Data Bank ... etc., for the commercial sector. Their U.S. based commercial counterparts are the Dun and Bradstreet Inc., and the Robert Morris Associates.

4.2.1.2 Limitations of Ratio Analysis

The three main limitations of ratio analysis commonly found in the financial literature are linked to the validity of published accounting data, to its static picture presentation of the firm and to its failure to take into account data that are not quantifiable.

a) validity of published accounts

As we have seen in the second chapter, there exists a large debate among accountants as to whether published accounts are representative of economic reality. However, it is agreed that published accounts represent a good proxy to economic reality since many financial studies based on published account data have been recognised as significant.

b) static picture of the firm

This criticism of ratio analysis is particularly related to ratios depicting the liquidity aspect of companies. Lemke (1970) underlines the fact that financial ratios present a static picture of what is essentially a dynamic process. The liquidity ratios reflect the liquid asset reservoir of the firm at the point in time when the balance sheet is compiled while the solvency aspect of the firms would be better represented if the rises and falls in liquid assets are depicted as they occur during the financial period.

In effect, the solvency of a company depends upon an adequate level of liquidity. If cash inflows and outflows are perfectly synchronized, the payments could be met by firms without them holding any liquid assets. However, this is rarely the case in reality and any of the items composing the current assets cannot be reduced permanently without affecting the running of the firm. This demonstrates that if solvency is to prevail cash inflows should cover cash outflows by a sufficient margin to allow for sudden rises in outflows or falls in inflows.

c) not quantifiable data

Financial ratio analysis fails to take into account factors such as management ability and economic, political and social situations surrounding the company (Benishay, 1971, 1973). Although such factors may be very important in explaining the success or failure of a company, they tend to point to the reasons for a company performance rather than to give a clear account of the company level of performance.

Non quantifiable data can serve the need of the analyst alongside financial ratios but cannot be substitutes for them. It is certain that, say, the lack of financial planning and control by management or the lack of sound marketing policies, would impair the performance of a company, but knowing this fact would not be sufficient to assess its level of performance.

On the other hand, financial ratio analysis would indicate areas of strengths and weaknesses that would be the consequences of the above cited factors. An amelioration of the financial ratios associated with the liquidity position of a firm would reveal an improved performance regarding this aspect but the causes of this improvement could be numerous. Among others a better cash budgeting by the management or a more supple monetary policy by the government can be mentioned as significant reasons.

Other less important controversies are regarding which value to use as denominator of ratio related to profitability and velocity and the possible mathematical pitfalls accompanying the use of ratios.

Recently, some financial researchers, Taffler (1976; 1982) and Mao (1976) among others, have advocated the use of average or beginning of year figures rather than the usual year-end figures for items placed in the denominator of profitability and turnover ratios. Such ideas stem from the fact that profit and sales should be directly related to capital. Since the amount of capital held by a firm may vary during the period under analysis, the use of an average value gives a better estimate of the amount of capital utilized to generate the level of profit and sales arrived at, at the end of the financial year, while opening balance sheet figures would ensure that companies disposing of parts of their assets to improve their year-end results would not show a better profitability and velocity than they have really achieved.

The mathematical pitfalls of financial ratios are mainly due to their form. The presentation and interpretation of ratios can often be ambiguous. Although they may appear too straightforward, few examples can illustrate their possible misuses. When averaging ratios, two methods that lead to entirely different results can be utilized. The first is to calculate a simple arithmetic mean e.g. $(.80 + .20)/2 = .50$ while the second is to weight the average by a measure of size. e.g. $\frac{1}{8} \times .80 + \frac{7}{8} \times .20 = .275$ if the size of the second firm is seven times larger. No systematic rule can be accepted as to which procedure to choose. The choice will depend upon the goals of the analysis.

The interpretation of financial ratio changes can also be misleading. For example, a firm wishing to achieve a better inventory turnover may tend to reduce its level of inventory. Its actions may lead to an increased stock velocity but at the same time, lead to a level of inventory too low to avoid any disruptions and consequently loss of sales that could weaken its market position. Any changes in financial ratios should therefore be related to changes in both items from which they are constructed.

Another abuse would be to give too great an importance to financial ratios that are constituted of items that are hardly significant in the financial statement of a firm. This is particularly crucial when comparing the financial profile of two companies.
An example could be illustrated as follows for two firms of equal size:

FIRM	A	B
Bank Loans	1000	10
Total long term debts	5000	20
Ratios	.20	.50

Looking at the ratios only, one could conclude that firm B tends to rely more heavily on bank loans as a source of long term financing than firm A. But the important information here is that the total long term debts of firm B are negligible, whereas they could represent a substantial item in the financial statement of firm A. This stresses the fact that in such a situation absolute number should also be provided to avoid any misjudgment.

The points raised above clearly show some of the limitations and possible misuses of financial ratios. Although they are important to bear in mind when assessing a company's financial position, there is enough evidence, from the many studies published recently, indicating that financial ratios are very powerful predictors and remain the main tools of analysing financial aspects of companies' performance.

4.2.1.3. Choice of Financial Ratios.

Review of the financial literature indicates that no authoritative source on the utilization of specific financial ratios can be found. Although financial ratios have been extensively used, generalization of the results of previous studies has not been possible owing to a lack of understanding of financial ratios inter-relationships and to the specificity of the phenomena under study.

Consequently, it was decided to have recourse to articles and textbooks on financial analysis and to select those financial ratios that revealed a certain predictive ability or were favoured by financial analysts.

A survey of the major studies was carried out. Although not completely exhaustive it encompassed the most significant and recent contributions. It was felt that rather than screening all the studies which advanced a financial ratio as having intrinsic explanatory or predictive ability, it was preferable to identify only the studies that were recognised as valuable in the financial literature. This approach was adopted because the number of retained ratios would have been too large otherwise and thus tautological and confusing. Moreover, some of the older studies were not included. Although having made in their own time a major impact in the field of financial analysis, the criticism surrounding their methodical approach put the validity of their findings into question.

Altogether twenty four studies and textbooks were surveyed. Table 4.1 below presents the financial ratios found useful in the studies and textbooks. The studies could be broadly classified into five categories :

1. Prediction of bond rating and future rate of return rankings (5,8). (The figures between the brackets refer to the numbering of studies employed in Table 4.1)

2. Analysis of the characteristics of merged firms (18)

3. Prediction of firm financial difficulties (1,2,3,4,6,7,9,11, 12,14,17)

4. Identification of ratios that differentiate most between, below and above average performing firms (16)

5. Selection of ratios that are the most representative of a company's financial profile (9,13,15)

Although most of the ratios used in the studies under categories 1,2,3,4 have shown a high accuracy in predicting the financial state of companies it should be noted that their capability to differentiate between those firms has been investigated in relation to the study of specific phenomena. Hence their predictive ability is impaired by the impossibility to generalize these findings. However, they represent a starting point to any financial study and can be complemented

TABLE 4.1

RATIOS FOUND IN STUDIES AND TEXTBOOKS

STUDIES AND TEXTBOOKS / RATIOS	STUDIES																		TEXTBOOKS					
	1 Beaver 1966	2 Temri 1966	3 Altman 1968	4 Daniel 1968	5 Horrigan 1968	6 Deakin 1972	7 Edminster 1972	8 O'Connor 1973	9 Blum 1974	10 Pinches et al 1975	11 Taffler 1976	12 Altman et al 1977	13 Laurent 1979	14 Dambolena and Khoury 1980	15 Taffler and Sudarsanam 1980	16 Harrington 1981	17 Betts and Belhoul 1982	18 Hosino 1982	1 Foulke 1961	2 Goldofsky and Oliva 1972	3 Lev 1974	4 Mao 1976	5 Van Horne 1977	6 Weston and Bigham 1978
1 NI/TA	*					*												*			*		*	
2 NI/NW								*		*				*								*	*	
3 NI/WC				*																				
4 NI/SA		*			*			*						*								*	*	
5 Earning per Share																					*			
6 Ear.Share/Sh.Price								*													*			
7 EBIT/TA			*							*	*	*	*		*		*					*		
8 Cash/TA						*				*														
9 Cash/Funded Exp.										*														
10 Cash/CL						*																*		
11 CA/CL	*	*				*				*		*						*	*		*	*	*	
12 CA/TA						*																		
13 QA/TA						*					*													
14 QA/CL						*				*					*		*			*	*	*	*	*
15 QA/QI													*											
16 QA/St									*															
17 QA/CA																	*							
18 St/CA				*																				
19 St/WC														*					*					
20 CL/NW							*												*					
21 CL/St								*																
22 WC/FA	*		*	*		*																		
23 WC/NW				*							*													
24 WC/NCE															*		*							
25 Quick Flow									*															
26 LTL/TA													*											
27 LTL/TL				*																				
28 LTL/NW				*														*	*					
29 LTL/WC														*					*					
30 TL/TA	*					*				*							*							
31 TL/NCE											*													
32 NW/TL		*			*			*	*						*			*	*		*	*	*	
33 Market Equity/TD			*						*															
34 EBIT/T.INT												*	*								*	*		
35 EBIT/																							*	*
36 Retained Earn./TA			*									*												
37 Reserves/NI													*											
38 FA/NW														*										
39 SA/CA						*									*	*								
40 SA/QA						*																		
41 SA/WC		*			*	*	*	*					*						*					
42 SA/Cash						*																		
43 SA/NW					*		*					*							*					
44 SA/FA				*									*											
45 SA/Net Plant										*														
46 SA/St		*		*			*			*	*		*			*							*	
47 SA/TA			*					*		*								*				*	*	
48 SA/Wk.in Prog.																*								
49 SA/T.Employees																*								
50 SA/CR		*											*							*			*	
51 Cst.of Gds.Sold/St										*									*	*	*		*	*
52 CF/TL	*					*																		
53 Fund Flow/CL							*																	
54 VA/TA															*									
55 VA/T.Employees																*								
56 FA/VA																*								
57 Days Debtors										*						*			*	*	*		*	*
58 Days Creditors																	*						*	

by ratios widely accepted in the financial literature.

As most of the finance textbooks put forward the usefulness of financial ratios, they include at least a chapter listing the most vital ratios in their author's view. Their effectiveness has generally been proved by empirical evidence and accordingly they represent the kind of measures that any financial analyst would include in his battery of ratios.

Altogether 58 financial ratios were identified. They were classified to investigate whether they covered all the firm's financial dimensions.

The definitions of the components of the variables presented in Table 4.1 are listed in appendix IX.

4.2.1.4 Financial Ratio Classification

The two main methods of classifying financial ratios are by source and according to the financial aspects of the firm's operations.

The classification by source is as follows:

1. Balance Sheet ratios
2. Profit and Loss Account ratios
3. Mixed ratios

This last category includes ratios whose components are derived from both the balance sheet and the profit and loss account. A typical example is the return on total asset ratio. This classification may be useful but does not indicate which financial dimensions are investigated. A better classification in that view would be according to financial aspects of firms' operations. Traditional approaches define four classes.

1. Profitability ratios
2. Liquidity ratios
3. Solvency ratios
4. Efficiency (turnover) ratios

This classification is seen as user orientated since management will primarily be looking at profitability while a lender will be concerned with solvency ratios.

Although this classification presents the advantages of clearly defining four financial dimensions, it has recently been challenged and new dimensions have been found to be measured by financial ratios (Pinches et al, 1973, 1975; Taffler, 1976, 1980; Laurent, 1979; Courtis, 1978)

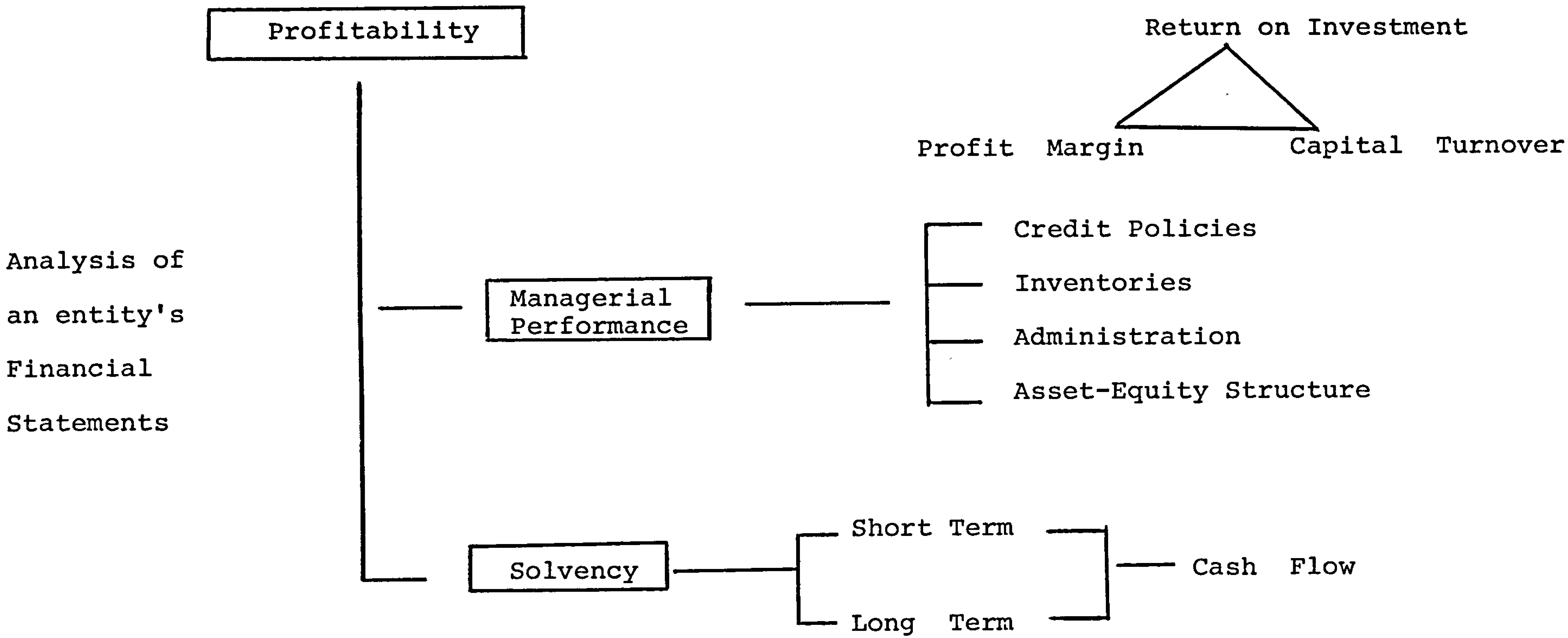
Courtis (1978) pointing out the lack of work "done towards producing a theory of financial ratio analysis which (a) identifies the linkages between different ratios and (b) then explains how these various ratios inter-relate to map a profile of corporate financial characteristics ", proposed a new way of classifying ratios. His categoric framework illustrated in Figure 4.1 outlines three major areas - profitability, solvency and managerial performance. The first two categories are found in traditional classifications, however, the managerial performance area is a new concept in ratio classification and is rarely mentioned in the financial literature. This area includes such issues as the time it takes to receive payment from customers, the time taken to pay suppliers, the length of cash conversion cycle, the turnover of inventory, the cost efficiency of operations, and the relative "balance" of debt - equity - working capital - assets components within the overall structure of the financial position. (Courtis, 1978).

Investigation of these three areas will give direct answers to crucial questions about three vital aspects of a firm's life :

a) Is the enterprise making any money?

b) Is the management any good?

c) Is the company going to stay in business?



FINANCIAL RATIOS CATEGORIC FRAMEWORK

Developed by Courtis

FIGURE 4.1

TABLE 4.2

RATIO CLASSIFICATION AND FREQUENCY

1 PROFITABILITY

a) Return on Investment	b) Profit Margin	c) Capital Turnover
1 - NI/TA (4)	7 - NI/SALES (5)	8 - SALES/WL (7)
2 - NI/NW (4)		9 - SALES/NW (4)
3 - NI/WL (1)		10 - SALES/FA (2)
4 - EARNING PER SHARE (1)		11 - SALES/NET PLANT (1)
5 - EAR. SHARE/SHARE PRICE (2)		12 - SALES/TA (5)
6 - EBIT/TA (8)		13 - SALES/T.EMP (1)

II SOLVENCY

a) Short Term Liquidity

14 - CA/CL (9)
15 - CA/TA (1)
16 - QA/TA (2)
17 - QA/CL (9)
18 - QA/QL (1)
19 - QA/CA (1)
20 - CASH/TA (2)
21 - CASH/FV.EXP (1)
22 - CASH/CL (2)
23 - CL/NW (2)
24 - WC/TA (4)
25 - QUICK FLOW (1)
26 - SALES/CA (3)
27 - SALES/QA (1)
28 - SALES/CASH (1)

b) Long Term Solvency

29 - TL/TA (4)
30 - NW/TL (9)
31 - TL/NLE (1)
32 - MANGN./EQUITY/TL (2)
33 - EBIT/T.INT. (4)
34 - LTL/NW (3)
35 - EBIT/Fd. CHARGE (2)

c) Cash Flow

36 - CF/TL (8)
37 - FF/CL (1)

III MANAGERIAL PERFORMANCE

a) Credit Policy	b) Inventory	d) Administration	c) Asset-Equity Structure
38 - DAYS DEBTORS (7)	41 - SALES/ST (7)		48 - WL/NW (2)
39 - DAYS CREDITORS (1)	42 - SALES/WORK PROG. (1)		49 - WL/NLE (2)
40 - SALES/DEBTORS (4)	43 - C.G/ST (6)		50 - LTL/TA (1)
	44 - CL/ST (1)		51 - LTL/TL (1)
	45 - ST/CA (1)		52 - LTL/WC (2)
	46 - ST/WC (2)		53 - FA/NW (1)
	47 - QA/ST (1)		54 - RF/TA (1)
			55 - RES/NI (1)

A complete answer to any of these questions would need a more detailed analysis hence the extension into sub-sections as shown in Figure 4.1.

Following the same approach the 58 financial ratios were classified (Table 4.2). Although 58 ratios may appear to be a large number of variables it is pointed out that this list is not completely exhaustive and that, as mentioned earlier, larger numbers of ratios have been selected in previous studies. The fact that those ratios fail to represent the Administration dimension highlights this point. However, as Courtis (1978) stated, the presence of collinearity between financial ratios makes the information provided by some ratios redundant especially within the different categories defined in his framework. This corroborates earlier findings by Horrigan (1965) who stated that:

> " This presence of collinearity is both a blessing and a curse for financial ratio analysis. It means that only a small number of financial ratios are needed to capture most of the information ratios can provide, but it also means that this small number must be selected very carefully."

From this statement it can be deduced that certain financial ratios contain specific information and that by selecting a set of ratios carefully most of the corporate financial characteristics can be covered. Furthermore, any additional ratios to that set would provide very little information and would bring confusion.

Therefore, it was decided, in a first time, to select only financial ratios which had been found useful in more than one study or textbook and then to make certain that the final set of ratios would include information on all the companies' financial dimensions as defined by Courtis (1978).

The value added ratios were not included in Table 4.2 as these types of ratios were not considered in Courtis' (1978) analysis. Furthermore, for reasons explained in the preceding chapter, value added measures could not be computed. These financial ratios have been found to represent a dimension on their own, (Taffler and Sudarsanam, 1980) and seem to be related to the profitability.aspect of firms.

4.2.1.5. Final Choice of Ratios

The financial ratios with the highest frequency are the current ratio, the acid-test ratio, the net worth over total liability ratio, the profit before taxes and interest over total asset ratio, the working capital turnover ratio, the days debtor ratio and the profit before taxes and interest over total asset ratio. Then to a lesser extent one found the total asset turnover ratio, the net profit over total assets, net profit over net worth, the profit margin, the working capital over total asset ratio, the total liability over total asset ratio, the interest coverage ratio, the net worth turnover ratio and finally the account receivable turnover ratio.

All but one ratio put forward by textbook writers have been found to have some intrinsic predictive or explanatory ability by researchers but one can notice the obvious lack of ratios under the administration heading of the managerial performance dimension. Besides the cash-flow and credit-policy are poorly covered. Although the lack of representation of the administration and credit-policy categories could be explained by the difficulties to collect data in order to compute these ratios, the low number of ratios under the cash-flow category could be due to the novelty of the cash flow concept rather than the lack of data.

The final list of financial ratios comprises all the ratios that were found useful at least in more than one study or textbook but for four. These ratios were not included because of lack of data. They are the earning per share over price of share ratio, the market equity over total asset ratio, the earnings before taxes and interest over fixed charge ratio and the cost of goods sold over inventory ratio. Although these four ratios could have strengthened the analysis it is felt that they come from categories that are well covered except for the inventory turnover ratio.

Moreover, the sale to inventory ratio is a good substitute for the inventory turnover ratio and has been recognised as more useful by researchers than the inventory turnover ratio itself.

Looking at Table 4.3 we notice the absence of the administration category. The financial ratios that would be included in this category such as operating expenses to gross margin, cost of sales to sales or operating expenses to total

TABLE 4.3

FINAL LIST OF RATIOS

I PROFITABILITY

a) Return on Investment	b) Profit Margin	c) Capital Turnover
R1 = NI/TA	R5 = NI/SALES	R6 = SALES/TA
R2 = NI/NW		R7 = SALES/NW
R3 = EBIT/TA		R8 = WC/SALES
R4 = (EBIT/NCE)		R9 = SALES/FA

II SOLVENCY

a) Short-Term Liquidity	b) Long-Term Solvency	c) Cash-Flow
R10 = SALES/CA	R18 = NW/TL	R22 = CF/TL
R11 = CA/CL	R19 = NW/LTL	R23 = (CF/CL)
R12 = CL/NW	R20 = TA/TL	R24 = (CF/WC)
R13 = CASH/CL	R21 = EBIT/T.INT	R25 = (CF/TA)
R14 = WC/TA		
R15 = CASH/TA		
R16 = QA/CL		
R17 = QA/TA		

III MANAGERIAL PERFORMANCE

a) Credit Policy	b) Inventory	c) Asset-Equity Structure
R26 = DAYS DEBTORS	R29 = SALES/ST	R33 = WC/NW
<u>R27 = SALES/DEBTORS</u>	<u>R30 = ST/WC</u>	R34 = WC/NUE
R28 = (DAYS CREDITORS)	R31 = (CL/ST)	<u>R35 = LTL/WC</u>
	R32 = (ST/CA)	R36 = (NW/TA)

assets could not be computed because the information needed is not available from the published accounts of companies. Besides, some of the categories have been strengthened especially the inventory and cash flow categories. The ratios, between brackets in Table 4.3 that are added to those selected previously, are taken from those proposed by Courtis (1978) and from those utilized by the author in past studies (Betts and Belhoul, 1982a and 1982b).

The final list comprises thirty six financial ratios. All the categories are represented except the administration category for reasons given above. The number of financial ratios under each heading is more or less equal with the exception of the short term liquidity category which presents financial ratios experiencing various degrees of liquidity and specificity, from the broader and medium term current asset over current liability ratio to the more specific and very short term cash over current liabilities ratio. This larger representation could mean that the short term liquidity dimension could be broken down into more sub-categories that would represent more closely the companies' liquidity characteristics.

In fact Pinches et al (1974), Taffler (1976), Taffler and Sudarsanam (1980) showed that a cash position dimension together with a working capital position and a quick assets position dimension could be separated from the more general liquidity dimension.

4.2.2 OTHER FINANCIAL VARIABLES

The use of other financial variables besides ratios has become a widespread practice in financial analysis. The need to have a better picture of the financial characteristics of firms leads to the introduction of measure of size, stability and trend alongside financial ratios.

This was particularly evident with the advent of multi-variate statement analysis when models were developed with the aim of taking into account all the financial aspects of companies. Although financial ratio analysis is the starting point and the base of any method devised to assess the financial profile of companies, such approaches have shown that a firm's financial stability is, as well, a very important aspect of a firm's characteristics.

4.2.2.1 Measures of Stability

Measures of stability can be classified in three broad categories:

1. decomposition measures
2. variance type measures
3. measures associated with linear regression (standard error of estimate)

As measures in the last category gave inferior results (Dambolena and Khoury 1980) and as they require more computational time they were not considered in this study.

4.2.2.1.1. Decomposition Measures.

Decomposition analysis has a wide field of applications. Theil (1972) showed that it could be satisfactorily extended to areas of social and administrative sciences: economy, sociology, psychology, political science, management science, accounting etc.

When a given total is separated into a number of components, one may want to determine how the total is divided between the various components and how this "dividedness" is affected by changes over time. Statistical decomposition analysis provides an answer to these questions but our main concern in this section lies with the degree of stability of a firm's structure. Therefore our interest will be directed towards answers to the second question.

Lev (1974) points out that the decomposition technique can be naturally applied to financial analysis since:

-financial statements are divided into different classifications such as assets, liabilities, revenues, and costs.

-structural changes in the firm's resource allocation occurs whether due to external effects (environmental changes) or internal effects (management decisions.)

The decomposition measure presented in this section are an attempt to measure these changes of resource allocation. Firstly the mathematical formulae will be described and then their applications to financial statement items will start from more general to more specific areas e.g.: balance sheets, total assets and total liabilities.

THE MATHEMATICAL FORMULAE

An example will help understand the calculation of decomposition measures. Let us take a quantity A that is split into several items for two successive periods of time.

	Period t	period t+1
item 1	a_{1t}	a_{1t+1}
item 2	a_{2t}	a_{2t+1}
item 3	a_{3t}	a_{3t+1}
Total	A_t	A_{t+1}

Table 4.4 DECOMPOSITION TABLE

Now if we denote by $p_1 = a_1t/A_t$. the relative share of item 1 in period t, by p_2 that of item 2 in period t and p_3 that of item 3 in period t and denote by q_1 to q_3 the corresponding proportions in period t+1 the decomposition measure is defined as follows:

$$DM = \sum_{i=1}^{3} q_i \log \frac{q_i}{p_i} \qquad (1)$$

(the base of the logarithm in (1) is left to the user's choice. Logarithm to the base e has been selected as this is the most widely used)

DM measures the degree of variation in the relative shares of the different items in A taking place during the period (t, t + 1). When DM takes the value of zero which is its minimum, this indicates that the proportions of the various items in A have not changed during the period investigated. On the other hand a positive value of DM reveals that differences have occurred in the corresponding relative shares of the items between the periods t and t+1. The larger the pairwise differences the higher the value of DM. It should be noted at this stage that a value of DM equal to zero does not indicate that the absolute values of the various items are unchanged. A change in absolute values can be accompanied by unaltered relative shares. This point indicates that decomposition measures are measures of structural change and instead of taking each item separately it is their relative share changes that is taken in totally.

The generalization of the decomposition measure to M items is straightforward. The general formula is :

$$DM = \sum_{i=1}^{m} q_i \log \frac{q_i}{p_i} \qquad (2)$$

where p_i (i=1 to m) is the relative share of i^{th} item in period t and q_i the corresponding proportion in period t + 1.

BALANCE SHEET DECOMPOSITION MEASURE

The balance sheet decomposition measure is derived from the conventional classification of balance sheet items into four basic categories: current assets, current liabilities, fixed assets and long term liabilities plus shareholder's fund. By dividing each of the four categories by their sum (twice the total assets or liabilities plus shareholder's fund) we obtain four ratios which are presented in Table 4.5. The notation indicates that the balance sheet is regarded in each period as a bivariate array.

The corresponding balance sheet decomposition measure is defined as:

$$\text{BSDM} = \sum_{i=1}^{2} \sum_{j=1}^{2} q_{ij} \log \frac{q_{ij}}{p_{ij}} \qquad (1)$$

where the same properties are those described in the preceding paragraph hold.

TOTAL ASSET AND TOTAL LIABILITY DECOMPOSITION MEASURE

In this case the change measured is the change in the different items composing the asset side or

	Assets		Liabilities		Total	
	year t	year t+1	year t	year t+1	year t	year t+1
Current	p11	q11	p12	q12	p1	q1
Fixed	p21	q21	p22	q22	p2.	q2.
Total	p.1=.5	q.1=.5	p.2=.5	q.2=.5	.1	1

TABLE 4.5 DECOMPOSED BALANCE SHEET

liability side of the balance sheet. The degree of decomposition will vary with the importance given to each item or group of items. Table 4.6 gives the degree of decomposition adopted thereafter. p_{ai} ($i = 1,\ldots,4$) denotes the relative share of the total asset i^{th} item in year t and q_{ai} the corresponding relative share value in year t-1. p_{li} and q_{li} ($i = 1,\ldots,4$) are calculated in the same manner for the total liabilities.

The total asset decomposition measure is defined as

$$\text{TADM} = \sum_{i=1}^{4} q_{ai} \log \frac{p_{ai}}{q_{ai}}$$

while the total liabilities decomposition measure is defined as

$$\text{TLDM} = \sum_{i=1}^{4} q_{li} \log \frac{p_{li}}{q_{li}}$$

Here again the larger the value, the greater the structural change between year t and year t + 1.

During the description of the decomposition measures the structural change measured was over a period of one year. However, these measures can be applied to estimate structural changes over any

	TOTAL ASSETS		TOTAL LIABILITIES		
	year t	year t + 1	year t	year t + 1	
Net fixed assets	pa1	qa1	pl1	ql1	Equity
Inventory	pa2	qa2	pl2	ql2	Long term Liabilities
Debtors	pa3	qa3	pl3	ql3	Creditors
			pl4	ql4	Short Term Borrowings
Cash & Equivalent	pa4	qa4			
Total	1.o	1.o	1.o	1.o	Total

Table 4.6 DECOMPOSED TOTAL ASSETS AND TOTAL LIABILITIES

period of time. The evaluation of structural change over a two year period of time was considered in this study alongside the one year period of time. To differentiate between the measures, BSDM 1, TADM 1 and TLDM 1 refer to decomposition measures over one year while BSDM 2, TADM 2 and TLDM 2 refer to the same measures over the two year period of time.

It should be noted that other decomposition measures such as fixed assets or long term liabilities plus shareholder's fund measures of decomposition could have been calculated as well as current assets and current liabilities decomposition measures, but the information available was not detailed enough to permit meaningful calculations. Beside the variability they would have measured is to some extent considered by the measures of stability discussed below.

4.2.2.1.2. Variance Type Measures.

The idea of using variance type measures as indices of stability originated with the advent of modern portofilio theory. An individual investing money in the capital market will be faced with the problem of selecting securities with optimum future outcome. The estimate of this rate of return will be based on past performance of the chosen shares. However, the predicted outcome of the securities will be very rarely perfectly accurate and generally the investor will experience some differences between his predicted and realised rates of return. Hence he will predict different outcomes for each share and associate to them probability of occurrence. The larger the number of possible outcomes and the more evenly spread their probability of occurrence, the larger the uncertainty of the future rate of return and therefore the higher the risk associated with that particular security.

In the following example, two shares are considered with the same expected outcome of say, fifteen per cent. However, the chance that the predicted rate of return differs from the future outcome are not similar. Figure 4.2 gives the different outcomes and the probability attached to them for security 1 while Figure 4.3 gives those of security 2.

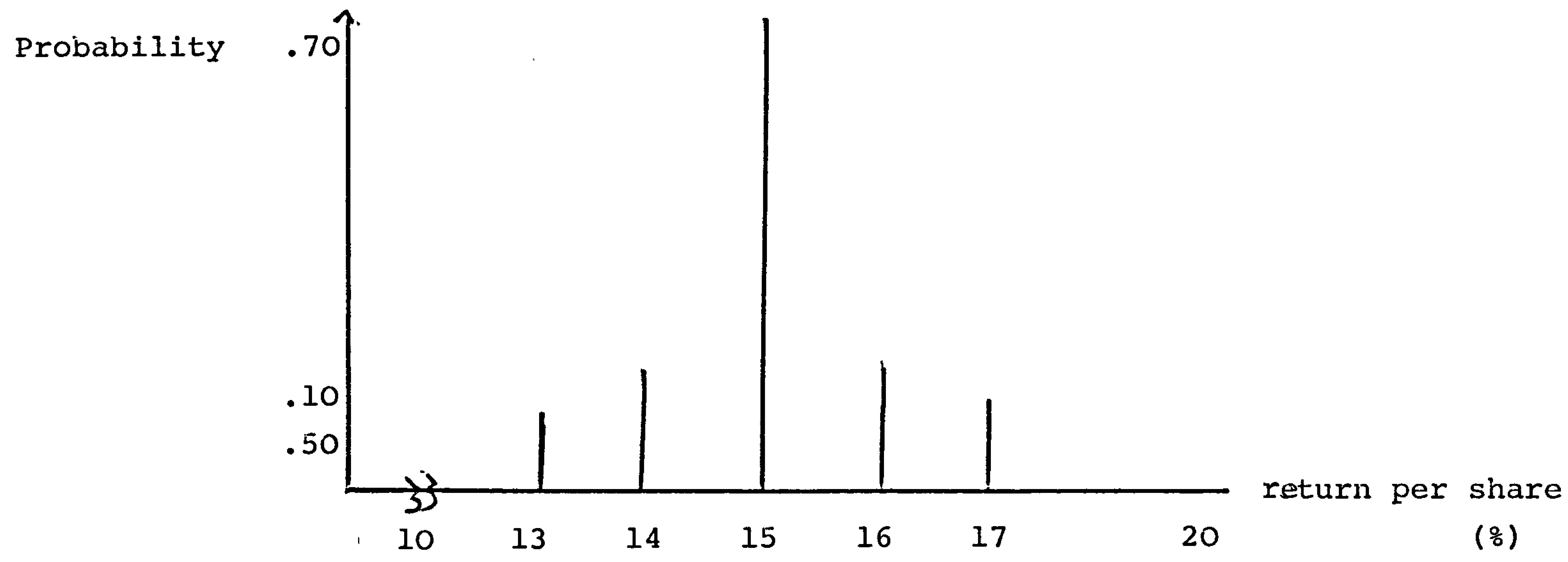


Figure 4.2 Forecast of share I rate of return

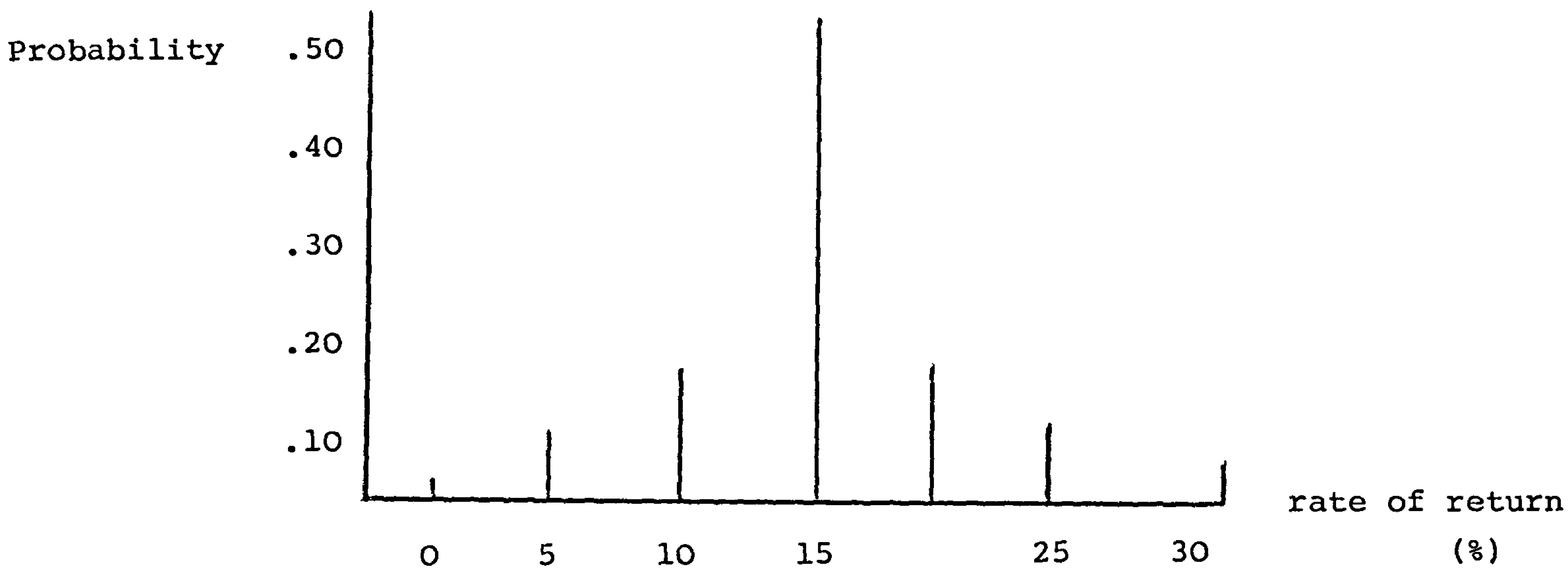


Figure 4.3 Forecast of share II rate of return

Figure 4.2 and 4.3 indicate that the uncertainty regarding share II outcome is much larger than that of share I. While share I could realise a rate of return spreading from fourteen per cent to seventeen per cent, the possible outcome of share II ranges from zero per cent to twenty five per cent. It is obvious that a prospective investor would not regard those shares in the same fashion despite an equal expected rate of return. An individual investing money in share II may see his capital increase by nearly a third in a year's time but he could, as well, find himself with no gain at all at the end of the year. Certainly, some investors would be very reluctant to invest money in share II and would prefer instead the safer terms of investing money in share I.

This point illustrates that to take any decisions an investor has to consider two factors:-

1. expected outcome,
2. uncertainty regarding the outcome that is measured by the "extent to which the actual return may deviate from the predicted one". Lev (1974)

This approach is known as the two dimensional investment model since it assumes that the future rate of return of a security can be evaluated using a probability distribution. Two statistics can be calculated to summarize it. The mean or expected value which measures the central tendency of the distribution and variance which measures the dispersion of the distribution around its mean. The estimation of these two parameters is often calculated on past behaviour of the security. The implicit assumption is that time series of a security outcome may be considered as a random sample from a distribution of future rate of return. If a share has been having a constant outcome for, say, the last ten years then it would be probable that its rate of return for the present year will be the same. On the contrary a security that has failed to keep its outcome close to a certain value in the past, will make a prediction of the present year rate of return much more difficult to estimate.

Taking the two securities mentioned earlier and assuming that the probability has been computed from past observations, the two statistics would be:-

SHARE	MEAN	ST. DEVIATION
I	15%	1.154
II	15%	5.685

reflecting the higher risk associated with Share II since it has a much higher standard deviation for the same expected value.

The standard deviation expressed in that manner represents, in fact, the degree of stability of the performance of a security over a certain period of time. This concept of stability of performance has been introduced into the more general field of financial analysis. At the beginning, it was confined to the variability of earnings. Fisher (1959) in his model predicting bond risk premium included among the explanatory variables a measure of stability of earnings expressed by the coefficient of variation of the companies' net income before taxes over a period of nine years.

This new idea of including the stability of earnings in the variables assessing companies' performance was emphasised once again by Blum (1974) where in his Failing Company Model, the standard deviation of the net income over a period of three years was among the variable he selected and included in a discriminant function identifying possible failures amongst going companies. This concept was taken even further when Altman et al (1977) and Blum (1974) extended it to the variability of ratios themselves. Blum (1974) calculated the standard deviation of the quick assets to inventory ratio while Altman et al (1977) considered the stability of the earnings before interest and taxes to total asset ratio. Although both studies were concerned with the problem of ratio stability, Altman et al (1977) used the normalised measure of the standard error of estimate around a ten year trend of the ratio. This method of estimation was later found to be less effective than the more usual variance type measure by Dambolena and Khoury (1980).

Their study addressed the question of ratio stability as a whole. They argued that the stability of every ratio should be assessed and not just that of earnings or any other particular ratio. They selected nineteen ratios and evaluated the stability of each one in four different manners:-

1. the standard deviation of the ratio over three year periods.
2. its standard deviation over four year periods.
3. its standard error of estimate around a four year linear trend.
4. its coefficient of variation over four year periods.

Discussing the study results, they pointed out that the ratio stability concept added much weight to "the conceptual framework of models predicting corporate bankruptcy". They noted that, although retaining standard deviations over four year periods, the standard deviations over three year periods yielded very similar results while results produced by the standards error of estimate were slightly less significant and those obtained using coefficients of variations were much inferior.

Following the same lines, Betts and Belhoul (1982b) showed the usefulness of stability measures in their study on U.K. based companies. Standard deviation over three year periods were computed on all the twenty eight ratios selected and two of them entered the final discriminant function which showed great accuracy in identifying companies in financial difficulties up to three years before bankruptcy occurred.

In the present study the standard deviation are calculated on all the thirty six selected ratios. The span of time over which they were computed is limited to three years because the data available cover at most seven years for each company. Considering a lengthier period would have otherwise reduced the number of periods to be analysed. Furthermore, as mentioned by Dambolena and Khoury (1980) there appears to be no gain from lengthening those periods.

THE MATHEMATICAL FORMULA

The standard deviation of ratio i (i = 1-36) over the j^{th} period was defined as follows -

$$SR_{i,j} = \sqrt{\frac{\sum_{k=1}^{n} (R_{i,j+k-1} - \overline{R}_{i,j})^2}{n}}$$

where:

$\overline{R}_{i,j}$ is the mean of ratio i (i=1-36) for period j (e.g. three successive years. Example: $\overline{R}_{i,1} = \frac{R_{i,1} + R_{i,2} + R_{i,3}}{3}$)

$R_{i,j+k}$ is ratio i (i=1-36) for year j+k.

The number of periods was equal to five.

n is the length in years of the interval of time considered, in this case three years.

The stability measures are a description of past behaviour of financial ratios for the periods analysed. They are not used in the prediction of future events. The financial ratios can then be considered as fixed rather than random variables explaining the use of n as the denomination of the variance formula.

4.2.2.2 MEASURES OF TREND AND CHANGE

These measures were included in order to establish whether companies that experience a higher growth rate were more likely to be amongst the well performing group. The rates of growth were looked at from two angles:-

1. trend over the periods over which the stability of the financial ratios were assessed.
2. Changes over the previous year.

The variables on which these measures were calculated included total assets, sales, inventory, creditors, and debtors. The last three measures were considered because they are related to sensitive areas. The problems experienced by companies can often be traced back to over stocking or deficient credit policies. It would then seem sensible to expect more efficient companies to have a better control of them. The other two measures are directly related to size. Company growth is seen as an achievement by most managements but growth is very much dependent on profit. It would then be relevant to discover whether a high rate of growth means a high level of performance.

The formulae employed to calculate these measures are as follows:-

1. Measures of Trend.

Assuming a natural growth, the value of the variable at time t is given by;

$$x_t = a + e^{tb} \tag{1}$$

The average growth over n periods of time (year) is equal to:

$$\left[\frac{e^{(n+1)b} - e^{nb}}{e^{nb}} + \frac{e^{nb} - e^{(n-1)b}}{e^{(n-1)b}} + \ldots \frac{e^{2b} - e^{b}}{e^{b}} \right] / n = e^{b} - 1$$

The least square estimate, b, is calculated by regressing the annual value of the variable for each year of the relevant period using the following logarithmic form derived from;

$$\log x_t = \log a + bt + u_t$$

As for the stability measures, the aim of this measure of trend is not to predict future value of x's but to describe past trend of the variables which can therefore be considered as fixed.

2. Change over the previous year.

This measure was computed as follows:-

$$CH_t = \frac{X_{t+1} - X_t}{X_t}$$

Both measures of trend and of change over the previous year were expressed as percentages. TRTA, TRSA, TRIN, TRCR, TRDEB refer to trends in total assets, volume of sales, inventories, creditors and debtors. CHTA, CHSA, CHIN, CHCR and CHDEB was used to specify the measures of change over the previous year of the same items.

4.2.2.3 MEASURES OF SIZE

Company size has been found to be a contributing factor to the identification of bankruptcies (Altman et al, 1977). The inclusion of such measures was to test their significance with respect to the problem presently studied. The variables selected were two of three that are traditionally selected to measure the size of a company: Total assets, volume of sales and number of employees. The total number of employees could not be considered due to missing information as explained in the preceding chapter. Total assets were taken inclusive of current liabilities, associated companies, intangibles and investments and sales were taken gross of value added tax.

SIZE I and SIZE 2 respectively refer to total assets and volume of sales.

To conclude this section on other financial variables, one must bear in mind the limits of trend measures and of stability measures estimated by the standard deviations. In both cases, a small number of variables are used to calculate them. From a statistical viewpoint these measures are meaningless but as pointed out earlier, they are a description of past behaviour and are not considered for inference purposes. For example, the stability measure is a description of the variability of a particular ratio over the last three years and not an estimate of its general stability.

Furthermore, lengthening the period of time besides the constraints due to the availability of data, would not suit the analysis as the focus of interest is to assess whether alterations of any financial aspects of a company could lead to a change in its level of performance. The lead time between those two events would certainly be short hence the selection of a three year period.

4.3 TESTING THE NORMALITY OF THE DATA

As the discriminant rule is optimum when the data are separately multivariate normal, their distribution were examined. Although the separate univariate normality of each variable is not a sufficient condition to ensure the multivariate normality of the data set, it was thought that multivariate normality would be more likely since if this is the case, the marginal distribution of each variable should be normal (Taffler,1982).

In order to test the normality of the variables a goodness of fit test was performed. There are two types of tests available:

(a) graphical tests.

(b) analytical tests.

Graphical tests are based on visual examination of plots. The variables are plotted using special scaling, in this case a normal probability scale would be used. This results in the points falling on an appropriate straight line. Visual inspection of such plots would indicate whether the variables are following a normal distribution. The lack of fit can be quantified by estimating the residual sum of squares of the least square fitting of a line through the points (Bain,1978). The resulting coefficient correlation can also be used as an indice of goodness of fit. The main criticisms concerning graphical tests are related to their dependence upon visual inspection. However they are always useful at the initial stages of investigation.

Analytical methods of testing overcome this problem. They are derived from the distribution of the sample values.

4.3.1 KOLMOGOROV - SMIRNOV TEST

This test is based on the distribution of the values of cumulative probabilities. If N observations are arranged in ascending order, the experimental distribution function is given by:-

$$ECDF(i) = \frac{i}{N}$$

where $i = 1,\ldots,N$

The test statistic Dmax is given by:-

$$D_{max} = \sup_{i=1,N} \{|F(i) - i/N| \cup |F(i)-(i-1)/N|\}$$

where $F(i)$ is the value of the hypothesised cumulative distribution function in the present case the cumulative normal distribution.

Critical rules at different levels of significance are given in appendix V. The null hypothesis is that the variables come from a normal distribution and the test is one tailed.

4.3.2 CHI-SQUARE TEST

The observations are firstly divided into K classes. The observed frequency of each class, is estimated (number of occurrences). The test consists in evaluating if the differences between the observed and expected frequencies are significant enough to lead to rejection of the hypothesised distribution as a good fit. The test statistic is computed as follows:

$$W = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i}$$

Where O_i is the observed frequency of the i^{th} class

E_i is the expected frequency of the i^{th} class given by the probability P_i of any observation falling in class i multiplied by the total number of observations (N). W has a chi-square distribution as N tends to infinity.

This test requires a minimum of five observations per class. Usually eight classes are selected. The number of degrees of freedom to find the critical values of the chi-square distribution is given by:

$$df = k - s - 1$$

where s is the number of parameters of the hypothesised distribution, in the present case s equals two for the normal distribution. The main disadvantages of the chi-square test are its sensitivity to extreme values and to the number of classes selected. As a consequence the Kolmogorov-Smirnov test for goodness of fit was preferred and used in the analysis.

Every variable was tested for each year. In addition, square root, log normal and reciprocal transformation as suggested by Kirk (1968) to improve normality were also employed. Truncation of the data was performed to reduce the effect of extreme outliers. Variables lying more than three standard deviations from the mean were replaced by the mean. The number of terms concerned was always very little, never greater than one per cent of the number of observations.

Dmax values were computed for each variable and for its transforms as well. If the value of D max was reduced using a transformation, the variable would then be expressed using that transformation. A list of the variables transformation retained together with their level of significance is given in Table 4.7.[1] Most of the variables are significant at more than the .05 level but it should be noted that for a certain number of variables the null hypothesis is rejected. This should be borne in mind when the discriminant analysis is performed. If any variable that is not distributed normally is selected then the consequences on the performance of the model should be evaluated.

The variables for which the reciprocal transform led to an improvement in normality will be expressed hereafter as their inverse. Therefore R10, R21, R29 and R35 will be expressed as CA/SALES, LTL/NW, ST/SALES and WC/LTL respectively.

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1 The computer programmes used to calculate and test the data are given in Appendix X.

TABLE 4.7: TRANSFORMATION AND NORMALITY TESTING

	Variable	Transform.		Level of Significance	
		Ratios	Stab.	Ratios	Stab.
1	EBIT/TA	NONE	LOG	A	C
2	EBIT/NCE	NONE	LOG	A	F
3	EBT/TA	NONE	LOG	A	C
4	EBIT/NW	NONE	LOG	A	C
5	EBT/SALES	NONE	LOG	A	C
6	SALES/TA	LOG	LOG	C	F
7	SALES/NW	LOG	LOG	D	B
8	WL/SALES	NONE	LOG	E	E
9	SALES/FA	LOG	LOG	C	D
10	SALES/CA	RECI	LOG	C	B
11	CA/CL	LOG	LOG	C	C
12	CL/NW	LOG	LOG	C	C
13	CASH/CL	LOG	LOG	B	A
14	WL/TA	NONE	LOG	C	B
15	CASH/TA	LOG	LOG	B	A
16	QA/CL	SQRT	LOG	C	C
17	GA/TA	NONE	SQRT	C	C
18	NW/TL	LOG	LOG	C	C
19	EBIT/T.INT.	NONE	LOG	C	B
20	TL/TA	NONE	SQRT	E	C
21	NW/LTL	RECI	LOG	D	C
22	CF/TL	NONE	LOG	A	A
23	CF/CL	NONE	LOG	A	A
24	CF/WC	NONE	LOG	A	A
25	CF/TA	NONE	LOG	A	C
26	DAYS DEBT.	NONE	LOG	C	C
27	SALES/DEBT	NONE	LOG	C	D
28	DAYS CRED.	SQRT	LOG	D	D
29	SALES/St	RECI	LOG	A	B
30	INV/WC	NONE	LOG	A	B
31	CL/INV	RECI	LOG	A	B
32	INV/CA	NONE	LOG	C	B
33	WC/NW	NONE	LOG	B	C
34	WC/NE	NONE	LOG	C	C
35	LTL/WC	RECI	LOG	C	C
36	NW/TA	NONE	SQRT	A	C

LOG = lognormal

RECI = reciprocal

SQRT = square root

A : Less than .01

.057 B 70.01

.057 C 7.1

.17 D 7.15

.157 E 7.20

F : More than .20

Variable	Transform.	Sign.Level
BSDM1	LOG	D
TADM1	LOG	D
TLDM1	LOG	B
BSDM3	LOG	D
TADM3	LOG	D
TLDM3	LOG	b
INC 1	NONE	A
INC 2	NONE	A
INC33	NONE	A
INC 4	NONE	A
INC 5	NONE	A
TR 1	NONE	A
TR 2	NONE	A
TR 3	NONE	A
TR 4	NONE	A
TR 5	NONE	A
SIZE 1	NONE	A
SIZE 2	NONE	A

4.4 UNDERSTANDING THE FINANCIAL DIMENSIONS REPRESENTED BY THE VARIABLES

Knowing the financial dimensions represented by each variable would certainly help in giving a meaning to the variables that will enter the discriminant function. If each variable is known to be associated with a particular aspect of a firms financial characteristics, it would definitely be simpler to analyse which financial dimension is of importance to the problem investigated and to understand the varying level of firms performance.

As mentioned in the preceding section, financial ratios have always been grouped into sets that should contain very specific information about companies. Such groupings evolved from the traditional four category model (Profitability, Liquidity, Solvency and Efficiency) to the more complete categoric framework proposed by Courtis (1978) and discussed in the preceding section. The selection of the ratios were done along the lines proposed by Courtis (1978) and categorised according to his model. But it would be of interest to investigate whether the empirical grouping of the financial ratios would be the same as that presented in Table 4.3 and whether these categories contain specific information.

Courtis (1978) addressed partially those questions when he pointed out that financial ratios present some degree of collinearity. This presence of collinearity among financial ratios can be attributed to two sources:

- The use of common components as the denominators or numerators of the ratios.

- The tendency of some elements of the balance sheet, and profit and loss account to move in the same direction.

Table 4.8 illustrates the pattern of collinearity that can be due to the use of common elements in constructing financial ratios. The same components are often employed. Total assets are found as the denominator of nine ratios while sales appear six times as numerator. But more important is the presence of common elements in the financial ratios classified under different headings (i.e. Return on investment, Credit Policy) and even under the three different overall categories (i.e. Profitability, Solvency, Managerial Performance). Another point worth noting is that none of the ratios has unique components. They all employ components that have been used in constructing at least one other financial ratio. Had some ratios with unique components been present this would not have

TABLE 4.8: VISUAL DISPLAY OF MULTICOLLINEARITY

Denominators \ Numerators	Cash	Cash Flow	Creditors	Current Assets	Current Liabilities	Debtors	EBIT	Long Term Liabilities	Net Income	Net Worth	Quick Assets	Sales	Stocks	Total Liabilities	Working Capital	TOTALS
Current Assets												SL	IN			2
Current Liabilities	SL	CF		SL							SL					4
Debtors												CP				1
Fixed Assets												CT				1
Long Term Liabilities										LS						1
Net Capital Employed							RI								AE	2
Net Worth					SL				RI			CT			AE	4
Sales			CP			CP			PM						CT	4
Stocks					IN							IN				2
Total Assets	SL	CF					RI		RI	AE	SL	CT		LS	SL	9
Total Interests							LS									1
Total Liabilities		CF								LS						2
Working Capital		CF						AE					IN			3
TOTALS:	2	4	1	1	2	1	3	1	3	3	2	6	2	1	4	36

The abbreviations used in the inside of the table refer to the category defined in Table 3:

RI = Return on Investment

PF = Profit Margin

CT = Capital Turnover

SL = Short Term Liabilities

LS = Long Term Solvency

CF = Cash Flow

CP = Credit Policy

IN = Inventory

AE = Asset-Equity Structure

insured their independance from the rest of the ratios since as we have noted earlier some of their elements may move in the same direction more or less proportionately. As examples, one can take sales and cost of goods sold or the level of inventory and sales or simply total assets and the level of activity (sales) or profitability.

The information deducted from the visual inspection of Table 4.8 indicates that Courtis'(1978) framework, although being a very comprehensive approach to the selection of financial ratios may not be consistent with empirical groupings of ratios. Pinches et al (1974), Laurent (1979), and Taffler and Sudarsanam (1980) who carried out research on the empirical groupings of ratios failed to bring out separate dimensions for the profit margin and cash flow position that were both part of the profitability dimension in their findings. On the other hand, some of the categories such as Asset-Equity Structure and Short Term Liquidity could be broken down into more sub-categories:i.e. Fixed assets management and Working capital management (Laurent 1979), cash position (Pinches et al, 1974). It should be noted that the financial ratios employed in those studies covered all the categories of Courtis' framework but for the Administration category because most of the information needed to construct ratios falling in that category is not available from the published accounts.

The three studies mentioned above used Factor Analysis as their method of analysis if one considers Principal Component Analysis as one of its variants.

4.4.1 FACTOR ANALYSIS AS A GROUPING METHOD

The problem of grouping can be approached from two different angles. Observations can be grouped into categories on the basis of similarities among themselves or one may look at the inter-correlations among the observations and group together those that are more closely related.

The technique used in the first case is cluster analysis where a logical and systematic search procedure is undergone to identify homogeneous clusters. The procedure starts by grouping the two most similar observations. Then it localises another observation not already in the cluster which is the most similar to the previous ones. This new observation is the next candidate for inclusion in the cluster unless the degree of similarity is not high enough. In this case a new cluster is created along side the previous one and the same procedure is followed again until all the observations are grouped. This technique which has been used in financial studies (Gupta and Huefner, 1972; Jensen, 1971; Meyers, 1973) presents the advantage of forcing all the observations into groups but as

Overall and Klett (1972) pointed out it has the disadvantage of forming groups based on simple Euclidean distance. Besides, they have found cluster analysis methods sensitive to sampling variability,in that results derived from one sample do not reappear consistently leading to the necessity of repeating extensively the analysis until the obtained groupings are representative of the population being studied.

Factor analysis is the technique employed in the second case. This is the method that will be used later in the study because it does not present the limits of cluster analysis and has been widely applied to the grouping of financial ratios enabling a comparison with earlier findings. A description of factor analysis will be presented below.

4.4.1.1 DESCRIPTION OF FACTOR ANALYSIS

Factor analysis encompasses different multi-variate procedures developed to analyse the inter-relationships of a set of variables. Its main objective is to linearly transform a set of variables into a smaller number of new variates that have the property of being uncorrelated.

The earliest contributions to factor analysis were made by the psychologist Charles Spearman (1904) and by Karl Pearson (1901) who suggested the method of principal axes, later known as the method of principal components. Spearman's work was based upon his theory of general intelligence whereby, in a battery of intellectual activity tests, there exists a common factor that is measured by all the tests (general intelligence factor) and a specific factor that is measured only by one test and by no others in the battery. The mathematical development of his general intelligence theory led him to the concept of his two factor method. His work was later developed by Thurstone (1931, 1938, 1947) who questioned the general intelligence theory and proposed a multiple-factor model that reflected his belief about the existence of several primary mental abilities as opposed to one general mental ability. Thurstone's model was neverthless a continuation of Spearman's concept in that the information contained in a set of variables can be expressed in the form of common factors and a specific factor that includes an error term factor. The common factors would be less numerous than the initial variables and would facilitate the interpretation of the information included in the variables.

On the other hand, Pearson (1901) started from a different viewpoint. He made no distinction between common and unique factors. His method applied a linear transformation to the variables analysed in order to produce a set of independent and standardized new variables. This method was known as the principal axes method and was later fully developed by Hotteling (1933). It is now called principal component analysis. This method as stated earlier transforms a set of correlated variables into a set of statistically independent linear combinations. The first such linear combination, principal component, is that which accounts for a maximum of the total variation in the initial set of variables. The second principal component is uncorrelated with the first component and accounts for the maximum of the remaining variance. The n^{th} will be uncorrelated with $(n-1)$ previous principal components and will account for the maximum of the remaining variation. The process of extraction can be stopped when the variance accounted for by any additional principal is not statistically significant.

The difference between the two methods presented above are summarised in Lawley and Maxwell (1971) and in Mardia et al (1980). The first method is said to be correlation or co-variance orientated while principal component analysis is variance orientated. Another difference concerns assumptions in component analysis where the new factors are by definition linear function of the variables being analysed and therefore no question of hypothesis arises. In contrast, the first method of factor analysis requires that the elements of the unique factor be independent of each other and of the common factors. Although conceptually different these two approaches seek the same results and produce very similar results. Blackith and Reyment (1971) scrutinized a large number of factor analysis and principal component analysis studies and failed to see any superiority of one method over the other.

In the following analysis, the principal component method is used for the reasons mentioned below:-

1. The results it produces do not differ noticeably from those of factor analysis.
2. Principal component analysis is mathematically neater (Linderman et al, 1980) and yields results that are more readily interpretable.
3. Estimation of communalities to be placed in the diagonal of the correlation matrix is not required.
4. The computer time needed to arrive at the final set of components is shorter than with the other methods.
5. Principal component analysis was employed in two previous studies investigating the relationships among financial ratios (Laurent 1979, Taffler and Sadursanam,1980). Although Laurent's study was on companies based in Hong Kong, it was felt that accounting practices in use in Hong Kong were similar to those in use in the United Kingdom and that any divergencies that may arise in the findings of those two studies and the present analysis would not be attributed to the use of different techniques.

4.4.1.2 THE PROCEDURE OF PRINCIPAL COMPONENT ANALYSIS

The procedure of principal component analysis starts with a fundamental assumption that can be presented as follows:

$$p_{ik} = a_{i1} z_{1k} + a_{i2} z_{2k} + \ldots\ldots\ldots + a_{im} z_{nk} \qquad (1)$$

p_{ik} is a standard score for observation k (in our case company k) on principal component i

a_{i1} is the coefficient of the standardized variable 1 (financial variable i) corresponding to principal component i

a_{i2} is the coefficient of the standardized variable 2 corresponding to principal component i

a_{in} is the coefficient of the standardized variable n corresponding to principal component i

z_{ik} is the standard score of observation k on variable I

z_{2k} is the standard score of observation k on variable 2

z_{nk} is the standard score of observation k on variable n

Equation (1) illustrates the aim of principal component analysis i.e. to construct out of a set of variables, new variables which are linear combinations of the initial variables.
It should be noted that the unstandardized value of z_{ik} or its deviation from the mean could be employed. However, the values of the principal components would vary depending on the way in which the variables are measured. One has adopted the procedure of standardized variables because it is the most commonly used and is more general in that it can be applied to variables measured in different units.

The steps involved in principal component analysis can be summarized as follows:

a) definition of the fundamental equations
b) extraction of the principal components
c) decision on the number of principal components to be retained
d) rotation of the principal components
e) interpretation of the principal components

a) <u>FUNDAMENTAL EQUATIONS</u>

Equation (1) can be written in matrix form as

$$P_k = ZA_k \qquad (2)$$

where p is a vector n of the score on principal component k (k=1,..,n) for all the observations.
Z is the n,n matrix of standardized variables.

A_k is the vector of coefficients corresponding to principal component k (k = 1,...,n)

The variance of p is :

$$\frac{p_k' p_k}{N} = \frac{1}{N} A_k' Z' Z A_k \tag{3}$$

Since the principal components are in standardized forms, equation (3) is then equal to:

$$\frac{p_k' p_k}{N} = A_k' \frac{Z' Z}{N} A_k = A_k' R A_k \tag{4}$$

Where R is the correlation matrix of the initial set of variables. We now wish maximize the left hand term of (4) with respect to A_k, but we should impose some constraints on A_k :

1) Because of the fundamental assumption that the principal components should be independent from each other.
2) Otherwise the quantity $\frac{P'P}{N}$ could be made infinitely large.

This is done by 2) normalizing the vectors A_k (k=1,...,n) and by 1) setting their products with each other equal to zero.

Thus:

$$A_k{}' A_k = 1 \qquad k=1, n \tag{5}$$

$$A_k{}' A_l = 0 \qquad k\neq l;\ k=1,..,n;l=1,..,n \tag{6}$$

For a full discussion of these points see Johnston (1972) and Anderson (1958). The next stage is now to maximize (4) subject to (5),(6). We define

$$A_k = A_k{}' RA_k - \lambda_k \ (A_k'A_k - 1) - \sum_{i=1}^{k+1} n_i(A_k'A_i) \tag{7}$$

where λ and n_1, n_2.... n_{k-1} are lagrange multipliers. The vector of partial derivatives is

$$\frac{\partial \Delta}{\partial A_k} = 2RA_k - 2\lambda_k A_k - \sum_{i=1}^{k-1} n_i A_i \tag{8}$$

and we set it equal to 0. It can be shown (Anderson, 1958) that each of the langrange multiplier n_i is equal to zero.

Equation (7) can be then presented as:

$$RA_k = \lambda_k A \tag{9}$$

$$RA_k - \lambda A_k = 0 \tag{10}$$

$$(R - \lambda_k I)A = 0 \tag{11}$$

b) EXTRACTION OF THE PRINCIPAL COMPONENTS

As it can be noticed the problem is to solve equation (10) for A_k in which the λ_k s are the latent roots or eigenvalues of R and the Aks are the associated eigenvectors. In appendix I a method is presented to solve equation (11). The characteristic equation of R is derived :

$$|R - \lambda_k I| = 0 \tag{13}$$

which has n possible value of λ_k as R is a n x n matrix and n is the number of variables. The associated vectors A_ks are multiplied by the square root of the corresponding eigenvalues.

$$A_k = A_k \sqrt{\lambda_k} \tag{14}$$

to satisfy the condition

$$\lambda_k = \sum_{i=1}^{n} a_{ik} \tag{15}$$

where a_{ik} is an element of vector A_k (Harman 1970). The solution of equation (11) can be very tedious when n is large but several methods have been developed to overcome this problem. The most well known are

Thurstone's (1947) centroid method, Hotelling's (1933) iterative procedure and more recently methods based on the work of Jacobi (1846) and one proposed by Francis (1962, 1961) known as the Q-R method. In this study, SPSS[1] was used to perform the computations.

Some useful properties of normalized eigenvectors are that :

- the variance of each set of principal component scores is

$$\lambda_k \ (k = 1, \ldots, n)$$

- the continued product of the eignevalues is the determinant of R

$$\prod_{k=1}^{n} \lambda_k = |R|$$

- the sum of the eigenvalues is equal to the trace of R

$$\sum_{k=1}^{n} \lambda_k = \sum_{i=1}^{n} r_{ii} = tr(R)$$

From the above mentioned properties we can deduce that, since the trace of R is the total variance to be accounted for, the proportion of variance explained (V_k) by principal component k is represented by the ratio of the eigenvalue associated with it divided by the trace of R.

$$V_k = \frac{\lambda_k}{tr(R)} = \frac{\lambda_k}{n}$$

where n is the number of variables and of principal components

---

1 The PA1 procedure of SPSS is based on the Q-R method

If we assemble the resultant vectors A_k $(k=1,...,n)$ into a matrix A, equation (1) can be expressed as

$$P = X A \qquad (16)$$

and

$$P' = A' X' \qquad (17)$$

where the n principal components are given by the n x m matrix P. Since A is an orthoganal matrix, equation (14) can be inverted:

$$X' = A P' \qquad (18)$$

where the matrix A is known as the matrix of loadings. The loadings of each variable on the principal components are a form of correlation coefficient. They represent the importance of a given principal component for a given variable. Each element a_{ij} $(i=1,..,n;j=1,..,n)$ of A raised to the power two expresses the amount of variance in variable i that can be explained by principal component j. Likewise, the variance of a variable explained by all the principal components is given by the sum of squares of the respective loadings.

$$h^2_i = \sum_{j=1}^{n} a^c_{ij} \qquad (19)$$

h^2_i is generally referred to as the communality of variable i and should be equal to one if all the principal components are extracted.

c) CRITERIA FOR THE NUMBER OF COMPONENTS TO BE RETAINED

As the aim of principal components analysis is to reduce the dimensionality of the initial set of variables, the question is: how many principal components should we retain?

This aspect of principal component analysis has always been surrounded by a certain controversy. Statistical tests have been developed to evaluate the significance of the principal components but they are not completely satisfactory as the criterion depends upon the size of the sample. Other criteria that are commonly used have been suggested by Kaiser (1960) and Cattell (1966). Both criteria are based on the design of the extraction of the principal components, i.e. the first principal component corresponds to a higher eigenvalue (proportion of variance explained) than the second; the second corresponds to a higher than the third and so on.

Cattell's criterion or "scree test" is based on a graphical representation of the eigenvalues against the order of extraction of the principal components. The principal components that are retained are those for which the curve shows some curvature. Principal components below the point where the curve becomes a straight line are rejected. Figure 4.4 illustrates the rule.

SCREE TEST

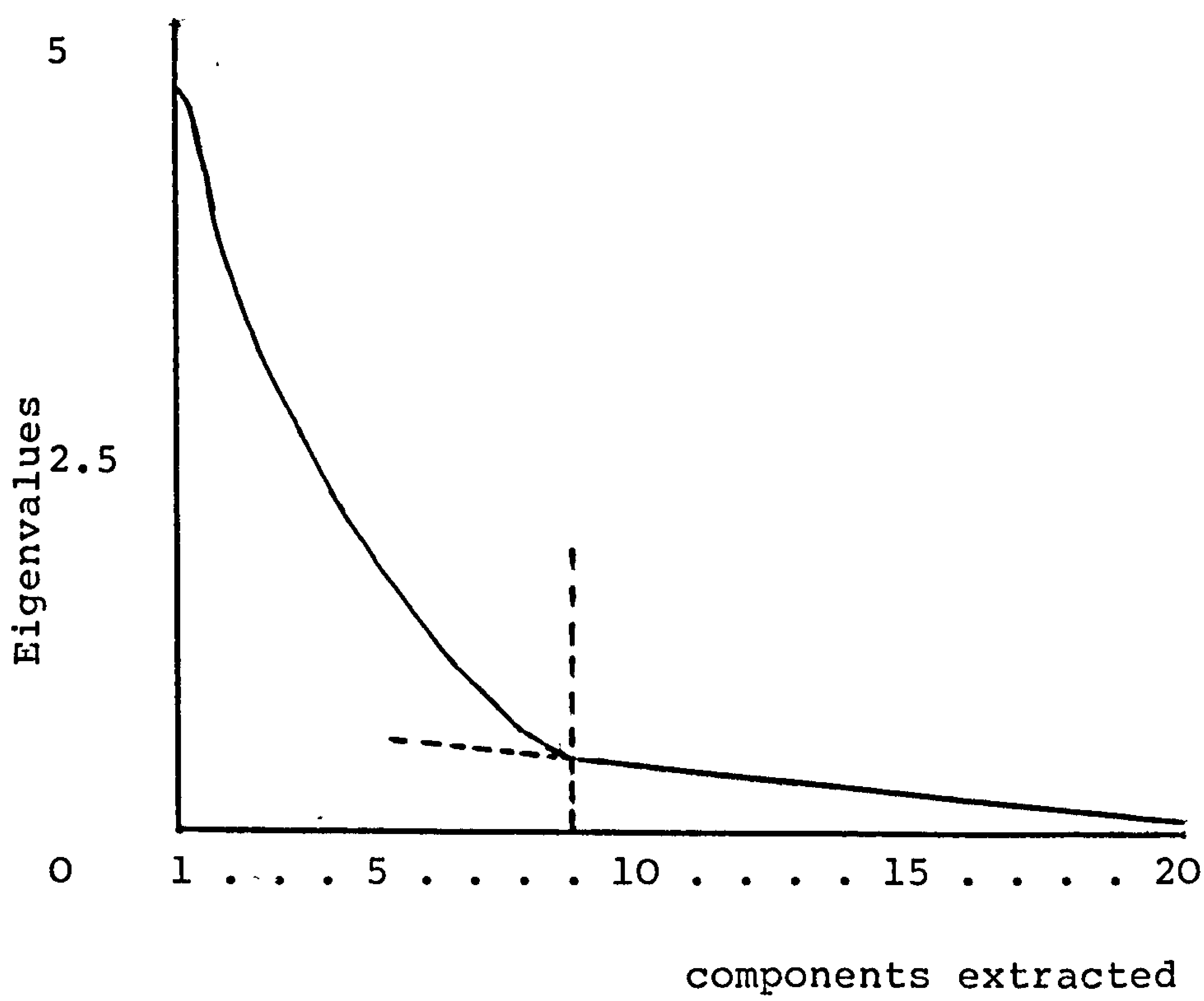


FIGURE 4.4

The number of principal components selected according to Cattell's criterion is nine in the example presented in Figure 1.

Kaiser's criterion is much simpler in its application. The decision rule is to select only those principal components that have an eigenvalue greater than one. The logic behind this criterion is put forward by Harman (1970) when he states that :

" Since the sum of all n roots is precisely n ..... if another dimension is to be added, it would be desirable to have it account for at least an average contribution."

Empirical evidence tends to show that the "scree test" retains more dimensions than Kaiser's criterion does and that Kaiser's rule is particularly reliable when the number of variables is between twenty and fifty. Besides, the number of components retained by applying Kaiser's criterion are generally interpretable as it is proved by the results of a large number of factor analytic studies. The Kaiser's criterion is selected as the decision rule for the reasons given above and because it was the criterion employed in the Taffler and Sudarsanam's (1980) study to which the results are to be compared.

d) ROTATION OF THE PRINCIPAL COMPONENTS

Once the selected number of principal components has been extracted, the patterning of the variables might not be meaningful since the order of principal component extraction depends on their importance. The first principal component so extracted will tend to represent a general dimension as most of the variable will significantly load on it. The remaining principal components will tend to be bipolar having approximately half of the variables loading positively on them and the other half negatively. It would then be difficult to identify the dimension represented by the principal components. Besides, each variable will tend to have negative as well as positive loadings on the different principal components adding more complexity. In order to simplify the principal component structure a rotation of the principal components is performed. Thurstone (1947) proposed some criteria to arrive at a simple structure which are the following:

1) Each row of the pattern matrix A should have at least one zero.
2) If there are m common factors (principal component) each column of A should have at least m zeros.
3) For every pair of columns of A, there should be several variables with elements equal to zero in one column, but not in the other.
4) For every pair of columns of A, a large proportion of the variables should have elements equal to zero in both columns, if there are four or more common factors.

5) For every pair of columns of A there should only a small number of variables with elements not equal to zero in both columns.

If an ideal solution could be reached following Thurstone's criteria the configuration of the simple structure of the pattern matrix based, say, on ten variables and four principal components, should look like this:

Variables	PRINCIPAL COMPONENTS			
	p1	p2	p3	p4
1	77	O	O	O
2	77	O	O	O
3	O	77	O	O
4	O	77	O	O
5	O	77	O	O
6	O	O	77	O
7	O	O	77	O
8	O	O	O	77
9	O	O	O	77
10	O	O	O	77

where 77 indicates a high loading on the principal component and O a near to zero loading. Such a new pattern facilitates the interpretation of the principal components and suggests distinct grouping of variables.

This method has directed for many years factor analysts in their attempts to find simple structure using graphic rotation. However, with the advent of high speed computers analytical solutions for the rotation problem were made feasible. The Quartimax-type methods were firstly developed. (Carroll, 1953; Saunders, 1953; Ferguson, 1954; Neuhaus and Wrigley, 1954) in which the focus was on simplifying the rows of the pattern matrix A. Each variable would have high loadings on the fewest possible factors and zero or close to zero loadings on the others. Several other methods were suggested involving oblique as well as orthogonal rotation. For a discussion of them, see Mulaik (1972).

The solution that will be presented below is due to Kaiser (1958) and is known as the Varimax method. This is a widely used method and has been chosen because it presents the advantage of achieving more closely Thurstone's simple structure criteria. The emphasis is on simplifying the columns and the quantity to maximise is:

$$V = \sum_{k=1}^{m} \left\{ \frac{n \sum_{i=1}^{n} (\ell_{ik}^2/h_i^2)^2 - \left(\sum_{i=1}^{n} \ell_{ik}/h_i \right)^2}{n^2} \right\}$$

where n is the number of variables

m is the number of factors

ℓ_{ik} is the new loading, for variable i on principal component k.

For each principal component Varimax rotation yields high loadings for a few variables and zero or near to zero loadings for the rest of the variables. As a consequence one important aspect of Thurstone's simple structure criteria is achieved. Furthermore the resulting principal components tend to be invariant under changes in the composition of variables (Kaiser, 1958).

e) INTERPRETATION OF THE PRINCIPAL COMPONENTS

As pointed out earlier, a principal component is a variable in the same sense that a financial ratio is a variable. The score obtained on a principal component is then a measure of some characteristic. However, instead of being a direct measure such as a financial ratio or a measure of stability, it is perceived indirectly since it is based on the values of the variables to which the principal component contributes the most. Therefore it is clear that what is measured by the principal component is directly related to what is measured by the variables that have significant loadings on it. Significant loadings in both positive and negative direction are considered. The question is now to determine what is a significant loading. If a variable had a loading of one on one of the principal components that component would be measuring an identical characteristic to that assessed by the variable. On the other hand a loading of zero would mean that no similar trait is measured by the variable and the principal component.

To evaluate the significance of loadings lying between these two extremes several tests have been developed. The more popular are those listed below:

1 An empirical test, based on a very crude rule-of-thumb which is to consider as significant only loadings with a value

greater than ± 0.30 provided the number of observations in the sample is greater than fifty.

2. A test based on the levels of significance of Pearson correlation coefficient. Having said that loadings could be assimilated to correlation coefficients some scholars have suggested to test them in the same way as Pearson correlation coefficient giving for sample comprising more than fifty observations a critical value of ± 0.346 at the one percent level. This fact gives some credit to the rule-of-thumb presented above.

3. The Burts-Banks' test (1947) takes into account the number of variables in the set and the order of extraction of the principal components. An adjustment is made to the standard error of the correlation coefficients in order to obtain the standard error of the loadings:

$$s(1) = s(r)\sqrt{\frac{n}{n+1+m}}$$

where n is the number of variables

m is the position of principal component.

The test tends again to give critical value of about ±0.30 when the samples are fairly large.

This value of about ±0.30 has been often criticized since it would mean that the variable has less than ten percent of its variance in common with the principal component. As a substitute to these tests, Comrey (1973) has given a table that could be a rough guide for the importance of the variables in the interpretation process.

SCALE OF LOADINGS

Orthogonal Component loadings	Percentage of variance	Ratings
.71	50	Excellent
.63	40	Very Good
.55	30	Good
.45	20	Fair
.32	10	Poor

As a consequence it was decided to consider only those loadings that were greater than 0.55 since they represent the ratings good and above. If a lower critical value was considered some variables could be found to load significantly on more than one component.

To conclude this discussion, one of the most important properties of a successful principal component analysis should be stated. That is the principle of factorial invariance as defined by Thurstone (1947). In the context of financial statement analaysis, this principle means that a financial variable associated with a principal component representing a particular characteristic of a firm financial profile, say, profitability, should, when moved from one battery of financial variables to another which involved the same common principal components, be significantly loading on the principal component that depicts the profitability dimension. This is not to mean than the common principal components should be the same for all population of companies. Firms drawn from countries with different accounting practices may exhibit different financial dimensions.

As noted earlier, the varimax rotation scheme tends to possess this invariance property. This fact is pointed out by Harman (1970) when he states that, although varimax factors do not have a greater explanatory meaning than those obtained from other methods, those: "obtained in a sample will have a greater likelihood of portraying the universe of varimax factors."

4.4.2 DIMENSIONALITY OF THE DATA

The principal components method was applied to the set of data comprising all the ratios and stability measures. The non-inclusion of measures of sizes and measures of trend is explained by the fact that these variables are associated with financial characteristics of companies that are not measured by financial ratios. In our earlier discussion about the selection of samples, it was shown that financial ratios are not correlated with size. On the subject of measures of trend it is felt that financial ratios and stability measures are not significantly associated with measures of trend or measures of change over the previous year since an increase or a decrease in the component forming a ratio would not incur a change in the financial ratio proportional to that increase or decrease. To take an example, consider the EBIT/TA ratio. An increase in total assets is not certainly leading to an increase in the ratio since its value depends on the value of EBIT as well. This means that a high or low value on the measures of trend or change would not indicate a high or a low value of particular financial ratios.

The results of the principal component analysis on the five years for which the stability data were available, indicates a certain independance between the stability measures and the financial ratios. None of the stability measures were significant loadings on principal components associated with financial ratios. This underlines the necessity of incorporating this fairly new concept of financial performance stability into any model aiming at representing or at taking into account all the financial characteristics of a firm.

Because of the independance between these two types of financial variables it was decided, for more clarity to analyse them separately. Principal component analyses on the thirty six ratios were performed for every year from 1972 to 1978. The analysis concerning the stability measures covered the period 1974 to 1978. The results of these two analyses are given in Tables 4.9 to 4.15 for the financial ratios and in Tables 4.16 to 4.20 for the stability measures. Only variables with significant loadings i.e. superior to .55 were reported. The results were generally analysed at first, then all the tables were scrutinized to assess the stability of the pattern matrices over time for each analysis. Then the naming of the principal component was attempted and a comparison between the two overall structures was made.

TABLE 4.9: VARIMAX ROTATED PRINCIPAL COMPONENTS - FINANCIAL RATIOS (1978)

RATIOS	PRINCIPAL COMPONENTS							
	1	2	3	4	5	6	7	8
7 - SALES/NW-	.81							
9 - SALES/FA-	.57							
12 - CL/NW-	.94							
18 - NW/TL-	-.93							
20 - TA/TL-	.94							
36 - NW/TA-	-.95							
8 - WC/SALES		.78						
11 - CA/CL -		.84						
14 - WC/TA-		.94						
31 - CL/ST-		.73						
33 - WC/NW-		.92						
34 - WC/NCE-		.80						
1 - EBIT/TA-			.91					
2 - EBIT/NCE-			.87					
3 - EBT/TA-			.89					
4 - EBIT/NW-			.74					
5 - EBT/SALES			.72					
22 - CF/TL-			.72					
23 - CF/CL-			.69					
25 - CF/TA-			.79					
6 - SALES/TA				-.74				
10 - CA/SALES				.77				
26 - DAYS DEBTORS				.83				
27 - SALES/DEBTORS				-.85				
28 - DAYS CREDITORS				.79				
16 - QA/CL					.74			
17 - QA/TA					.71			
32 - ST/CA					-.85			
21 - LTL/NW -						-.89		
35 - WC/LTL -						.56		
13 - CASH/CL -							.91	
15 - CASH/TL -							.94	
19 - EBIT/T.INT -								.81
29 - St/SALES -								.63
Variance explained (%)	24.0	14.9	13.5	10.3	6.0	5.4	4.3	3.1
Cumulative variance explained (%)	24.0	38.9	52.4	62.8	74.1	78.4	81.5	84.2

TABLE 4.10: VARIMAX ROTATED PRINCIPAL COMPONENTS - FINANCIAL RATIOS (1977)

RATIOS	PRINCIPAL COMPONENTS							
	1	2	3	4	5	6	7	8
7- SALES/NW -	.78							
12- CL/NW -	.92							
18- NW/TL -	-.94							
20- TA/TL -	.95							
36- NW/TA -	-.94							
8- WC/SALES -		.79						
11- CA/CL -		.83						
14- WC/TL -		.92						
24- WC/CF -		.58						
31- CL/St -		.76						
33- WC/NW -		.92						
34- WC/NCE -		.83						
1- EBIT/TA -			.92					
2- EBIT/NCE -			.83					
3- EBT/TA -			.90					
4- EBIT/NW -			.75					
5- EBT/SALES -			.74					
22- CF/TL -			.76					
23- CF/CL -			.70					
25- CF/TA -			.80					
6- SALES/TA -				-.74				
10- CA/SALES -				.78				
26- DAYS DEBTORS -				.84				
27- SALES DEBTORS -				-.84				
28- DAYS CREDITORS -				.79				
16- QA/CL -					.70			
17- QA/TA -					.75			
32- St/CA -					-.84			
9- SALES/FA						.55		
21- LTL/NW						-.93		
35- WL/LTL						.60		
13 CASH/CL							.92	
15 CASH/TA							.94	
19 EBIT/T.IN								.76
Variance Explained (%)	25.2	14.9	14.4	10.1	6.1	5.4	4.0	2.9
Cumulative Variance Explained (%)	25.2	40.1	54.5	64.6	70.7	76.1	80.1	83.0

TABLE 4.11: VARIMAX ROTATED PRINCIPAL FACTORS - FINANCIAL RATIOS (1976)

RATIOS	PRINCIPAL COMPONENTS								
	1	2	3	4	5	6	7	8	9
7- SALES/NW-	.78								
12- CL/NW-	.92								
18- NW/TL-	-.95								
20- TA/TL-	.96								
36- NW/TA-	-.97								
8- WC/SALES-		.80							
11- CA/CL-		.83							
14- WC/TA-		.93							
31- CL/St		.78							
33- WC/NW-		.92							
34- WC/NCE-		.87							
35- LTL/WC-		.56							
1- EBIT/TA-			.92						
2- EBIT/NCE-			.86						
3- EBT/TA-			.91						
4- EBIT/NW-			.82						
5- EBT/SALES			.77						
22- CF/TL-			.72						
23- CF/CL-			.61						
25- CF/TA-			.76						
6- SALES/TA-				-.73					
10-CA/SALES				.78					
26- DAYS DEBTORS-				.84					
27- SALES/DEBTORS-				-.85					
28- DAYS CREDITORS				.76					
16- QA/CL-					.69				
17- QA/TA-					.65				
32- St/CA-					-.83				
9-SALES/FA						.60			
21- LTL/NW-						-.88			
13- CASH/CL-							.91		
15- CASH/TA-							.93		
24- NC/CF-								.63	
29- SALES/St-								.79	
19- EBIT/I.INT-									.78
Variance explained (%)	24.3	15.0	13.9	10.1	6.6	5.3	4.1	3.0	2.9
Cumulative variance explained (%)	24.3	39.3	53.2	63.3	69.9	75.3	79.4	82.4	85.2

TABLE 4.12: VARIMAX ROTATED PRINCIPAL COMPONENTS - FINANCIAL RATIOS (1975

RATIOS	PRINCIPAL COMPONENTS							
	1	2	3	4	5	6	7	8
7- SALES/NW-	.78							
12- CL/NW-	.93							
18- NW/TL-	-.95							
20- TA/TL-	.95							
36- NW/TA-	-.94							
8- WC/SALES-		.81						
11- CA/CL-		.84						
14- WC/TA-		.93						
31- CL/St-		.74						
33- WC/NW-		.92						
34- WC/NCE-		.85						
1- EBIT/TA-			.92					
2- EBIT/NCE-			.80					
3- EBT/TA-			.89					
4- EBIT/NW-			.74					
5- EBT/SALES-			.69					
22- CF/TL-			.71					
23- CF/CL-			.66					
25- CF/TA-			.80					
6- SALES/TA-				-.74				
10- CA/SALES-				.78				
26- DAYS DEBTORS-				.85				
27- SALES/DEBTORS-				-.84				
28- DAYS CREDITORS-				.76				
16- QA/CL-					.72			
17- QA/TA-					.65			
32- St/CA-					-.85			
9- SALES/FA-						.56		
21- LTL/NW-						-.89		
35- WC/LTL-						.60		
13- CASH/CL-							.92	
15- CASH/TA-							.94	
19- EBIT/T.INT-								-.61
29- St/SALES-								.61
Variance explained (%)	23.0	15.6	12.8	10.8	6.8	5.4	4.2	2.9
Cumulative variance explained (%)	23.0	38.5	51.3	62.2	69.0	74.4	78.6	81.5

TABLE 4.13: VARIMAX ROTATED PRINCIPAL COMPONENTS - FINANCIAL RATIOS (1974)

RATIOS	PRINCIPAL COMPONENTS							
	1	2	3	4	5	6	7	8
4- EBIT/NW-	.73							
7- SALES/NW-	.80							
9- SALES/FA-	.57							
12- CL/NW-	.92							
18- NW/TL-	-.92							
20- TA/TL-	.94							
36- NW/TA-	-.93							
8- WC/SALES-		.79						
11- CA/CL-		.83						
14- WC/TA-		.92						
24- WC/CF-		.78						
31- CL/St-		.69						
33- WC/NW-		.92						
34- WC/NCE-		.82						
1- EBIT/TA-			.85					
2- EBIT/NCE-			.62					
3- EBT/TA-			.86					
5- EBT/SALES-			.62					
22- CF/TL-			.76					
23- CF/CL-			.66					
25- CF/TA-			.86					
6- SALES/TA-				-.69				
10- CA/SALES-				.77				
26- DAYS DEBTORS-				.84				
27- SALES/DEBTORS-				-.84				
28- DAYS CREDITORS-				.76				
21- LTL/NW-					-.86			
16- QA/CL-						.67		
17- QA/TA-						.64		
32- St/CA-						-.86		
13- CASH/CL-							.92	
15- CASH/TA-							.95	
30- St/WC-								.59
Variance explained (%)	23.7	15.8	13.5	10.2	6.4	5.8	4.2	2.8
Cumulative variance explained (%)	23.7	39.5	53.0	63.2	69.5	75.3	79.5	82.3

TABLE 4.14: VARIMAX ROTATED PRINCIPAL COMPONENTS - FINANCIAL RATIOS (1973)

RATIOS	PRINCIPAL COMPONENTS								
	1	2	3	4	5	6	7	8	9
7- SALES/NW-	.78								
12- CL/NW-	.93								
18- NW/TL-	-.95								
20- TA/TL-	.97								
23- CF/CL-	-.55								
36- NW/TA-	-.96								
8- WC/SALES-		.80							
11- CA/CL-		.84							
14- WC/TA-		.93							
24- WC/CF-		.77							
31- CL/St-		.72							
33- WC/NW-		.92							
34- WC/NCE-		.87							
1- EBIT/TA-			.93						
2- EBIT/NCE-			.82						
3- EBT/TA-			.90						
4- EBIT/NW-			.74						
5- EBT/SALES-			.63						
22- CF/TL-			.66						
25- CF/TA-			.78						
6- SALES/TA				-.68					
10- CA/SALES-				.77					
26- DAYS DEBTORS-				.82					
27- SALES/DEBTORS-				-.83					
28- DAYS CREDITORS-				.75					
9- SALES/FA-					.57				
21- LTL/NW-					-.86				
16- QA/CL-						.62			
17- QA/TA-						.66			
32- ST/CA-						-.85			
13- CASH/CL-							.62		
15- CASH/TA-							.66		
29- SALES/ST-								.71	
19- EBIT/T.INT.									.62
30- ST/WC-									.86
Variance Explained (%)	22.8	15.8	15.1	9.9	6.4	5.6	3.9	3.1	2.9
Cumulative Variance explained (%)	22.8	38.6	53.6	63.5	69.9	75.5	79.4	82.6	85.5

TABLE 4.15: VARIMAX ROTATION OF PRINCIPAL COMPONENTS - FINANCIAL RATIOS (1972)

RATIOS	PRINCIPAL COMPONENTS							
	1	2	3	4	5	6	7	8
7- SALES/NW-	.79							
12- CL/NW-	.91							
18- NW/TL-	-.94							
20- TA/TL-	.95							
36- NW/TA-	-.96							
8- WC/SALES-		.81						
11- CA/CL-		.87						
14- WC/TA-		.94						
24- WC/CF-		.67						
31- CL/St-		.71						
33- WC/NW-		.91						
34- WC/NCE-		.70						
1- EBIT/TA-			.92					
2- EBIT/NCE-			.85					
3- EBT/TA-			.93					
4- EBIT/NW-			.74					
5- EBT/SALES-			.66					
6- SALES/TA-				-.67				
10- CA/SALES-				.76				
26- DAYS DEBTORS-				.85				
27- SALES/DEBTORS-				-.85				
28- DAYS CREDITORS-				.76				
9- SALES/FA-					.58			
21- LTL/NW-					-.86			
35- WC/LTL-					.58			
22- CF/TL-						.77		
23- CF/CL-						.76		
25- CF/TA-						.79		
16- QA/CL-							.63	
17- QA/TA-							.55	
32- St/CA-							.83	
13- CASH/CL-								.93
15- CASH/TA-								.95
Variance explained (%)	22.1	16.1	13.6	10.8	6.7	5.8	4.2	3.3
Cumulative variance explained (%)	22.1	38.2	51.8	62.6	69.2	75.0	79.2	82.5

TABLE 4.16: VARIMAX ROTATION OF PRINCIPAL COMPONENTS - STABILITY MEASURES (1978)

STABILITY MEASURES	PRINCIPAL COMPONENTS										
	1	2	3	4	5	6	7	8	9	10	11
1- EBIT/TA-	.90										
2- EBIT/NCE-	.83										
3- EBT/TA-	.91										
4- EBIT/NW-	.73										
5- EBT/SALES-	.77										
29- St/SALES-	.69										
18- NW/TL-		.85									
20- TA/TL-		.93									
21- LTL/NW-		.60									
36- NW/TA-		.92									
39- TL/DM1-		.67									
42- TL/DM2		.70									
8- WC/SALES-			172								
11- CA/CL-			.87								
14- WC/TA-			.77								
16- QA/CL-			.68								
40- BSDM2			.55								
6- SALES/TA-				-83							
9- SALES/FA-				.72							
10- CA/SALES				.58							
27- SALES/DEBTORS-				.68							
33- WC/NW-					.76						
34- WC/NCE-					.67						
22- CF/TL-						.81					
23- CF/CL-						.77					
95- CF/TA-						.81					
30- St/WC-							.66				
35- WC/LTL-							.87				
38- TADM1-								.90			
41- TADM2-								.90			
13- CASH/CL-									.94		
15- CASH/TA-									.93		
17- QA/TA-										.74	
32- St/CA-										.87	
26- DAYS DEBTORS-											.75
28- DAYS CREDITORS-											.76
Variance explained (%)	24.2	8.9	8.1	7.5	5.7	4.9	3.8	3.6	3.4	3.1	2.5
Cumulative variance explained (%)	24.2	33.1	41.3	48.7	54.4	59.3	63.1	66.7	70.0	73.1	75.6

TABLE 4.17: VARIMAX ROTATION OF PRINCIPAL COMPONENTS - STABILITY MEASURES (1977)

STABILITY MEASURES	PRINCIPAL COMPONENTS										
	1	2	3	4	5	6	7	8	9	10	11
1- EBIT/TA-	.90										
2- EBIT/NCE-	.87										
3- EBT/TA-	.89										
4- EBIT/NW-	.86										
5- EBT/SALES-	.75										
29- St/SALES-	.66										
8- WC/SALES-		.58									
11- CA/CL-		.59									
14- WC/TA-		.85									
33- WC/NW-		.83									
34- WC/NCE-		.85									
40- ESDM2-		.56									
18- NW/TL-			.85								
20- TA/TL-			.93								
36- NW/TA-			.93								
42- TLDM2			.58								
6- SALES/TA-				.87							
7- SALES/NW-				.65							
9- SALES/FA-				.71							
10- CA/SALES-				.65							
27- SALES/DEBTORS-				.67							
22- CF/TL-					.82						
23- CF/CL-					.80						
25- CF/TA-					.80						
38- TADM1-						.90					
41- TADM2-						.90					
30- SALES/WC-							.58				
31- CL/St-							.59				
35- NC/LTL-							.84				
19- EBIT/T.INT-								.57			
31- CASH/CL-									.91		
15- CASH/TA-									.93		
17- QA/TA-										.76	
32- St/CA-										.81	
26- DAYS DEBTORS-											.79
28- DAYS CREDITORS-											.77
Variance explained (%)	22.0	10.0	8.6	6.8	6.4	4.9	3.9	3.6	3.4	3.0	2.8
Cumulative variance explained (%)	22.0	32.0	40.6	47.4	53.8	58.7	62.5	66.2	69.5	72.5	75.3

TABLE 4.18: VARIMAX ROTATION OF PRINCIPAL COMPONENTS - STABILITY MEASURES (1976)

STABILITY MEASURES	PRINCIPAL COMPONENTS											
	1	2	3	4	5	6	7	8	9	10	11	12
1- EBIT/TA-	.91											
2- EBIT/NCE-	.89											
3- EBT/TA-	.89											
4- EBIT/NW-	.86											
5- EBT/SALES-	.69											
14- WC/TA-		.80										
33- WC/NW-		.92										
34- WC/NCE-		.89										
40- BSDM2-		.55										
18- NW/TL-			.79									
20- TA/TL-			.95									
36- NW/TZ-			.91									
6- SALES/TA-				.89								
7- SALES/NW-				.67								
10- CA/SALES-				.79								
27- SALES/DEBTORS-				.71								
22- CF/TL-					.88							
23- CF/CL-					.82							
25- CF/TA-					.83							
11- CA/CL-						.79						
16- QA/CL-						.72						
37- BSDM1-							.60					
38- TADM1-							.86					
41- TADM2-							.86					
29- St/SALES								.57				
30- St/WC-								.60				
31- CL/St-								.63				
35- WC/LTL-								.84				
13- CASH/CL-									.92			
15- CASH/TA-									.93			
17- QA/TA-										.77		
32- St/CA-										.80		
26- DAYS DEBTORS-											.78	
28- DAYS CREDITORS-											.72	
19- EBIT/T.INT-												.60
21- LTL/NW-												.79
Variance explained (%)	19.3	11.2	9.2	6.6	6.6	5.5	4.0	3.6	3.2	3.1	2.6	2.5
Cumulative variance explained (%)	19.3	30.5	39.7	46.3	52.8	58.3	62.3	65.9	69.1	72.2	74.8	77.3

TABLE 4.19: VARIMAX ROTATION OF PRINCIPAL COMPONENTS - STABILITY MEASURES (1975)

STABILITY MEASURES	PRINCIPAL COMPONENTS											
	1	2	3	4	5	6	7	8	9	10	11	12
1- EBIT/TA-	.87											
2- EBIT/NCE-	.87											
3- EBT/TA-	.88											
7- EBIT/NW-	.79											
5- EBT/SALES-	.67											
12- WC/SALES-		.70										
18- NW/TL-		.69										
26- TA/TL-		.92										
36- NW/TA-		.92										
42- TLDM2-		.63										
14- WC/TA-			.65									
33- WC/NW-			.88									
34- WC/NCE-			.76									
8- WC/SALES				.65								
11- CA/CL-				.83								
16- QA/CL-				.72								
22- CF/TL-					.88							
23- CF/CL-					.82							
25- CF/TA-					.83							
6- SALES/TA-						.81						
10- CA/SALES						.77						
27- SALES/DEBTORS-						.71						
37- BSDN1-							.64					
38- TADM1-							.86					
41- TADM3-							.86					
29- St/SALES-								.61				
30- St/WC-								.55				
31- CL/St-								.63				
35- WC/LTL-								.83				
13- CASH/CL-									.92			
15- CASH/TA-									.94			
17- QA/TA-										.67		
32- St/CA-										.82		
19- EBIT/T.INT-											.57	
21- LTL/NW-											.81	
26- DAYS DEBTORS-												.77
28- DAYS CREDITORS-												.69
Variance explained (%)	20.7	10.1	8.8	7.2	5.6	5.2	4.5	3.9	3.6	3.0	2.5	8.5
Cumulative variance explained (%)	20.7	30.8	39.6	46.8	52.4	57.6	62.1	66.1	69.7	72.7	75.2	77.7

TABLE 4.20: VARIMAX ROTATION OF PRINCIPAL COMPONENTS - STABILITY MEASURES (1974)

STABILITY MEASURES	PRINCIPAL COMPONENTS											
	1	2	3	4	5	6	7	8	9	10	11	12
12- CL/NW-	.68											
18- NW/TL-	.71											
20- TA/TL-	.90											
36- NW/TA-	.90											
39- TLDM1-	.61											
42- TLDM2-	.72											
1- EBIT/TA-		.88										
2- EBIT/NCE-		.88										
3- EBT/TA-		.85										
4- EBIT/NW-		.84										
5- EBT/SALES-		.70										
14- WC/TA-			.65									
33- WC/NW-			.89									
34- WC/NCE-			.79									
8- WC/SALES-				.59								
11- CA/CL-				.81								
16- QA/CL-				.75								
38- TADM1-					.88							
41- TADM2-					.88							
6- SALES/TA-						.79						
7- SALES/NW-						.58						
9- SALES/FA-						.72						
10- CA/SALES-						.55						
27- SALES/DEBTORS-						.70						
22- CF/TL-							.87					
23- CF/CL-							.84					
25- CF/TA-							.78					
29- St/SALES-								.83				
31- CL/St-								.67				
35- WC/LTL-								.60				
13- CASH/CL-									.92			
15- CASH/TA-									.93			
26- DAYS DEBTORS-										.78		
28- DAYS CREDITORS-										.73		
19- EBIT/T.INT-											.70	
21- LTL/NW-											.76	
32- St/CA-												.74
Variance explained (%)	22.2	9.6	9.0	6.9	5.8	5.2	4.0	3.6	3.5	2.8	2.6	2.5
Cumulative variance explained (%)	22.2	31.8	40.8	47.7	53.5	58.8	62.8	66.3	69.9	72.6	75.2	77.7

4.4.2.1 GENERAL DISCUSSION OF THE TABLES

1) Financial Ratios

The number of principal components extracted applying Kaiser's rule varies from eight in years 1978, 1977, 1975, 1974 and 1972 to nine in years 1976 and 1973. The higher number of principal components resulted in the splitting of one component present in the other years, into two components for those two years.

Table 4.21 reveals that a large proportion of the variance contained in the financial ratios is explained by the retained principal components for each year. At least eighty one percent of that variance is explained. Some of the financial ratios do not load on any of the principal components. As indicated by Table 4.22 these ratios are not the same for each year. They seem to be associated with the same financial dimension when looking at the other years, but for the WC/CF and LTL/WC ratios which are otherwise loading on different principal components. These variables have very low values on their communality and therefore represent financial characteristics different from those pictured by the retained principal components. Concerning the variables loading significantly at least on one of the

TABLE 4.21: SUMMARY TABLE OF PRINCIPAL COMPONENT ANALYSIS (FINANCIAL RATIOS)

Year	Number of Factors Extracted	Variance Explained (%)	Communalities of Variables Loading Significantly at Least on one Component	
			Lowest	Highest
1: 1978	8	84.2	.44	.97
2: 1977	8	83.0	.39	.97
3: 1976	9	85.2	.55	.98
4: 1975	8	81.5	.46	.97
5: 1974	8	82.3	.41	.97
6: 1973	9	85.5	.59	.98
7: 1972	8	82.5	.55	.97

TABLE 4.22: FINANCIAL RATIOS NOT LOADING SIGNIFICANTLY ON ANY COMPONENT

Year	Variable	Communality
1: 1978	R24: WC/CF	.30
	R30: St/W	.28
2: 1977	R29:SALES/St	.30
	R30: St/WC	.23
3: 1976	R30: St/WC	.31
4: 1975	R24: WC/CF	.27
	R30: St/WC	.38
5: 1974	R19:EBIT/TINT	.24
	R20:SALES/St	.35
	R35:LTL/WC	.39
6: 1973	R35:LTL/WC	.39
7: 1972	R19:EBIT/TINT	.45
	R29:SALES/St	.42
	R30: St/WC	.22

components, their lowest communality presented in Table 4.21 shows that just under fifty percent of the variance of some of them is explained by the retained principal components. However, it should be noted that at most, two of these variables have such low values for their communality and that in general at least around seventy percent of their variance is explained by the retained components.

2) STABILITY MEASURES

In this case again, the number of principal components is fairly stable over the period analysed. The only different features are the emergence of a further component in the years 1977, 1976, 1975 and 1974 with the merging of two different components into one in year 1977.

Table 4.23 indicates, here again, that a large proportion of the total variance is explained by the retained principal components, at least seventy five percent. The presence of stability measures unrelated to any of the principal components is again noticeable. These variables are listed in Table 4.24 and seem to be more or less the same from year to year, but an important point is that the communality of most of these variables is greater than .50 with a large

TABLE 4.23: SUMMARY TABLE OF PRINCIPAL COMPONENT ANALYSIS (STABILITY MEASURES)

Year	Number of Factors Extracted	Variance Explained (%)	Communalities of Variables Loading Significantly at Least on One Component	
			Lowest	Highest
1: 1978	11	75.6	.70	.93
2: 1977	11	75.3	.64	.94
3: 1976	12	77.3	.66	.95
4: 1975	12	77.7	.58	.92
5: 1974	12	77.7	.61	.91

TABLE 4.24: STABILITY MEASURES NOT LOADING SIGNIFICANTLY ON ANY COMPONENT

Year	Variable	Communality
1: 1978	S7: SALES/NW	.73
	S12: CL/NW	.68
	S19:EBIT/T.IN	.62
	S24: WC/CF	.58
	S31: CL/St	.59
	S37: BSDMI	.61
2: 1977	S12: CL/NW	.67
	S16: QA/CL	.73
	S21: NW/LTL	.48
	S24: WC/CF	.55
	S27: BSDMI	.55
	S39: TLDMI	.56
3: 1976	S8: WC/SALES	.67
	S9: SALES/FA	.67
	S12: CL/NW	.75
	S24: NC/CF	.46
	S39: TLDMI	.48
	S42: TLDM2	.60
4: 1975	S7: SALES/NW	.80
	S9: SALES/FA	.70
	S12: CL/NW	.70
	S24: WC/CF	.51
	S39: TLDM1	.64
	S40: TADM2	.56
5: 1974	S17: QA/TA	.61
	S24: NC/CF	.50
	S30: St/WC	.76
	S37: BSDM1	.67
	S40: BSDM2	.58

number of those stability measures having more than sixty five percent of their variance explained by the retained factors. This means that, even though those stability measures are not significantly associated with a particular component, the information they carry is present in the rest of the variables, and that they do not represent specific dimensions of their own.

Table 4.23 indicates that the lowest proportion of the variance of any variables accounted for by the common factors is high for all the year, more than sixty percent but for year 1975 where only fifty eight percent is accounted for.

These first general points show that the principal components extracted from the financial ratios and the stability measures are representative of the information contained in these two sets of variables and this for each year for which the analysis has been carried out.

4.4.2.2 STABILITY OF THE PATTERN MATRICES OVER-TIME

The stability of the pattern matrix over time will be assessed in four different ways by examining:

1) The number of financial variables that are associated with different financial characteristics from year to year,

2. The order of extraction of the principal components.

3. The number of factors extracted.

4. The value of the loadings on the principal components.

1. <u>Financial ratios</u>

The matrix of loadings presents a fairly stable pattern over time. Very rarely do financial ratios that represent a financial dimension in any one year, load on a principal component representing a different characteristic in the other years. This only occurs to four financial ratios: EBIT/NW, SALES/FA, CF/CL and LTL/WC and only once with the exception of SALES/FA for which this occurs twice. These ratios have loadings on the principal component to which they are most often associated, just above the 0.55 limit. Besides their second highest loading value is always associated with the principal component to which they move in those particular years.

Regarding the order in which the principal components are extracted, one notes that if the year 1978 is taken as reference for the numbering of the components, they are extracted in the same order for the first four years. If all the years are taken into account then the same order of extraction is repeated for the first four components. The variance accounted for by these four factors represents on average about seventy six percent of the total variance explained and the variance accounted for by each of the other components is more or less equal. This indicates that even though some changes may appear in the order of extraction of the principal components the generalisation of the financial dimensions is not too greatly affected.

Turning to the question of the number of principal components extracted, it was noted earlier that this ranges from eight to nine. But the emerging important fact is that the extraction of a further component resulted in the splitting of the dimension represented by factor 8 of year 1978 into two dimensions. It is, therefore, worth pointing out that the emergence of this new principal component was not the representation of a new financial dimension but rather the breaking up of one of them into two independent characteristics that are otherwise taken into account by the extracted principal components. Besides one remarks that for the year 1972, it is principal component I that splits into two components. However this happens only in that year and does not affect greatly the pattern stability.

Most of the loadings on the principal components to which they are significantly associated are very much the same from year to year for each variable. This again indicates a fairly stable pattern matrix over time.

From the points discussed above, it can be deduced that the matrix of loadings is stable overtime and that an overall classification of the financial ratios could be attempted. The financial dimensions they represent could be as well generalised.

2. Stability measures

The consistency with which the stability measures load on the same principal components from year to year is even greater than that found in the analysis of the financial ratios. Only one measure assessing the stability of NW/LTL is associated with different components. Therefore, here again, the groupings of the stability measures are very much the same over the period of time considered.

On the contrary, the order in which the principal components are extracted seems to be less stable than in the preceeding analysis. However the order of extraction is more or less the same. That is if a principal component representing a certain dimension is the first to be extracted in any one year, it would never be extracted among the last ones in any other year. Thus taking as reference year 1978, table 4.25 that shows the differences in the position of the principal components, indicates that the order of extraction reveals a certain stability with the principal components extracted among the firsts being so consistently over the entire period of time. The same is true for components extracted among the lasts.

The discrepancy appearing in the number of principal components extracted indicates that in year 1978, a dimension that is consistently appearing in the other year is not represented. Year 1977 presents the particularity of having a global dimension that is otherwise represented by two principal components. (III and IV: according to the classification of table 4.25). However, these added factors do not represent dimensions that are not accounted for in the other years thus emphasising again the stability of the pattern matrix.

Coming to the question of loadings, not much difference is noticeable between the value of the loadings from year to year. This, as expected, corroborates the points discussed above and stresses the fact the pattern matrix is fairly stable over time.

TABLE 4.25: ORDERING OF THE COMPONENTS (STABILITY MEASURES)

REFERENCE YEAR 1978	YEAR 1977	YEAR 1976	YEAR 1975	YEAR 1974
I	I	I	I	II
II	III	III	II	I
III	II	II	III	III
IV	IV	IV	VI	VI
V		VI	IV	IV
VI	V	V	V	VI
VII	VII	VIII	VIII	VIII
VIII	VI	VII	VII	V
IX	IX	IX	IX	IX
X	X	X	X	XII
XI	XI	XI	XII	X
	VIII	XII	XI	XI

From the present discussion, the conclusion that both pattern matrices are stable over time can be reached. These results are of particular importance since that will permit a generalisation of the findings and an identification of the financial dimensions represented by the battery of variables utilised in this study. Combining the results from each year will lead to a better picture of the financial profile of the firms than if only one year was considered.

4.4.2.3 OVERALL CLASSIFICATION

The information gained from the analysis for each year were pooled together. Two tables were drawn illustrating the dimensions emerging from the re-arrangement of the results. Table 4.26 is concerned with the financial ratios while table 4.27 is dealing with the stability measures. The pooling was straight forward for the variables loadings on the component representing the same financial dimension for each year. When some variables appeared only a few times and seemed not to belong to that particular dimension, they were not considered. When a dimension was split into two in some years, it was preferred to represent it as a unique financial dimension depending on the evolution over time.

The order of extraction of the factor was not taken into account.

(i) Financial ratios.

Altogether eight common financial dimensions were singled out. These eight dimensions were present in all the years but for year 1972 where principal component H was not extracted. For the years 1973 and 1976 which exhibit the particularity of having a further principal component extracted resulting in the splitting of dimension H, it was thought preferable to represent them as a unique component. Hence the financial ratios loadings on these two principal components were classified under financial dimension H. Concerning the splitting of factor C in year 1972, the problem was approached in the same fashion.

(ii) Stability measures.

The overall pooling of the results lead to the identification of eleven common dimensions. These eleven factors were extracted in each year except for year 1978 where factor K is not apparent. Here again, for the years in which an extra principal component was extracted, the two dimensions resulting from the splitting of one overall dimension were represented as a unique factor. Table 4.27 reveals that this is occurring for dimension C.

TABLE 4.26: OVERALL CLASSIFICATION (FINANCIAL RATIOS)

A) FINANCIAL LEVERAGE

	Y1	Y2	Y3	Y4	Y5	Y6	Y7
7. SALES/NW	B	C	C	C	B	C	C
12. CL/NW	A	A	A	A	A	A	A
18. NW/TL	A-	A-	A-	A-	A-	A-	A-
20. TA/TL	A	A	A	A	A	A	A
36. NW/TA	A-	A-	A-	A-	A-	A-	A-

B) WORKING CAPITAL MANAGEMENT

	Y1	Y2	Y3	Y4	Y5	Y6	Y7
8. WC/SALES	C	C	B	B	C	B	B
11. CA/CL	B	B	B	B	B	B	B
14. WC/TA	A	A	A	A	A	A	A
24. WC/CF		D			C	C	D
31. CL/St	C	C	C	C	D	C	C
33. WC/NW	A	A	A	A	A	A	A
34. WC/NCE	B	B	B	B	B	B	C

C) RETURN ON INVESTMENT

	Y1	Y2	Y3	Y4	Y5	Y6	Y7
1. EBIT/TA	A	A	A	A	B	A	A
2. EBIT/NCE	B	B	B	B	D	B	B
3. EBT/TA	B	A	A	B	B	A	A
4. EBIT/NW	C	C	C	C		C	C
5. EBT/SALES	C	C	C	D	D	D	D
22. CF/TL	C	C	C	C	C	C	*C
23. CF/CL	D	C	D	D	D		*C
25. CF/TA	C	B	C	D	D	C	*C

D) BUSINESS TURNOVER (EFFICIENCY)

	Y1	Y2	Y3	Y4	Y5	Y6	Y7
6. SALES/TA	C-	C-	C-	C-	D-	D-	D-
10. SALES/CA	C	C	C	C	C	C	C
26. DAYS DEBTORS	B	B	B	B	B	B	B
27. SALES/DEBTORS	B	B	B	B	B	B	B
28. DAYS CREDITORS	C	C	C	C	C	C	C

E) LIQUIDITY

	Y1	Y2	Y3	Y4	Y5	Y6	Y7
16. QA/CL	C	C	D	C	D	D	D-
17. QA/TA	C	C	D	D	D	D	D-
32. St/CA	B-	B-	B-	B-	B-	B-	B

F) DEBT POSITION

	Y1	Y2	Y3	Y4	Y5	Y6	Y7
9. SALES/FA		D	D	D		D	D
21. NW/TL	B	A	B	B	B	B	B
35. LTL/WC	C	C		C			C

G) CASH POSITION

	Y1	Y2	Y3	Y4	Y5	Y6	Y7
13. CASH/CL	A	A	A	A	A	C	A
15. CASH/TA	A	A	A	A	A	C	A

H) INTEREST COVERAGE

	Y1	Y2	Y3	Y4	Y5	Y6	Y7
19. EBIT/T.INT	B	D	D	C		C	
29. SALES/St	C		*D	C		C	
30. St/WC					C	*C	

LOADING CODIFICATION

A ≥ .90

.80 ≥ B > .90

.70 ≥ C > .80

.55 ≥ D > .70

* preceding a loading code indicates that the variable is associated with a different component resulting from the splitting of the dimension considered.

- signifies a negative loading.

TABLE 4.27: OVERALL CLASSIFICATION (STABILITY MEASURES)

A) RETURN ON INVESTMENT STABILITY

	Y1	Y2	Y3	Y4	Y5
1. EBIT/TA	A	A	A	B	B
2. EBIT/NCE	B	B	B	B	B
3. EBT/TA	A	B	B	B	B
4. EBIT/NW	C	B	B	C	B
5. EBT/SALES	C	C	D	D	C

B) FINANCIAL LEVERAGE

	1	Y2	Y3	Y4	Y5
12. CL/NW				D	C
18. NW/TL	B	B	C	D	C
20. TA/TL	A	A	A	A	A
36. NW/TA	A	A	A	A	A
39. TLDM1	D				D
42. TLDM2	C	D		C	D

C) WORKING CAPITAL MANAGEMENT STABILITY

	Y1	Y2	Y3	Y4	Y5
8. We/SALES	C	D	*D	*D	
11. CA/CL	B	C	*C	*B	*B
14. WC/TA	D	B	B	C	C
16. QA/CL	D		*D	*D	*D
33. WC/NW	*C	B	A	B	B
34. WC/NCE	*D	B	B	C	C
40. BSDM2	C	C	C		

D) CAPITAL TURNOVER STABILITY

	Y1	Y2	Y3	Y4	Y5
6. SALES/TA	B	B	B	B	C
7. SALES/NW		D	D		D
9. SALES/FA	C	C	C	C	C
10. SALES/CA	D	D			D

E) CASH FLOW POSITION STABILITY

	Y1	Y2	Y3	Y4	Y5
22. CF/TL	B	B	B	B	B
23. CF/CL	C	B	B	B	B
25. CF/TA	B	B	B	B	C

F) INVENTORY MANAGEMENT STABILITY

	Y1	Y2	Y3	Y4	Y5
29. SALES/St			D	D	B
30. St/WC	C	C	C	C	
31. CL/St		C	C	C	C
35. LTL/WC	B	B	B	B	D

G) STRUCTURAL STABILITY

	Y1	Y2	Y3	Y4	Y5
37. BSDM1			D	D	
38. TADM1	A	A	B	B	B
41. TADM2	A	A	B	B	B

H) CASH POSITION STABILITY

	Y1	Y2	Y3	Y4	Y5
13. CASH/CL	A	A	A	A	A
15. CASH/TA	A	A	A	A	A

I) LIQUIDITY STABILITY

	Y1	Y2	Y3	Y4	Y5
17 QA/TA	C	C	C	D	
32 St/CA	B	B	B	B	C

J) CREDIT MANAGEMENT STABILITY

	Y1	Y2	Y3	Y4	Y5
26 DAYS DEBTORS	C	C	C	C	C
28 DAYS CREDITORS	C	C	C	D	C

K) INTEREST COVERAGE S STABILITY

	Y2	Y3	Y4	Y5
19 EBIT/T.INT	D	D	D	C
21 NW/TL		D	B	D

LOADING CODIFICATION

.90 ⩽ A

.80 ⩽ B < .90

.70 ⩽ C < .80

.55 ⩽ D < .70

* Preceding a loading code indicates that the variable is associated with a different component resulting from the splitting of the dimension considered.

4.4.2.4 NAMING OF THE DIMENSIONS

Following Comrey's (1973) guidelines the identification of the nature of the principal components was attempted. He defines the conditions that would facilitate the naming of the principal components as such:

1) The higher the loadings, the greater is the degree of over-lapping true variance between the variable and the principal component and the more the principal component is like the variable.

2) The more factor pure a variable is that defines a factor, the easier it is to make inferences regarding the nature of the factor.

3) The greater the number of variables with a substantial loading on the principal component, the easier it is to isolate what the factor probably represents.

To help assess the weight of the loading a codification was used in the overall classification tables 4.26 and 4.27.

i) <u>Financial ratios</u>.

<u>Principal Component A.</u> The financial ratios that have the highest loadings are clearly concerned with the

long term solvency of firms. Ratios such as the net worth to total liabilities and total liabilities to total assets have always been associated with the debt-paying ability of companies. The higher the net worth to total liability ratio, the greater the protection of the lenders. The total assets to net worth and total liabilities to total assets are also employed as alternative ratios to measure the degree of leverage of companies. The presence of the sales to net worth ratio might be explained by the use of net worth in constructing three of the other ratios belonging to this group.

Principal Component B. Most of the ratios grouped under this component use working capital as either their numerator or denominator. It is therefore concerned with the use, the financing and the turnover of working capital and so represents the firm's ability in managing its working capital. The current assets to current liability ratio generally associated with the short term liquidity might in fact be more related to the working capital of a firm since its elements (current assets and current liabilities) are those from which the level of working capital is derived.

Principal Component C. The ratios contributing most to this factor are picturing the return on investment aspect of firms with the only exception of the profit margin.

However, this ratio has been found to be significantly correlated with return on investment ratios (Centre for Interfirm Comparison, 1978) and is expected to be so since the higher the profit margin, the greater the return on investment.

The presence of cash flow ratios may seem less obvious as they have often been associated with solvency but the findings of studies on the empirical groupings of financial ratios have shown them to be closely related to the profitability dimension.

Principal Component D. All the ratios related to this component represent the operational efficiency of a company and indicate the effectiveness with which a company's assets are utilized. This financial aspect is particularly important since it has a direct impact on the firm's overall performance. A reduction in the velocity of capital could lead to a reduction in profitability. The five financial ratios are each concerned with specific assets except for the sales over total asset ratio which is a measure of overall efficiency. Hence the nature of this factor is business turnover.

Principal Component E. Three ratios load significantly on this factor. Each of them is clearly related to short-term liquidity. The quick assets to current liabilities often called the acid test ratio, focuses on assets that can readily be turned into cash. It is then a very strict test of liquidity. The inventory to current assets is concerned with the degree of liquidity of the current assets. It estimates the amount of current assets that are the less liquid. The quick assets to total assets measures the degree of liquidity of a firm's assets as a whole.

Principal Component F. The ratio that appears consistently over the whole period of time is net worth to long term liabilities and is depicting the debt position. The long term liabilities to working capital ratio is very closely related to it. However, the presence of the fixed assets turnover ratio is difficult to understand but it should be noted that the value of its loading is much lower than that of the other two. That would mean that only part of the information contained in this ratio is common to that factor.

Principal Component G. These two ratios represent the cash position. They can be considered to assess the short-term liquidity of a firm in even a more stringent fashion than the acid test ratio.

Principal Component H. The ratio with the highest loadings and one that appears more often is the interest coverage ratio. It is therefore assumed that this dimension represents the interest coverage.

However it should be pointed out that this principal component was particularly unstable over the time period covered and that certain doubts remain about what is its exact interpretation.

ii) Stability Measures

One would expect the overall classification of the stability measures to be the same as that of the financial ratios. Financial ratios that belong to a same group are considered to be likely to vary in the same direction. However, it was felt that since not all the financial ratios within a grouping had the same loadings, their respective stability might be slightly different, leading to some variations in the groupings of stability measures compared to the overall classification of the financial ratios.

Differences could be noticed in the number of principal components extracted. This was due to the addition of decomposition measures and to splitting of certain groupings of financial ratios.

Principal Component A. This component measures the degree of stability of firms' return on investment. The variables loading on this components are concerned with the stability of profitability ratios.

Principal Component B. This component relates to long-term solvency stability. The variables belonging to this grouping are all measuring the stability of ratios associated with the long term solvency dimension with the addition of the two total liability decomposition measures.

Principal Component C. This component represents the stability of performance regarding working capital management.

Principal Component D. The variables associated with this component are all assessing the stability of capital turnover performance.

Principal Component E. The three variables loading significantly on this factor are related to cash flow position stability.

Principal Component F. Most of the variables are concerned with the measurement of the inventory management stability.

Principal Component G. The variables loading on this factor are all decomposition measures and so are considered to measure the structural stability of companies.

Principal Component H. This component clearly relates to the cash position stability.

Principal Component I. The variables loading significantly on this component are measuring the stability of ratios associated with the liquidity dimension. They clearly represent the stability of the liquidity aspect of a firm.

Principal Component J. These two stability measures are concerned with the stability of managerial performance concerning credit.

Principal Component K. This factor measures the stability of the last dimension described in the principal component analysis of financial ratios and is therefore termed interest coverage stability.

The emerging points in this analysis, besides the extraction of a factor only due to descomposition measures are:

a) The formings of two stability dimensions out of a single grouping of financial ratios.

b) And the disappearance of the debt position category.

This indicates that the financial ratios within certain categories do not vary exactly in the same direction. The stability of the profitability dimension is better assessed by looking at both the variability of the ratios under component A and E. Likewise the stability of the business turnover and the interest coverage dimensions would be better assessed by considering both components D and J for the business turnover and components F and K for the interest coverage aspect. However, the dimensions uncovered in the set of financial ratios are all represented in the overall classification of stability measures.

4.4.3. COMPARISON WITH THE FINDINGS OF OTHER STUDIES

To the knowledge of the author only three studies were found to be directly related to the analysis of the preceding sections. These studies were articles written by Pinches et al (1974), based on American data, Laurent (1979) analysing Hong Kong based companies and Taffler and Sudarsanam (1980) based on U.K. data. Although the third study was seen as the most relevant for comparison purposes, it was felt that the accounting practices that are in force in the U.S.A. and Hong Kong were not too different from those in force in the U.K.

The three studies attempted to arrive at an empirical classification of financial ratios using factor analysis as the method of grouping. They presented some differences in their results but overall the same dimensions were apparent. The apparition of new dimensions from one study to another was due essentially to the inclusion among the variables of financial ratios that were not presented in the battery used in the other studies. The results of the present analysis were also consistent with those of the other studies and particularly with those of Taffler and Sudarsanam. The same dimensions were present in both studies except for the cash position and interest coverage that did not come up in the

Taffler and Sudarsanam's study and for the value added position, creditors position and dividend position that did not emerge in the present study. But as noted earlier for the apparent differences between the three studies, this was due to the use of financial ratios that were not utilized in the other studies. More important is the similarity of the financial ratios significantly loading on principal components representing financial dimensions common to the two studies and the consistency revealed by the value of their loadings from one study to the other.

The likeness of the results from all the studies allows a generalization of the classification of financial variables and reveals that ratios that have been traditionally associated with particular dimensions of a firm, may in fact be measuring totally different aspects of it. The striking similarity between results of the present study and of the Taffler and Sudarsanam's study indicates that groupings of financial variables using factor analysis are very stable and that even though the samples used were different in the number of their cases and in the time period chosen, a generalization of the dimensions underlying U.K. based data can be readily attempted.

4.4.4 COURTIS' FRAMEWORK IN THE LIGHT OF THE PRESENT FINDINGS

A criticism of Courtis' framework formulated earlier was the possibility of ratios under different headings to be measuring common financial dimensions but more important is that it could happen to financial ratios belonging to the three different overall classes.

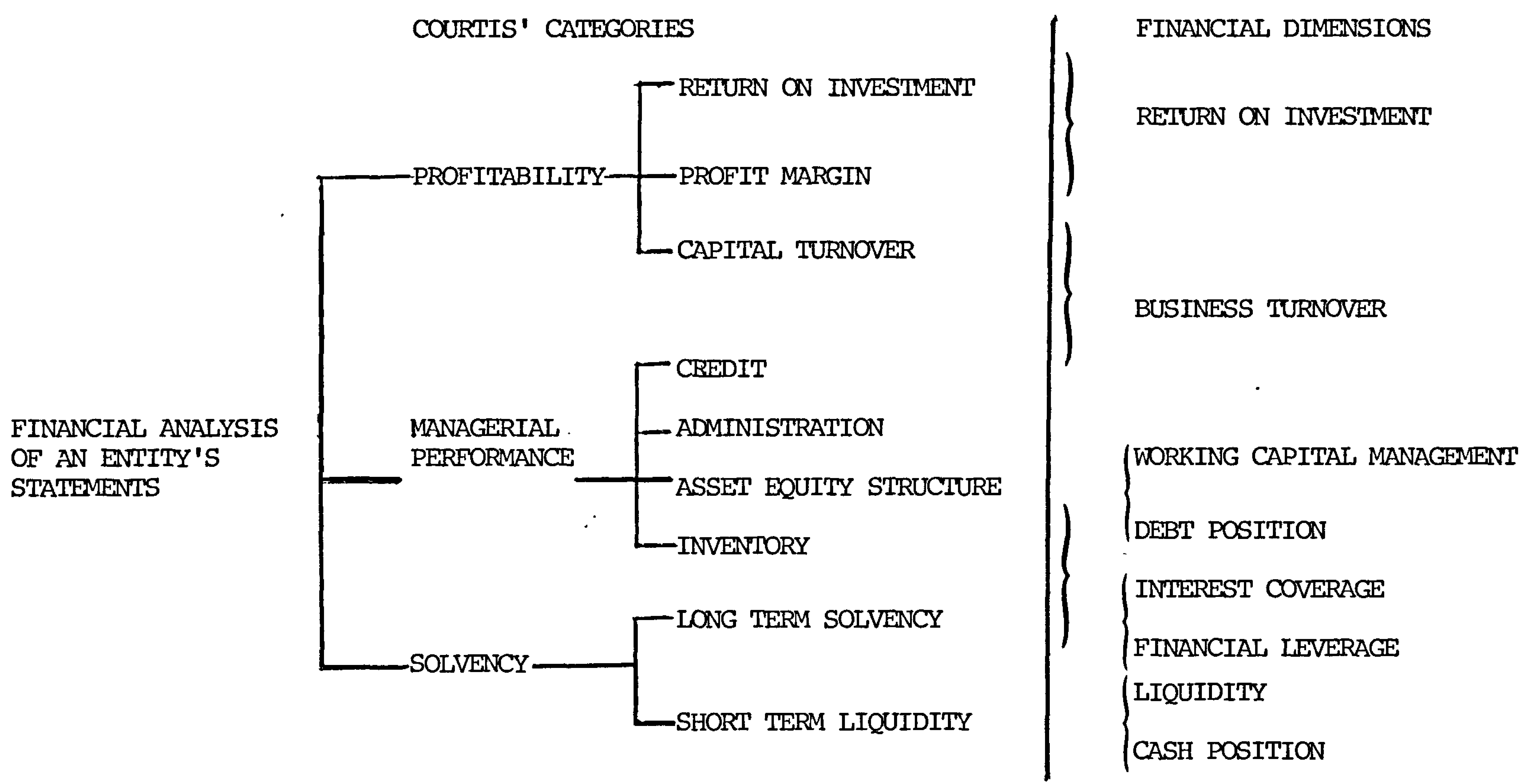
From figure 4.4 it becomes obvious that a profit margin dimension separated from return on investment is not present in the data. The same goes for capital turnover and credit management, and inventory and long-term solvency although this last statement is not as clear cut. The grouping of ratios that are generally thought to represent inventory management with the interest coverage ratio is difficult to understand and further research in that area would certainly bring more clarity to the dimensions represented by those financial ratios.

On the other hand categories such as Asset-equity structure, long-term solvency and short-term liquidity could be broken down into more sub-categories.

From the above discussion Courtis' framework may seem to present some deficiencies regarding the definition of some of its categories but the overall classes have been found to be consistent with most

FIGURE 4.4.

COURTIS' FRAMEWORK IN RELATION TO THE IDENTIFIED FINANCIAL DIMENSIONS

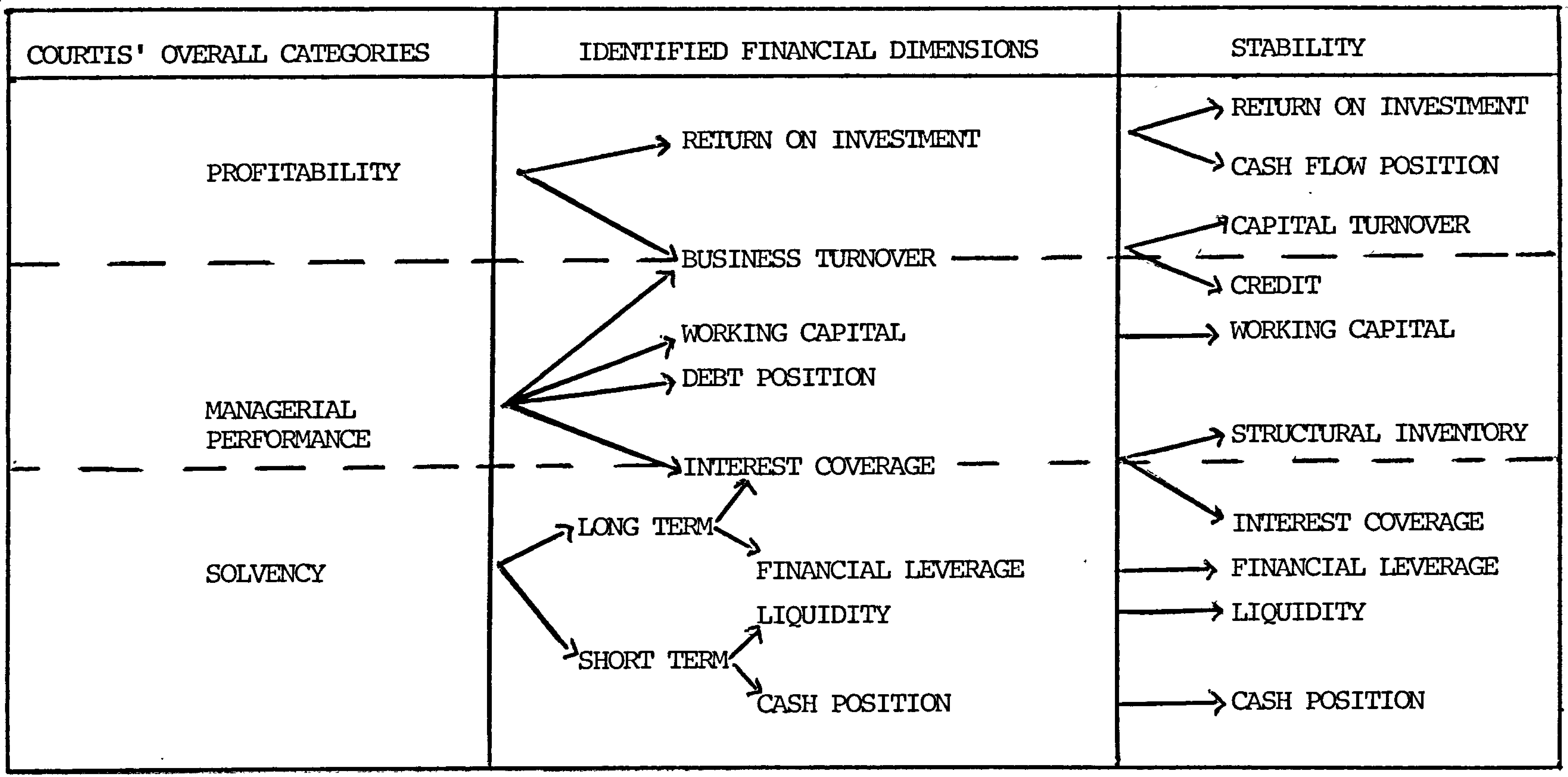


of the findings of related studies. It would then seem appropriate to redesign a framework on the basis of Courtis' three overall classes but that would take into account the results concerning the stability of the identified dimensions.

Figure 4.5 is a graphical representation of the new framework and reveals that although some of Courtis' categories disappear when the financial ratios were empirically grouped together, they are again present when the stability of the groupings is examined. This stresses the fact that each financial ratio belonging to one group can measure some aspect of the dimension they associate to, and not all of them and that the financial dimension identified represents all the characteristics of the financial ratios associated to it. Therefore, the stability of the dimension will depend on the stability of its constituents. For example, if we take the return on investment dimension, it is clear that the cash flow ratios even though being associated with it represents some other aspects since their loadings are inferior to those of the other return on investment ratios. Thus, their stability may be expected to be different from that of the other return on investment ratios and would measure other aspects of the overall stability of the return on investment dimension.

FIGURE 4.5

A GLOBAL FINANCIAL CATEGORIC FRAMEWORK



4.4.5 DO THE VARIABLES BELONGING TO A GROUPING MEASURE A UNIQUE TYPE OF INFORMATION ?

The classifications of financial ratios has always been done with the aim of finding homogeneous groupings that would measure specific characteristics of a firm. It would than be interesting knowing whether the information contained in a specific set of ratios is unique and whether given other specific sets that information is not redundant. Pohlman and Hollinger (1981) have attempted to answer these questions. Using cononical correlation analysis and its related redundancy indexes, they tested two models, the traditional four category model and the Pinches et al (1974) seven category model. They concluded that the distinct groups of financial ratio in both models did not contain totally specific information and that most financial information is very much inter-related. However, their findings concerning Pinches et al's model showed that the redundancy of information in a set of ratios given other distinct groups, was not significant for the variables having the highest loadings on the factor associated with the financial dimension they represented. The mere fact that a high loading means a great overlapping in true variance between the variable and the factor would explain that by considering financial ratios with lower and lower loadings the specificity of the information they carry will decrease and become more and more related to that represented by the other factors. Therefore, the groupings arrived at by using factor analysis if considered separately may not portray only one aspect of a firm's financial profile but the general information contained in each of them will be more related to the dimension they represent than to any other.

It can then be concluded that the grouping of financial ratios and of stability measures defined in the classification tables 4.26 and 4.27 can be used in the identification of the dimensions that are of importance for the discirmination between well performing and less well performing companies.

4.5 CONCLUSION

This chapter was an attempt at selecting the financial variables that should be the most relevant in relation to the objectives of study. Such a new concept as stability of performance was taken into consideration. Financial ratio stability measures and decomposition measures were selected. The second part of this chapter endevoured to isolate the underlying dimensions of the set of variables. The set of data was analysed using the principal component method. Eight dimensions were found to represent the set of financial ratios while eleven characteristics came up in the analysis of the stability measures. On the basis of these findings a categoric framework was modelled along the lines of Courtis' (1978) approach to allow a better understanding of the dimensions represented by the selected variables.

CHAPTER 5

THE DISCRIMINANT MODELS

CHAPTER 5

5.1 INTRODUCTION

In this chapter the financial characteristics of the two samples of companies are compared. It seeks to establish whether the financial characteristics of the well performing companies are markedly different from those of the less well performing companies. The analysis proceeds in three stages.

Firstly, the eight hundred and twenty one companies are divided into two groups, the group of companies that had an average efficiency during the last three years, (1978, 1977, 1976) placing them among the the top fifty percent and the group of less well performing firms that comprised the rest of the companies. Discriminant runs were performed and the variables selected to enter the final model.

Secondly, the companies that were not on average, among the top fifty percent regarding their overall efficiency during the four first years analysed (1972,1973,1974, 1975) were picked up from the sample of well performing companies. The same was done about the companies that were on average below the fifty percent line in the sample of less well performing firms. This resulted in having a group of companies numbering one hundred and three that rose from a less well performing status to a well performing one. The other group was composed of companies that could be considered on the whole period of time analysed as less well performing. This group comprised three hundred and nine firms. Discriminant analyses of the two groups were carried out to find out whether any changes would appear in the financial characteristics of companies that just reached a higher level of performance. The years covered were 1977 and 1976, the two first years during which the companies could be considered to have reached a level of high performance.

Finally, the last stage is concerned with identifying potentially well performing companies. The two last samples are analysed for the years 1972, 1973, 1974 and 1975. All the companies are low performers but those of the first group are later among the well performing group and are therefore considered as potentially high performers. It is then of interest to find out whether the potentially well performing companies reveal particular traits in their characteristics that could help identify them.

The three stages of the analysis can be summarised as follows:

a) Identification of well performing firms.
b) High efficiency and its impact on a firm's financial characteristics.
c) Identification of potentially well performers.

However, before proceeding with the analysis, a description of the method used in selecting the variables will be discussed together with technique used to test whether there is any departure from the assumptions underlying valid application of the discriminant model.

5.2 SELECTION OF VARIABLES IN THE DISCRIMINANT MODEL

There are many reasons for not using the whole set of variables. In this case, the purpose of the study being exploratory as well as analytical, it is not known which financial characteristics are relevant to the problems investigated. The procedure utilised was to gather as much information as possible on every financial aspect of the firms and to determine the set of variables most relevant for the identification of the underlying structure of the problem.

The gathering of the information led us to isolate ninety variables that could be of interest. A linear discriminant function including all those variables would be hardly manageable. In effect, such a model would require a large number of computations and would be difficult to use by those who are mathematically unsophisticated, furthermore, if the model is used as a monitoring device for the whole economy, the cost of gathering and processing such a vast amount of information for each and every firm would certainly be prohibitive.

For the above reasons it seemed preferable to select the smallest subset of variables possible without unduly affecting the performance of the resulting discriminant function based on the reduced vector of characteristics.

5.2.1. METHODS OF VARIABLE SELECTION

Several methods exist to select dependent variables in discriminant analysis. Their aim is to find the "best" subset of variables out of the list of variables submitted. They can be discussed in relation to the goals of discriminant analysis. Generally two such goals are identified:

1. Description

   The user will be concerned with the discriminant function, its coefficient and the distance between the centroids of the two populations.

2. Prediction.

   The user will be interested in rendering the discriminant model operational. His concern will be with the percentage of correct classifications.

5.2.1.1 Methods associated with the descriptive case

The most popular one is the stepwise method available in program packages such as the SPSS (1975) and the BMDP (1977). The program starts by selecting one variable then adds up the other ones in turn until the addition of a new variable does not contribute to the discriminatory power of the function. Each time a new variable is entered into the "best" subset, the variables already selected are examined again to test whether their contribution is still significant in the light of the added variable and are removed from the "best" subset if not. The criteria for selecting the variables are:

- SPSS : Wilkes' Λ ,Mahalanobis' distance and Rao's V, a generalised distance measure.

- BMDP : Wilks' Λ

Another method was proposed by McCabe (1975). This method is based on Furnival's (1971) algorithm for examining all possible subsets. Furnival's algorithm has been implemented for the selection of the optimum subset in regression analysis and is available in the BMDP computer package. However McCabe's method which locates the subset of variables with the minimum value of Wilks' Λ is not readily available at Bradford University.

5.2.1.2 Methods associated with the predictive case

One such method has been proposed by McLahlan (1976) for the case of two populations. His method is based on the conditional risk of misclassification. An approximate confidence level which corresponds to no increase in the conditional risk of deleting a variable or a subset of variables is obtained.

Habbima and Hermans (1977) have developed a program ALLOG - 1 based on the estimation of classification rate which chooses the "best" subset of variables.They recommend their program for whose primary aim is predictive. However ALLOG-1 is not widely available and,as they pointed out, the computer time is prohibitive for straightforward analysis of large scale problems.

The selection of variables in discriminant analysis could also be based on the interdependence of the variables among themselves. Beale et al (1967) and Jolliffe (1972, 1978) have studied this interdependence problem in relation to multivariate analysis as a whole and to the discarding of variables in principal component analysis. However, Farmer and Freund (1975) have shown that, in the MONOVA model which is similar to the discriminant model (see Chapter 3), techniques discarding variables which are highly correlated with these already selected are not the most effective. They compared four of the various procedures that have been suggested for removing variables in one-way MONOVA. Therefore, step down or backward elimination techniques delete at each step the variable which:

1. Has the largest R^2 value computed from the rows of the data matrix.
2. Has the smallest correlation with the best linear discriminant function.
3. Has the smallest correlation with one of the two best linear discriminant functions.
4. Induces the smallest change in Wilk's Λ .

They concluded that the procedure based on the decomposition of Wilks' Λ was the most efficient. This does not seem unlikely since Cochran (1962) has indicated that for the two variable cases correlation between the variables might in fact improve the discriminant model if the correlation is fairly high. As a consequence, the method of variable selection chosen was the stepwise procedure based on Wilks' Λ .

5.2.2. Stepwise Selection of Variables Based on Wilks' Λ .

Let W and B respectively be the within and the between sum of square and product matrices as defined in chapter 3 for p variables. T, the total sum of square and product matrix, is equal to W + B. Then

$$\Lambda(1,2,\ldots,p) = \frac{|W(1,2,\ldots,p)|}{|T(1,2,\ldots,p)|} \tag{1}$$

is called Wilks' lambda. If a variable is added then a partial Λ statistic can be derived as follows:

$$\Lambda\ (p+1) = \frac{\Lambda(1,2,3,\ldots,p,p+1)}{\Lambda(1,2,3,\ldots,p)} \tag{2}$$

which measures the increment in the value of Λ .

The corresponding F statistic (Rao 1973)

$$F = \frac{n-g-m}{g-\Lambda}\ \frac{1-\Lambda\ (p+1)}{\Lambda\ (p+1)} \tag{3}$$

can be used to test the significance of the change from Λ to $\Lambda(p+1)$ provided that the added variable is arbitrary and not the one that maximises F.

This F statistic is utilised to enter and to remove variables in the stepwise procedure. The first step consists in evaluating for each variable the univariate F ratio used in the ANOVA technique. The variable with the highest value is entered into the discriminant function. The next step consists in evaluating the F statistic (3) for all the variables not included in the discriminant function. The F statistic is then called F to enter. The variable with the largest F to enter is the next candidate for selection if its F value is larger than a specified threshold, F in, in our case, 1.0 which is the default value of the SPSS. Once a variable has entered, all the variables in the subset are re-examined. The F statistic (3) is calculated for each variable and is known as F to remove. The variable with the lowest F to remove is deleted if its F value is smaller than a second threshold value, F out (not necessarily the same as for F in) the default value of F out in the SPSS is again equal to 1.0. The procedure stops when none of the remaining variables has an F to enter greater than F in. The best subset so selected is the one that would account for most of the difference between the two population. However one may wish to estimate its performance in relation to the percentage of correct classification.

MacLachlan (1980) comparing results obtained with the method of selecting variables based on the conditional error rate he proposed (MacLachlan, 1976) and those obtained by selecting variables based on the F statistics (Rao, 1973) concluded that there is a close correspondence between the two methods. He stated that:

> "Provided that the significance level of the F - test is not set at too conservative a level, there should be a fairly high degree of confidence that the overall error rate is not increased by the selection decision based on the F - test".

But as pointed out by Rencher and Larson (1980) the F - statistic (3) does not follow an F distribution when it is maximised at each stage. They added that the Wilks' Λ statistic (1) is also biased under selection when the subset of p variables is the best or near the best subset. This bias in Λ could cause problems such as:

a) The inclusion of too many variables in the subset. Some variables which do not contribute to the separation between the two groups might be selected as a consequence. This would lead to sampling variability. Different subsets would emerge from a repetition of the procedure on different samples.

b) The selection of a totally spurious subset leading to artificial separation and correct classification rates.

However, as Rencher and Larson indicated such problems will mainly arise when the number of variables is large with respect to the sample size. They noted that such situations commonly occurred but this is hardly the case in the present study where the sample size is fairly large.

Once the best subset of variables is selected, knowing the relative contribution of each variable to the overall performance of the discriminant model may help isolate the dimensions of importance in the problem under investigation.

5.2.3 RELATIVE IMPORTANCE OF INDIVIDUAL VARIABLES IN DISCRIMINANT ANALYSIS

Eisenbeis et al (1973) give a comprehensive survey of the most common methods that can be used to rank discriminant variables according to their importance. These methods give an idea about the weight of the variables and are by no means absolute tests. The lack of absolute tests concerning this aspect of discriminant analysis is due to the fact that only the ratios of the function coefficient are unique. Following Eisenbeis et al's approach the different methods are presented. They fall in three categories:

a) Univariate F test

The variables will be ranked according to the significance level of their corresponding F test:

$$Fj = \frac{(1 - \Lambda j)}{\Lambda j} (m_1 + m_2 - 2)$$

which is equivalent to the F test used in ANOVA and where $\Lambda j = Wjj / Tjj$ is the Wilks' lambda for the j^{th} variables. The Fj are distributed as $F(1, m_1 + m_2 - 2)$. The lower the significance of Fj, the greater the discriminatory power of the variable on an univariate basis and hence the higher its rank.

b) Standardized Coefficients

Golderber (1964) has shown that the standardized coefficients are similar to the beta weights of regression analysis. The weighted vector is obtained by multiplying the elements of the vector ofdiscriminant coefficientsby the square roots of the corresponding elements, Wii, of the within group matrix of sum of squares and products defined above.

The values of the weighted coefficients estimate the contributions of the individual variables to the discriminatory power of the function and can as well serve to rank the variables.

These two methods do not take into account the interdependence of the variables. As a result their use might be suspect since taking into account the correlation between the variables might lead to a totally different ranking.

c) Stepwise Procedures

All three methods discussed below are all related to the test of significance on Wilks' Λ described in Chapter 3.

1. Conditional-delation selection

Each variable included in the discriminant model is removed in turn. The Wilks' Λ corresponding to the p - 1 remaining variables are computed and is called the residual Wilks' lambda of the variable that has been removed. The variable with highest residual Wilks' lambda is the most significant in the p variable discriminant model. The variable with the second highest residual Wilks' lambda is the second most significant, and so on, until all the variables have been ranked.

2. Forward selection

This ranking of the variables is directly derived from the application of the method described in the preceding section. The order of entry of the variables will be their ranking. The first variable that enters is the most significant and is ranked first. This procedure is repeated until the p variables have entered the discriminant model.

3. Backward selection

This method of ranking is based on the residual Wilks' lambda described above. It reverses the process of the forward selection and differs from the conditional delation selection method in that it estimates the residual Wilks' lambda every time a variable is taken out. The procedure starts by considering the p variables and drops the variable with the highest Wilks' lambda. This is repeated for the p - 1 variables, and so on, until all the variables have been removed. Their order of removal is inversely related to their contribution ranking. The last variable to leave is interpreted as the most significant variable.

The last three methods, even though taking into account the correlation that exists among the discriminant variables, do not assess the relative importance of each variable. The only information that is derived from them is a ranking of the variable significance. Another that is not given by Eisenbeis et al has been originally suggested by Mosteller and Wallace (1963) and used by Taffler (1976).This method is based on the contribution of each variable to the Mahalanobis distance.

d) <u>Mosteller and Wallace measure</u>

The relative discriminant power of the j^{th} variable is given by:

$$M_j = \frac{c_j (\bar{X}_{j1} - \bar{X}_{j2})}{\sum_{i=1}^{p} c_i (\bar{X}_{i1} - \bar{X}_{i2})}$$

where:

C_j is the discriminant coefficient corresponding to the j^{th} variable.

$\bar{X}_j$ is the mean of variable j in group 1

and $\bar{X}_j$ is the mean of variable j in group 2.

The denominator of the ratio is the Ma halanobis distance D^2 between the two groups. The sum of the M_j should normally sum to one, however, this is not always the case and is seen as a serious drawback to the measure.

The first five methods were compared by Eisenbeis et al (1973) and gave results that were somewhat different. Hence they recommended their application with great care and pointed out that except for variables that are consistently ranked at the same position by most of the methods, a clear cut idea on the contribution of the others is much more difficult to be reached.

5.3 TESTING THE ASSUMPTIONS UNDERLYING VALID APPLICATION OF LINEAR DISCRIMINANT ANALYSIS

The optimisation of the discriminant model depends on the assumption of separate multivariate normality for the two populations and equality of the variance covariance matrices.

5.3.1. TESTING FOR MULTIVARIATE NORMALITY.

Several tests for multivariate normality have been developed. A discussion about their application can be found in Andrews et al (1973) and in Malkowich and Afifi (1973) but most of them are difficult to implement. However, Mardia (1970) has developed a test for multivariate skewness and kurtosis that has been programmed (Mardia and Zemroch, 1975). He defines the measures:

$$b_{1,p} = \frac{1}{n^2} \sum_{i=1}^{n} \sum_{j=1}^{n} \left\{(X_i-\bar{X})\ S^{-1}\ (X_j-\bar{X})\right\}^3$$

and

$$b_{2,p} = \frac{1}{n} \sum_{i=1}^{n} \left\{(X_i - \bar{X})\ S^{-1}\ (X_i - \bar{X})\right\}^2$$

of multivariate skewness and kurtosis of a set of n independent p variate observations $X_1, X_2, \ldots X_n$ where:

$\bar{X}$ denotes the sample mean vector

and

S the sample variance covariance matrix.

He then derives:

$$A = \frac{n}{6}\ b_{1,p}$$

and

$$B = \left[(b_{2,p} - \{p(p+2)\}\right] \Big/ \left\{8p\ (p+2)/n\right\}^{1/2}$$

where n is the number of observations. These two statistics follow respectively a χ^2 distribution with $p(p + 1)(p +2)/6$ degrees of freedom and a standard normal distribution, $N(0,1)$ and can be tested accordingly. The null hypotheses are : $b_{1,p} = 0$ and $b_{2,p} = p(p+2)$ respectively. A rejection of the null hypothesis can be described as an indication of skewness or kurtosis accordingly.

Two other approaches can be readily applied to test the multivariate normality of a set of n independent p variate observations:

i) Although normality of each of the marginal distribution of a vector variate does not ensure that it is distributed multivariate normal, normality of every possible linear component of that vector variable would lead to it being multivariate normal in distribution. Accordingly, a principal component analysis can be carried out on the set of data to be examined and each of the resulting components separately tested for normality using the test described in the preceding chapter. (χ^2 and Kolmogorov-Smirnov tests). If normality is not rejected for any of the principal components then we can conclude that the data is distributed multivariate normal (Cooley and Loohnes, 1971).

ii) The second approach is based on the method of contour. If a population is multivariate normal then one way to describe its distribution is in terms of an ellipsoid whose size is specified by the value of the quadradic form:

$$V = (X_i - \bar{X})'S^{-1}(X_i - \bar{X})$$

where

X_i is an n element vector

$\bar{X}$ the vector of means

and S is the variance covariance matrix.

The larger the value of V the lesser the density at that point. The values of V follow a χ^2 distribution with n degrees of freedom. Therefore, we can obtain the value of χ^2 beyond which a certain proportion of points is expected to be. That value is known as a centour (centile centour). Comparing the proportion of observation in our samples lying beyond a certain centour with the expected value, the normality of the sample distribution can be rejected or accepted. Alternatively, as suggested by Malkowich and Afifi (1973), the hypothesis that V is distributed as χ^2 is tested using univariate test statistics such as the Kolmogorov-Smirnov test. A modified quadratic form can as well be used:

$$V^* = (X_i - \bar{X}^*_2)'S^{-1}(X_i - X^*_1)$$

where

X_i and S are the same as above

and $\bar{X}^*_i$ is the mean vector of remaining cases. The i^{th} case is not included in the calculation of the means.

The statistic derived from V^*

$$F = \frac{V^*}{1 - 1/n - V^*} \quad \frac{n - p - 1}{p}$$

has F distribution with p and (n - p -1) degrees of freedom. n is the number of cases. The proportion of observations lying beyond a certain centour can be determined from F distribution tables in this case, comparing the actual and expected proportion, the multivariate normality of the sample can be evaluated.

This second approach together with the test developed by Mardia (1970) will be used to test the multivariate normality of the data. This approach was preferred to the first, because most of the information needed to apply it is given in the computer outputs of the packages used for the discriminant analysis. Besides it can give an indication of the length of the tails of the distribution according to the centour selected i.e. 95% and 99% centour. Such results could not be obtained by using the first approach. Mardia's test is as well an indication of the shape of the distribution. This information can be of interest since the discriminant model is affected differently according to the kind of departure from normality. The same can be said for tests concerning the equality of variance covariance matrices.

5.3.2. EQUALITY OF VARIANCE COVARIANCE MATRICES.

A criterion for testing the equality of g variance covariance matrices,

$$H_o: \quad \Sigma_1 = \Sigma_2 = \Sigma_3 = \text{-------} = \Sigma_g$$

derived from the work of Bartlett (1937), has been suggested by Box (1949). Since the population variance covariance matrices are generally unavailable, samples estimates of the k dispersion matrices are utilized. Box defines the criterion as

$$M = n \log |S| - \sum_{i=1}^{2} (n_i \log |S_i|)$$

where

S is the pooled variance covariance matrix of the g groups, S_i is the variance covariance matrix of group i

n, n_i represent respectively the total number of observations and the number of observations in group i.

Two parameters are required to test the significance of M

$$A_1 = \left(\sum_{i=1}^{g} \frac{1}{n_i} \quad \frac{1}{n} \right) \frac{2p^2 + 3p - 1}{6(g - 1)(p + 1)}$$

$$A_2 = \left(\sum_{i=1}^{g} \frac{1}{ni^2} \quad \frac{1}{n^2} \right) \frac{(p-1)(p+2)}{6(g - 1)}$$

If $A_2 - A_1^2$ is positive then

$$F = \frac{M}{b}$$

follows a F distribution with f_1 and f_2 degrees of freedom where

$$f_1 = .5\ (g - 1)\ p\ (p + 1)$$

$$f_2 = (f_1 + 2)\ /\ (A_2 - A_1^2)$$

and

$$b = f_1\ /\ (1 - A_1 - f_1\ /\ f_2)$$

If $A_2 - A_1$ is negative, the following is used:

$$f_1 = .5\ (g - 1)\ p\ (p + 1)$$

$$f_2 = (f + 2)\ /\ (A_1^2 - A_2)$$

$$b = f_2\ /\ (1 - A_1 + 2\ /\ f_2)$$

and

$$F = f_2 M\ /\ f_1\ (b - M)$$

follows an F distribution with f_1 and f_2 degrees of freedom.

If the results from the test indicate an unequality of the variance covariance matrices of the two groups, a quadratic discriminant function should be fitted but before reaching this conclusion one should examine the impact of non-multivariate normality on Box criterion as well as on the quadratic and linear discriminant rules, and the test for equality of group mean vectors.

5.3.3. INFLUENCES OF NONMULTIVARIATE NORMALITY

The Box's criterion proposed for testing equality of group variance covariance matrices is particularly badly affected by nonmultivariate normality, and as such, less robust than the test it is supposed to justify. Hopkins and Clay (1963) have found this to be true for leptokurtic non-normal bivariate distributions. Mardia (1971, 1974) has shown that tests for equality of group variance covariance matrices are sensitive to multivariate kurtosis but not so much to multivariate skewness.

Hence, the result from the test described above should be considered with great care if the assumption of multivariate normality does not hold. In the circumstances the test will yield biased results but the size and direction of the bias is not apparently known. When the presence of multivariate normality is not clearly established, the fitting of a quadratic discriminant function according to the result from the test for the equality of variance covariance matrices is not so straightforward. Besides, the quadratic discriminant model gives poorer results than the linear discriminant model in this particular situation.

Lachenbruch et al (1973) assessing the impact of nonmultivariate normality on the linear discriminant function found that the total error rate was increased for the two group case. They also noted that the individual error rates were distorted. The error of one of the groups was substantially above the real optimum rate while that of the second group decreased in a similar fashion. This seems the only study to date to have studied this aspect of the discriminant analysis problem. However Lachenbruch et al considered only three cases, where normal data were transformed log normal, logit normal and $\sinh^{-1}$ normal. Therefore their results are particularly related to such kinds of distributed data.

The effect of non-normality on the analysis of variance test seem less pronounced. Multivariate analysis of variance (MANOVA) is found to be robust to non-normality (Mardia 1971). This implies that the test used to measure the difference between the two group mean can be applied even though the data are not multivariate normal distributed and that the results obtained can be used to assess the difference between the mean vector of the two groups.

5.3.4. INEQUALITY OF VARIANCE COVARIANCE MATRICES.

As we have seen in chapter 3, the optimal rule is a quadratic discriminant function when the variance covariance matrices are unequal Gilbert(1969) studied the particular case when the variance covariance matrix of one group is a direct multiple of the variance covariance matrix of the other group. She assumed that the covariance matrix in the first group was equal to I, the identity matrix, and that of group two equal to dI. She compared the error rates when using both a quadratic and a linear function. Her conclusions were that the quadratic and linear functions behave similarly when the separation between the groups is large and when the value of d is not too far from 1.0. However, this study assumed that the parameters were the true population parameters. Hence the results are about optimum error rates.

Marks and Dunn (1974) studied the case where the true parameters are unknown. They compared the sample linear discriminant function, the best linear classification rule when the variance covariance matrices are unequal proposed by Anderson and Bahadur (1962) and Clunies-Ross and Riffenburgh (1960) and the sample quadratic discriminant function. Their conclusions are quite similar to Gilbert's findings. The sample linear discriminant function gave quite satisfactory results when the variance covariance matrices are not too different. The quadratic function performed better only when the variance covariance matrices were very different and when the samples were very large.

The impact of unequal variance covariance matrices on tests for equality of group centroids is not as well defined. Eisenheis (1978) stated that

> " rejection of the hypothesis of equal group dispersions may have a significant and undesirable impact on the test for the equality of group means."

Nevertheless, it may be assumed that the impact is proportional to the difference between the matrices and that a small diference would not affect tests for the equality of group mean vectors too badly.

5.3.5. LINEAR Vs QUADRATIC DISCRIMINANT MODEL

From the above evidence, the question of fitting a quadratic function is very much dependent on the validity of the assumption that the samples are multivariate normal distributed. In the present study the fitting of a linear discriminant function was favoured because it was felt that the quadratic discriminant model would be very badly affected by departure from the basic assumptions and that it would be of less practical utility for the following reasons:

A) <u>A priori reasons</u>

Several recent studies have shown that financial data are not distributed multivariate normal. Eisenbeis et al (1973) found that financial data on banking organisations do not follow a multivariate normal distribution. The same conclusions were reached by Taffler (1976) for financial ratios in a study on bankruptcy. More recently Pinches (1978) and Pinches et al (1977) using Mardia's (1970) tests for multivariate skewness and kurtosis showed again that financial data are not multinormal.

As it is discussed below the assumption of multivariate normal distribution of the sample data is of particular importance for the quadratic discriminant model.

B) <u>Statistical reasons</u>

The quadratic discriminant function is seriously affected by deviations from normality. Lanchenbruch (1975) indicated that the quadratic form is not robust to non-normality particularly if the distribution has longer tails than the normal. On the opposite the linear discriminant function is more robust to non-normality. It was first derived as a distribution-free technique (Fisher, 1936) and is seen as appropriate for groups where multivariate normality is not exactly satisfied (Mardia et al, 1979). Further it is hoped that the separation between the group will be wide which is a situation where the quadratic discriminant rule does not bring any improvements in the results as discussed above.

c) Practicality reasons

The use of a quadratic discriminant function leads to a drastic increase in the number of parameters to be estimated. Its complexity would then require more computations to be done, for the model to be operational. This could deter some potential users as the application of the model would not be as straightforward as for a linear discriminant function.

If the model is to be used in a repetitive manner then the quadratic discriminant rule would imply a much larger number of calculations and hence more cost in computation. Furthermore, the interpretation of the significance of the financial characteristics in relation to the problem under study would be obscured by the use of a quadratic function.

5.4. ANALYSIS OF THE DATA

As already noted the analysis was divided into three parts, the first two parts analysing the differences in firm financial profile brought about by a level of efficiency higher than average. The third part was concerned with the particularities of those firms' financial characteristics in their pre-well performing period. Consequently, this section will be divided into two broad subsections:

the high performance period and the pre-well performing period. This break down of the analysis into two parts was done with two reasons in mind. It was felt that the financial characteristics of the potential well performing firms would not be the same after they have reached an above average level of performance and that the examination of the financial variables to test whether conflicting signals from year to year were emitted would be facilitated.

5.4.1. THE WELL PERFORMING PERIOD

This period covered the years 1978, 1977 and 1976. The analysis of this period looks firstly at the companies that have sustained a high level of efficiency for at least three years to year 1978. This will lead to a general model of performance assessment. Then, the financial profiles of those companies will be analysed in their two first years of above average efficiency to try to assess the direction and the extent of the changes in their financial dimensions. This would help to point at the areas of importance in identifying companies performing better than average.

5.4.1.1. Analysis of conflicting signals

At this stage of the analysis, our main concern is not yet to indentify the financial variables relevant to the problem but simply to discard variables that are emitting conflicting signals from year to year and to examine variables that are giving information which is opposite to that expected.

The mean of every variable in each group was calculated. Their difference between group was then examined. It was expected that the means of the financial ratio in the high performance group would present a better image of their associated dimension than those of the low performance group. At the same time, it was anticipated that the stability measures would have a lower mean in the group of well performing companies and that the measures of change and trend would be lower on average in the group of less well performing firms.

Concerning conflicting information being emitted, this was assessed by looking at the direction of the difference of the variable means between groups. If the same difference direction was not consistently repeated over the three years for a particular variable then that variable was removed from the analysis as one would consider that once companies have reached a high level of efficiency and shown on average a higher (a lower) mean value for certain variables they would do so consistently afterwards if they remain in the high performance group.

The directions of the between group mean differences are presented in table 5.1 - The pattern of difference directions for the financial ratios is very stable with the only exception of inventory over working capital which had two negative and one positive differences. The other noticeable points are the negative differences for the net worth, working capital turnover ratios. The sign of the difference of these two ratios could be explained by the positive difference observed on the net worth to total asset and working capital to total asset ratios being larger than the positive difference observed on the total asset turnover ratio. The positive difference on the days debtors ratio is more difficult to explain. It could be due to possibility that more profitable companies tend to give more credit facilities to their customers. However, these conclusions should be taken with some reserves since it is not yet known if these differences are statistically significant.

The pattern of difference directions concerning the stability measures is less stable. Nineteen of them are emitting conflicting signals and only thirteen of the remaining twenty two have negative differences. This would seem to indicate that the stability of performance is not so much significant in the problem investigated or that the indices chosen to measure stability are not as reliable as it was thought. A similar situation was encountered by Betts and Belhoul(1982b) in their analysis on failing companies. Some of the twenty nine financial ratios which they used had a higher mean score on their ratio stability measure in the group of going concerns against all expectations. Nevertheless, the number of financial ratios concerned was smaller in proportion. Besides some of the stability measures proved to be highly significant

TABLE 5.1. DIRECTION OF DIFFERENCES

VARIABLE NAME	1978		1977		1976		OVERALL		EXPECTED	
	RATIOS	RATIO STABILITY	RATIOS	RATIO STABILITY	RATIOS	RATIO STABILITY	RATIOS	RATIO STABILITY	RATIOS	RATIO STABILITY
1. EBIT/TA	+	-	+	+	+	-	+	C	+	-
2. EBIT/NUE	+	-	+	-	+	-	+	-	+	-
3. EBIT/TA	+	-	+	+	+	-	+	C	+	-
4. EBIT/NW	+	-	+	-	+	-	+	-	+	-
5. EBIT/SALES	+	-	+	+	+	-	+	C	+	-
6. SALES/TA	+	-	+	-	+	-	+	-	+	-
7. SALES/NW	-	-	-	-	-	-	-	-	+	-
8. WC/SALES	+	+	+	+	+	-	+	C	-	-
9. SALES/FA	+	-	+	+	+	-	+	C	+	-
10. CA/SALES	+	-	+	-	+	+	+	-	-	-
11. CA/CL	+	+	+	+	+	+	+	+	+	-
12. CL/NW	-	-	-	-	-	-	-	-	-	-
13. CASH/CL	+	+	+	+	+	+	+	+	+	-
14. WC/TA	+	+	+	+	+	+	+	+	+	-
15. CASH/CA	+	+	+	+	+	+	+	+	+	-
16. Q+/CL	+	+	+	+	+	+	+	+	+	-
17. QA/TA	+	+	+	+	+	+	+	+	+	-
18. NW/TL	+	+	+	+	+	+	+	+	+	-
19. EBIT/T.INT.	+	+	+	+	+	+	+	+	+	-
20. TA/TL	+	-	+	-	+	+	+	C	+	-
21. LTL/NW	-	-	-	+	-	+	-	C	-	-
22. CF/TL	+	+	+	+	+	+	+	+	+	-
23. CF/CL	+	+	+	+	+	+	+	+	+	-

CONTINUED OVER

TABLE 5.1. DIRECTION OF DIFFERENCES (CONTINUED)

VARIABLE NAME	1978		1977		1976		OVERALL		EXPECTED	
	RATIOS	RATIO STABILITY	RATIOS	RATIO STABILITY	RATIOS	RATIO STABILITY	RATIOS	RATIO STABILITY	RATIOS	RATIO STABILITY
24. WC/CF	-	-	-	-	-	-	-	-	-	-
25. CF/TA	+	-	+	+	+	+	+	C	+	-
26. DAYS DEBTORS	+	-	+	+	+	+	+	C	-	-
27. SALES/DEBTORS	+	-	+	-	+	-	+	-	+	-
28. DAYS CREDITORS	-	-	-	-	-	-	-	-	-	-
29. ST/SALES	-	-	-	-	-	-	-	-	-	-
30. ST/WC	+	-	-	-	-	-	C	-	-	-
31. ST/CL	+	-	+	-	+	-	+	-	+	-
32. ST/CA	-	-	-	-	-	+	-	C	-	-
33. WC/NW	+	-	+	+	+	+	+	C	+	-
34. WC/NCE	+	-	+	+	+	+	+	C	+	-
35. WC/LTL	+	-	+	-	+	-	+	-	+	-
36. NW/TA	+	-	+	-	+	+	+	C	+	-

CONTINUED OVER

TABLE 5.1. TABLE OF DIFFERENCES (CONTINUED)

VARIABLE NAME	1978	1977	1976	OVERALL	EXPECTED
BSDM1	-	-	+	C	-
TADM1	-	+	-	C	-
TBDM1	-	+	+	C	-
BSDM3	-	+	+	C	-
TADM3	-	+	-	C	-
TLDM3	-	+	+	C	-
TRAT	+	+	+	+	+
TRSA	+	+	+	+	+
TR1NV	+	+	+	+	+
TR DEBT	+	+	+	+	+
TR CRED	+	+	+	+	+
CHAT	+	+	+	+	+
CHSA	+	+	+	+	+
CHINV	+	+	+	+	+
CH DEBT	+	+	+	+	+
CH CRED	+	+	+	+	+
SIZE 1 (TA)	+	-	-	C	
SIZE 2 (SALES)	+	-	-	C	

\+ positive mean group difference

\- negative mean group difference

C conflicting signals

which emphasized the importance of the performance stability concept in the study of bankruptcies and in financial analysis as a whole.

In the present case, it should be noted however that out of the eighteen stability measures whose difference directions changed during the period investigated, sixteen had a negative difference between mean groups in year 1978 which seems to indicate that a sustained high level of efficiency leads to a more stable financial structure. But it was not sure whether this observed increase in stability in the final year of analysis was genuine, as some of the difference directions fluctuated from negative in year 1976 to positive in year 1977, and to negative again in year 1978. This could be noticed for ratio stability measures: S1, S3, S5, S9 and for decomposition measures: TADM1 and TADM3. Although only six of the eighteen measures examined had such a behaviour, it can not be proved that those eighteen stability measures are in fact indicating an improved stability unless a longer period of time is analysed and the improved stability repeated for consecutive years. As a consequence these measures were not considered in further analysis.

Concerning the measures of trend and change, they all showed a positive difference. The measures of size on the contrary switched from negative differences to positive differences in the last year.

5.4. 1.2. Identification of well performing firms

The first sample is composed of firms that have been on average among the top fifty percent performers over the years 1978, 1977 and 1976. The other sample comprised the companies that were not eligible for inclusion in the first sample. Their respective number of cases was four hundred and ten and four hundred and eleven. All the eight hundred and twenty one companies that were selected according to the criteria defined in chapter 3 were included in the analysis.

A) Univariate analysis of between group differences

The difference between groups was tested using the F test described in Appendix VIII. The use of the F test rather than the more usual t test was due to the fact that the result of the F test is given as part of the outputs of the discriminant analysis computer program. The variables considered were those that will be included in the discriminant analysis. The variables emitting conflicting signals plus the stability measures that showed positive differences between groups were discarded as it would not make sense to assume that the greater the financial instability of a firm the higher its level of performance.

The hypothesis tested was:

$$H_o: \quad U_w = U_1$$

where:

U_w is the mean of a variable coming from the population of well performing companies.

U_l is the mean of a variable coming from the population of less well performing companies.

Inspecting table 5.2 one sees that the null hypothesis of no difference between group is rejected in most of the cases.

This is particularly true of the financial ratios with the only exception of total asset, debtors and fixed asset turnovers, days debtor, working capital over cash flow, and long term liabilities over net worth. All the financial ratios representing the profitability dimension are all highly significant as expected. The same observations were made concerning the long term solvency, the short term liquidity, the cash position and the interest coverage dimensions. The dimensions exhibiting several financial ratios indicating no significant differences between groups were the business turnover and debt position dimensions. The financial ratios associated with the working capital management position exhibited highly significant differences between groups but for one.

Concerning the stability measures, the differences were highly significant as well. All the stability dimensions were not represented as some of the stability measures were removed from the analysis. The six dimensions that were examined (profitability stability, financial leverage stability, capital turnover stability, inventory management stability and credit management stability) exhibited significant differences between groups.

TABLE 5.2: SIGNIFICANCE OF BETWEEN GROUP DIFFERENCES 1978

(Univariate F test)

	VARIABLES	MEAN		STANDARD DEVIATION		LEVEL OF SIGNIFICANCE **
		WELL PERFORMING	LESS WELL PERFORMING	WELL PERFORMING	LESS WELL PERFORMING	
RATIOS:						
R7	SALES/NW	1.2057	1.3779	0.5160	0.6725	A
R12	CL/NW	4.3116	4.6013	0.5237	0.6556	A
R18	NW/TL	4.4926	4.2145	0.4920	0.5863	A
R20	TA/TL	200.8501	180.4292	52.8322	57.2731	A
R36	NW/TA	47.3356	40.8290	11.6060	13.2871	A
R8	WC/SALES	19.4985	13.81974	12.2846	12.0218	A
R11	CA/CL	5.1937	5.0145	0.3036	0.2943	A
R14	WC/TA	28.0743	19.9126	14.3781	14.6687	A
R24	WC/CF	375.9734	432.6476	262.6180	1125.7184	C
R31	St/CL	0.9000	0.7600	0.4900	0.3700	A
R33	WC/NW	60.9277	49.8440	31.2465	36.5152	A
R34	WC/NCE	43.7662	34.1301	20.8959	23.0974	A

CONTINUED OVER

TABLE 5.2: SIGNIFICANCE OF BETWEEN GROUP DIFFERENCES 1978 (CONTINUED)

(Univariate F test)

	VARIABLES	MEAN		STANDARD DEVIATION		LEVEL OF
		WELL PERFORMING	LESS WELL PERFORMING	WELL PERFORMING	LESS WELL PERFORMING	SIGNIFICANCE **
RATIOS:						
R1	EBIT/TA	15.1949	8.0826	3.8930	3.6264	A
R2	EBIT/NCW	24.0304	14.2974	6.7731	7.7029	A
R3	EBIT/TA	13.8152	5.7679	4.2608	3.9931	A
R4	EBIT/NW	33.5937	20.5982	11.2990	15.7393	A
R5	EBT/SALES	9.5143	4.0920	4.4143	3.4681	A
R22	CF/TL	17.3368	8.9469	8.8566	6.9912	A
R23	CF/CL	26.6199	13.3558	14.6522	11.8758	A
R25	CF/TA	8.4964	4.9932	3.4006	3.5013	A
R6	SALES/TA	0.4242	0.4230	0.5160	0.6725	C
R10	CA/SALES	0.4323	0.4030	0.1538	0.1597	A
R26	DAYS DEBTORS	62.5820	61.6984	27.5429	27.6324	C
R27	DEBTORS/SALES	10.9329	9.2792	21.3688	15.7188	C
R28	DAYS CREDITORS	7.3051	7.6235	1.4134	1.5926	A

CONTINUED OVER

TABLE 5.2: SIGNIFICANCE OF BETWEEN GROUP DIFFERENCES 1978 (CONTINUED)

(Univariate F test)

	VARIABLES	MEAN		STANDARD DEVIATION		LEVEL OF SIGNIFICANCE **
		WELL PERFORMING	LESS WELL PERFORMING	WELL PERFORMING	LESS WELL PERFORMING	
RATIOS:						
R16	QA/CA	9.6643	8.71521	1.9856	1.7275	A
R17	QA/TA	32.8269	30.69?9	11.4235	10.9433	A
R32	St/CA	47.3596	47.8911	16.1456	16.9819	A
R9	SALES/FA	1.6935	1.6839	0.5795	0.7413	C
R21	LTL/NW	0.1703	0.1832	0.0901	0.1121	C
R35	WC/LTL	2.7611	1.7234	5.2647	2.5301	A
R13	CASH/CL	1.4266	0.5531	1.7558	1.8328	A
R15	CASH/TA	0.3525	0.3934	1.7177	1.7758	A
R19	EBIT/T.INT.	62.3954	6.0886	206.3833	9.1738	A
R29	St/SALES	0.2264	0.5288	0.1252	1.1773	A
STABILITY MEASURES:						
S2	EBIT/NCE	1.0109	1.1844	0.7761	0.9464	A
S4	EBIT/NW	1.4672	1.6593	0.8016	0.8903	A

CONTINUED OVER

TABLE 5.2: SIGNIFICANCE OF BETWEEN GROUP DIFFERENCES 1978 (CONTINUED)

(Univariate F Test)

	VARIABLES	MEAN		STANDARD DEVIATION		LEVEL OF SIGNIFICANCE **
		WELL PERFORMING	LESS WELL PERFORMING	WELL PERFORMING	LESS WELL PERFORMING	
STABILITY MEASURES						
S12	CL/NW	2.3080	2.7548	0.8950	1.1069	A
S 6	SALES/TA	-2.4221	-2.2113	0.8771	0.9042	A
S 7	SALES/NW	-1.2018	-0.8282	0.9499	1.0506	A
S10	SALES/EA	-1.8131	-1.7062	0.8835	0.9564	B
S29	SALES/St	-2.4559	-2.4401	0.9454	1.0516	C
S30	St/WC	2.8091	3.6008	1.3194	1.7542	A
S31	CL/St	2.5491	2.7230	0.9831	1.1461	B
S35	LTL/WC	2.7824	3.3444	1.5138	1.8763	A
S27	Days Debtors	-0.6978	-0.6124	1.1823	1.1283	C
S28	Days Creditors	1.5054	1.7416	0.7945	0.8583	A
S24	WC/CF	4.3306	5.2733	0.9558	1.4872	A

CONTINUED OVER

TABLE 5.2. SIGNIFICANCE OF BETWEEN GROUP DIFFERENCES 1978 (CONTINUED)

(Univariate F Test)

VARIABLES	MEAN		STANDARD DEVIATION		LEVEL OF SIGNIFICANCE **
	WELL PERFORMING	LESS WELL PERFORMING	WELL PERFORMING	LESS WELL PERFORMING	
TREND AND CHANGE MEASURES					
1.TRTA	18.3453	10.9400	9.1863	10.9854	A
2.TRSA	20.8053	15.6138	16.3163	11.3850	A
3.TRIN	24.1737	14.9109	14.9226	15.8519	A
4.TRCR	20.3561	13.2523	13.6706	14.6607	A
5.TRDFB	81.1336	14.2208	14.4308	16.8523	A
6.CHTA	16.5730	7.6839	11.6182	15.2182	A
7.CHSA	16.6286	-0.4686	27.4052	209.4656	C
8.CHIN	20.8150	10.9980	19.2492	25.2641	A
9.CHCR	18.2709	8.5031	16.9817	20.0604	A
10.CHDEB	15.9490	8.6402	20.2274	23.2406	A
SIZE MEASURES *					
1.SIZE 1 (TA)	121952	120253	528471.5	336918.1	C
2.SIZE 2 (SALES)	180854	166836	811435.6	373424.7	C

* In thousand pounds. ** a) :Not significant at $\alpha = 0.01$ b) :Not significant at $\alpha = 0.05$ c) :Significant at $\alpha = 0.05$

The trend and change measures indicated also highly significant differences between groups but this was not observed on the measures of sizes. The conclusions which can already be drawn from this preliminary analysis is that marked difference exists between successful and less successful companies on all aspects of their financial characteristics with the exception of size. Some of the variables do not have equal variance and so the results of the test concerning those variables should be taken with some measure. However, their number is limited and would not affect the above conclusion.

b) Discriminant runs

A discriminant run was performed on all the selected variables. Twenty variables entered the discriminant function but some of the variables had coefficients with opposite sign to the sign of the difference between the well and less well performing company group means. One financial ratio, one stability measure and three measures of trend and change were among those variables as reported in table 5.3. Keeping them in the discriminant function would certainly lead to erroneous conclusions as the coefficients of the function give indications of the weight of each variable and of its direction in relation to the classification in the two groups. Taking as an example R1 (earnings before interests and taxes to total assets), the positive sign indicates that the higher its value on R1, the greater the chances of a company belonging to the well

TABLE 5.3. DISCRIMINANT COEFFICIENTS AND SIGN OF BETWEEN GROUP MEAN DIFFERENCES. (FIRST RUN)

VARIABLES	COEFFICIENTS	SIGN OF MEAN DIFFERENCES
R1:EBIT/TA	0.31848	+
R3:EBT/TA	0.17604	+
R6:SHES/TA	0.47646	+
R10:CA/SALES	3.54131	+
R15:CASH/TA	0.09218	+
R19:EBIT/T.INT	0.00090	+
R28:DAYS CREDITORS	-0.83918	-
R29:St/SALES	-0.028305	-
R33:WC/NW *	-0.00678	+
R35:WC/LTL	3.66553	+
S3:EBIT/NW *	0.22448	-
S7:SALES/NW	-0.21354	-
S24:WC/CF	-0.24549	-
S35:LTL/CF	-0.13017	-
TRAT	0.06211	+
TRSA *	-0.02313	+
TRIN *	-0.02617	+
TRCR	0.01368	+
CHIN	0.01564	+
CHCR *	-0.01680	+

* opposite signs

performing group. Therefore the examination of variables with opposite signs would lead to the conclusion that a lower (a higher) value of the variables is indicative of a successful company when in fact it is the opposite that is true. The case of S4 (earnings before interests and taxes over net worth stability measure) is illustrative of such a situation. The sign of the coefficient reveals that the higher the instability of the earnings before interests and taxes to net worth over the last three years, the better the performance level of the firm when this is rather a sign of low performance. These variables were thus removed from further discriminant runs. In addition, two more variables which were selected and which exhibited great differences in their variations from group to group were not considered further. They were variables R19 (earnings before interests and taxes over total interest charges) and R29 (inventory turnover) which happen to be associated with the same dimension.

The function resulting from this discriminant run is given in Table 5.4. It included eleven variables, but as previously, some had coefficients whose sign was opposite to the sign of their differences between group mean. Among the variables with opposite signs were a profitability measure and two measures of trend and change.

TABLE 5.4. DISCRIMINANT COEFFICIENTS AND SIGN OF BETWEEN GROUP MEAN DIFFERENCES (SECOND RUN)

VARIABLES	COEFFICIENT	SIGN OF MEAN DIFFERENCES
R1:EBIT/TA	0.12805	+
R3:EBT/TA	0.11148	+
R4:EBIT/NCE*	-0.0085	+
R10:CA/SALES	1.27249	+
R15:CASH/TA	0.04184	+
R28:Days creditors	-0.11041	-
S24:WC/CF	-0.13164	-
S35:LTL/WC	-0.04776	-
TRAT	0.02276	+
TRDEB*	-0.00452	+
CHSA*	-0.00054	+

* opposite signs

At this stage of the analysis, only one measure of trend or change (trend in total assets) was selected to enter the discriminant function. It was felt that an increased trend in total assets was a consequence of the success of the firm rather than an indication of good management. As pointed out earlier in chapter 3, growth is very much dependent on substantial profit being generated. Therefore it was preferred to compare differences between measures of trend or measures of change. In financial terms, sales are always related to debtors, creditors and inventory. It was then decided to calculate the following differences:

DIF 1 = TRSA - TRIN

DIF 2 = TRSA - TRCR

DIF 3 = TRSA - TRDEB

DIF 4 = CHSA - CHIN

DIF 5 = CHSA - CHCR

DIF 6 = CHSA - CHDEB

which would be a better indication of management success since a positive difference would mean than an increase of sales was obtained with a lesser increase in elements of the balance sheet that are generally very much related to them. This would indicate the ability of the firm's management in drawing good credit and inventory policies. These new six measures were subjected to discriminant analysis alongside the other variables but none of them proved to be significant. The next run completed without including any measures of trend or change since none of them was significant but for TRAT (trend in total assets) which turned out to be ambiguous regarding the interpretation of its meaning in relation to the problem investigated. This ensued in more financial ratios associated with the profitability dimension being selected as Table 5.5 indicates. However, some of them had the sign of their coefficient opposite the sign of their difference between group means. When removed, the final discriminant function was as follows:

$$\begin{aligned} z = {} & 2.70827 + 0.2017984R_2 - 1.1290 \ln R12 \\ & + 0.032377R14 + 0.1056062 \ln R15 + 0.075345R25 \\ & - 0.108633\ VR28 - 0.279733 \ln S9 - 0.377076 \ln S24 \\ & - 0.120409 \ln S35 \end{aligned}$$

which was the "best" model arrived at. It should be pointed out that other combinations of variables could give very similar results.

TABLE 5.5. DISCRIMINANT COEFFICIENTS AND SIGN OF DIFFERENCE BETWEEN GROUP MEANS (THIRD RUN)

VARIABLES	COEFFICIENT	SIGN OF MEAN DIFFERENCES
R1:EBIT/TA	0.10240	+
R3:EBT/TA	0.12001	+
R6:SALES/TA	0.26695	+
R10:CA/SALES	1.07649	+
R15:CASH/TA	0.04795	+
R22:CF/TL	0.01930	+
R23:RF/CL *	-0.00957	+
R27:DEBTORS/SALES	2.19198	+
R28:DATS DEBTORS	-0.09791	-
R32:St/CA *	0.00752	-
S6:SALES/TA	-0.12280	-
S7:SALES/NW	-0.09606	-
S10:SALES/CA *	0.07797	-
S24:WC/CF	-0.19446	-
S27:SALES/DEBTORS *	0.09902	-
S30:St/WC	-0.06184	-

* opposite signs

c) <u>Overall significance of the discriminant model</u>

The significance of a linear discriminant function is assessed by testing the separation between the populations. When the true parameters are not known, the usual practice is to use estimated parameters. A statistic which follows an F distribution can be computed using the D^2, Mahalanobis distance, or Λ, Wilks' lambda, as described in chapter 3.

The computed F statistic was:

$$F = 76.801$$

with 9 and 810 degrees of freedom which is significant at less than 0.001 level of significance ($F_{9,\infty} = 2.41$ for x = 0.001).

The corresponding

$$D^2 = 3.4009$$

and

$$\Lambda = 0.5399$$

The value of the F statistic indicates a large separation between groups on a multivariate basis which was anticipated from the results of the preceding univariate analysis. Therefore, one can conclude, that well performing companies exhibit a financial profile different from that of the less well performing companies. Such information can be used in identifying well performing companies as it was proposed earlier in the study.

The centroids of the two groups are:

well performing group: 1.70044
less well performing group: -1.70044

which are obtained by multiplying the variable means in each group by the discriminant function. They represent the means of the z-score in the well performing group and the less well performing group and give an indication of the central tendency of the distribution of the z-scores in each group. The value of the cut-off point which will serve to classify the companies in the two samples in order to assess the performance of the model, will lie between the values of the two group centroids.

Provided the data necessary to calculate the function variables are available, the model could then be used to classify any further company on the basis of its z-score and the value of the cut-off point. If the z-score value is greater than the cut-off point value, the company will be classified as coming from the well performing group. If it is smaller, it is assumed as coming from the less well perfoming group. The value of the cut-off point will depend on a priori information known about the populations and about the cost attached to any misclassification.

d) <u>Testing the underlying assumptions</u>.

The assumptions tested are multivariate normality and equality of the variance covariance matrices of the population of the two groups. The assumption of multivariate normality will be tested first as the test for equality of variance covariance matrices is sensitive to departure from normality. Therefore, if the assumption of multivariate normality is rejected, the result from the test for equality of variance covariance matrices should be taken with some reserves.

The statistics used to test the assumption of multivariate normality are those described in the preceding section. Two of them are proposed by Mardia (1970) and the other one is derived from the distribution of

$$V = (X_i - \bar{X})' S^{-1} (X_i - \bar{X})$$

which follows a χ^2 distribution with m (number of variables) degree of freedom.

Mardia's measures of skewness and kurtosis

$$b_{1,9} = \frac{1}{n^2} \sum_{i=1}^{n} \sum_{j=1}^{n} \left\{(X_i - \bar{X})' S^{-1} (X_j - \bar{X})\right\}^3$$

$$b_{2,9} = \frac{1}{n} \sum_{i=1}^{n} \left\{(X_1 - \bar{X})' S^{-1} (X_1 - \bar{X})\right\}^2$$

were calculated together with the associated statistic

$$A = \frac{n}{6} b_{1,9}$$

which has a χ^2 distribution with p(p-1) (p+2)/6 degrees of freedom.

$$B = \left[b_{2,9} - \left\{p(p+2)\right\}\right] \Big/ \left\{8p(p+2)/n\right\}^{\frac{1}{2}}$$

which is distributed as N(0,1).

For the well performing company group, the following results were obtained:

$b_{1,9}$ = 4.434

A = 302.990

and

$b_{2,9}$ = 112.857

B = 9.970

For the less well performing group, the results were:

$b_{1,9} = 5.833$

$A \quad = 399.561$

and

$b_{2,9} = 124.532$

$B \quad = \ 18.393$

Both measures are significant for the two groups. The 0.01 value of χ^2_{165} is 215.65. Both A's are much greater than this value and the B's are much greater than 2.58 which the corresponding value of the standardized normal distribution at the 0.01 level. As both values are highly significant for each group, the samples cannot be regarded as coming from multivariate normal distributions.

The second test was directed at testing whether the distribution had many outliers.

The technique utilized was to identify the number of observations that were lying outside the ninety five percent and ninety nine percent centiles. If that number was higher than the expected number then it could be concluded that the distribution departed from multivariate normality and that it presented many outliers.

TABLE 5.6. IDENTIFICATION OF OUTLIERS

GROUP	CENTILES			
	95%		99%	
well performing	9	(21)*	1	(4)*
less well performing	31		13	

* expected number of outliers for either group.

The less well performing sample presents much more value lying outside the ninety five and ninety nine percent centours than expected. This corroborates the information gained from the two other tests. As far as the well performing group is concerned, the number of such observations is smaller than the expected number. This again indicates a departure from normality and is consistent with the results from the test for multivariate skewness and kurtosis.

As a consequence the test for equality of variance covariance matrices should be treated with some caution. Applying Box's test for equality of variance covariance matrices, we obtain

Group	Rank	Log Determinant
well performing	9	10.774
less well performing	9	13.513
pooled variance covariance matrix	9	12.427

Box's M criterion is then equal to:

$$M = 230.57$$

and the corresponding F statistic is:

$$F = 5.0648$$

which is distributed as an F distribution with 45 and ∞ degree of freedom.

The hypothesis of equality of variance covariance matrices is therefore rejected since the value $F_{45,\infty}$ is approximately equal to 1.50 at the 0.01 level of significance.

The above results would imply that a quadratic discriminant function should be fitted. However the non-multivariate normality of the two data sets would have adverse consequences on the quadratic model.

Besides, as pointed out earlier, the results of the test for equality of variance covariance matrices are affected by departure from the assumption of normality. Therefore, it was thought wiser to fit a linear function as it is more robust to non-multivariate normality and as it is not completely clear whether the two variance covariance matrices are really different.

e) Contribution of variables selected to the discriminant model.

An examination of the constituent variables of the discriminant model in relation to the principal component analysis of chapter 4 reveals that distinct financial dimensions are directly associated with the level of performance of a firm. Table 5.7 indicates that seven of the financial dimensions are represented. Two of them are related to stability of performance.

Two of the constituent variables are associated with the Return on Investment dimension. The stability measure, S24 (cash flow) does not load significantly on any component which would imply from the analysis of chapter 4 that S24 does not measure a specific

TABLE 5.7. FINANCIAL DIMENSIONS ASSOCIATED WITH THE DISCRIMINANT MODEL.

VARIABLES	ASSOCIATED DIMENSION
R2:EBIT/NCE R25:CF/TA	RETURN ON INVESTMENT
R12:CL/NW	FINANCIAL LEVERAGE
R14:WC/TA	WORKING CAPITAL MANAGEMENT
R15:CASH/TA	CASH POSITION
R28:DAYS CREDITORS	BUSINESS TURNOVER
S 9:SALES/FA	CAPITAL TURNOVER STABILITY
S24:WC/CF	
S35:LTL/WC	INVENTORY MANAGEMENT STABILITY

* Not associated with any dimension.

stability dimension but carries information on different aspects of performance stability. The two other stability dimensions associated with the discriminant model are the Capital Turnover Stability and the Inventory Management Stability. The other financial dimensions were Financial Leverage, Working Capital Management, Cash Position and Business Turnover.

Nearly every aspect of a firm's financial profile is represented, which indicates that to be successful, a firm's management must be aware of the necessity to look after every area of concern. To concentrate and reach a good level of performance in only one aspect, does not mean that the firm as a whole is well performing. Furthermore, all the three overall categories defined by Courtis (1978) are associated with the discriminant model. As would be expected, this reveals that overall success of a firm depends on good managerial performances as well as profitability and solvency. A firm doing well in only one category, say, profitability, is by no means well performing, unless its performances regarding the two other categories are satisfactory.

Table 5.8. gives the ranking of the variables according to their contribution to the discriminatory power of the linear discriminant function. Although more discrepancies appear in the ranking of the last

TABLE 5.8. RANKING OF VARIABLES ACCORDING TO THEIR CONTRIBUTION TO THE DISCRIMINANT MODEL

VARIABLES	RANKING					
	F-Test	Standard Coefficient	Mosteller and Wallace measure	Conditional deletion	Forward stepping	Backward stepping
R2:EBIT/NCE	1	1	1	1	1	1
R12: CL/NW	5	2	3	2	2	2
R14:WC/TA	4	4	4	4	4	4
R15:CASH/TA	6	8	6	7	7	7
R25:CF/TA	2	6	5	6	6	6
R28: DAYS CREDITORS	8	9	9	8	8	8
S9:SALES/FA	9	5	8	5	5	5
S24:WC/CF	3	3	2	3	3	3
S35:LTL/WC	7	7	7	9	9	9

variables according to the different methods used, the most important contributors are R2 (earnings before interest and taxes to net capital employed), R12 (current liabilities to net worth), R14 (working capital to total assets) and S24 (working capital to cash flow) which are always more or less ranked in the same order.

Several methods were employed because as Eisenbeis et al (1973) pointed out, there does not exist a method that would give the exact contribution or order of contribution of the variables to the power of the model. In using different methods it was hoped that a similar ranking would emerge from the results of a method to those of another one, which would give more certainty about the contribution of each of the variables. The last four methods, described in section I of this chapter, were given more importance as they take into account the interdependence of the variables which is not considered by the two first methods.

All the methods ranked first the earnings before taxes and interest to net capital employed ratio, emphasising the need for a company to make substantial profits if it is to achieve a well balanced structure. The earnings ability of a firm will determine in the long run, its capability to borrow funds or to raise money on the capital market. It will, therefore, be apt to adapt to changes in the market, to invest in new techniques and to remain competitive. Without such a capacity to generate a certain return, a firm would impede its chances to grow and to secure a share of the market that would strengthen its position.

The variable ranked second, was the ratio of current liabilities to net worth. Its association with the long term solvency dimension stresses the importance of the magnitude of a firm's liabilities in relation to its overall performance. The higher the value of that ratio, the better the overall performance, since that would ensure that the fixed assets are not financed by current liabilities and that a large part of the financing comes from the firm's own capital, which would in turn, reduce the shareholders and lenders risk.

The two other variables that contributed strongly to the discriminant function, were the working capital to total asset ratio and the stability of working capital over cash flow. The first is related to the working capital dimension and measures the level of working capital available to the firm. The positive sign of its coefficient indicates that well performing firms tend to keep their level of working capital relatively higher than that of less well performing firms. This indicates that a greater portion of the current assets is contributed by the shareholders' fund and the long term liabilities. It ensures a more stable source of financing of the current assets and reflects the ability of the management in maintaining an adequate level of liquidity in order to meet the cash outflow of the company.

On the other hand, as discussed above, the stability of working capital to cash flow is rather a measure of overall stability. Therefore, the concept of performance stability is relevant to the problem investigated. Firms performing above average, have a more stable financial profile. That could reveal that fluctuations in the environment of successful firms is well perceived and anticipated by their management. Thus they would not lead to drastic changes in the financial profile of those firms. Management abilities are again directly translated in the measures of financial stability.

To a lesser degree of contribution, we found the cash to current liabilities ratio, the business velocity ratios and the two other stability measures. The velocity measures proved to be significant in Harrington and others (1980) study. Although, their study used different and more specific type of financial ratios, they noted that successful firms showed a better velocity than less successful companies. Among those ratios were current assets to sales, inventory to sales, work in progress to sales and fixed assets to sales.

To conclude, this paragraph on the contribution of variables to the discriminatory power of the model, it should be noted that financial aspects of a firm such as the business turnover and liquidity are of less importance in defining its level of overall performance than more essential aspects such as a well balanced structure, a capacity to earn profits, a good level of working capital and a good stability of financial performance.

f) Performance of the discriminant model.

The performance of a linear discriminant function is evaluated by its number of correct classifications. In chapter 3, several methods have been presented to estimate the probability of misclassification. Most of them assume that the data is distributed multivariate normal. This assumption, in the present case, was found not to be true.The use of the resubstitution method and of Lachenbruch's (1967) Jackknife method were preferred. These two techniques are distribution free. A further technique consisting of splitting the samples in two parts, one to derive the linear discriminant function and the other used to estimate the correct classification rates, was considered in some financial studies among other Altman (1968). However, it was criticized on the ground that the linear discriminant function based on the subsamples may be different from that based on the whole samples and that it should be recomputed using this additional data. Furthermore, the estimates of correct classification so derived suffer from the same problem and may be different from the population estimates. Rather than to waste data, it was decided to use the totality of the data available and to evaluate the performance of the discriminant model according to the two techniques mentioned above since the Lachenbruch's jackknife method gives almost unbiased estimates of misclassification.

Another point that should be taken into consideration when estimating the performance of the discriminant model is the setting of the cut off point. The cut off point is a value that lies on a line joining the centroids of the two populations. The extent to which it will depart from the mid-point is affected by two factors:

- the prior probability of a firm belonging to one of the groups.
- the cost of making an error of classification may differ

depending on whether a well performing firm is misclassified as less well performing (Type I error) or vice versa (Type II error).

Another consideration may be to minimize the rates of error in each group rather than the total rate of misclassification.

From the way in which the samples were drawn, the prior probabilities of belonging to either group was the same as it could be equally likely for a firm on a priori grounds to come from either group. So the cut off point based on prior probabilities would be equal to:

$$C = \log \frac{.5}{.5} = 0$$

as seen in chapter 3.

Regarding the impact of misclassification costs on the value of the cut off point, it should be noted that estimation of the ratio of these costs might differ from one user of the discriminant model to another. For example, an individual investing money may evaluate the cost of a type II error much higher than that of a type I error. For a firm trying to assess its level of performance, the costs of misclassification are of very little use. This emphasizes the versatility of such a discriminant model and the many ways in which it can be adapted to suit the need of the user.

In table 5.9, are presented the correct classification rates using both the resubstitution method and Lachenbruch's jackknife technique and a cut off point of zero.

TABLE 5.9. CLASSIFICATION MATRICES

RESUBSTITUTION METHOD		PREDICTED MEMBERSHIP	
		WELL PERFORMING	LESS WELL PERFORMING
ACTUAL MEMBERSHIP	WELL PERFORMING	88.5%	11.5%
	LESS WELL PERFORMING	18.2%	81.8%

JACKKNIFE METHOD		PREDICTED MEMBERSHIP	
		WELL PERFORMING	LESS WELL PERFORMING
ACTUAL MEMBERSHIP	WELL PERFORMING	88.3%	11.7%
	LESS WELL PERFORMING	18.7%	81.3%

The total percentage of correct classification is 85.1 percent and 84.8 percent according to the resubstitution and the jackknife method respectively. This high rate of correct classifications demonstrates the possibility of identifying well performing companies using information available from the published accounts in a very efficient manner. However, the slightly greater possibility of making a type II error can be corrected by moving the cut off point towards the centroid of the well performing group which results in a slight increase in the overall rate of correct classification. Table 5.10 shows the effect of setting the cut off at 0.11 on the correct rate of classification.

TABLE 5.10. CLASSIFICATION MATRICES

RESUBSTITUTION METHOD		PREDICTED MEMBERSHIP	
		WELL PERFORMING	LESS WELL PERFORMING
ACTUAL MEMBERSHIP	WELL PERFORMING	85.6%	14.4%
	LESS WELL PERFORMING	13.9%	86.1%

JACKKNIFE METHOD		PREDICTED MEMBERSHIP	
		WELL PERFORMING	LESS WELL PERFORMING
ACTUAL MEMBERSHIP	WELL PERFORMING	85.4%	14.6%
	LESS WELL PERFORMING	15.1%	84.9%

The decrease in the overall rate of misclassifications is very slight since the percentage of correct classifications are 86 percent and 85.1 percent according to the resubstitution and jackknife method respectively. However, the rate of misclassification in each group is now more or less even. This again shows that the cut off point should be set according to the need of the user. Furthermore, when there is some departure from the assumption, the cut off point defined as $\log \frac{c_2p_2}{c_1p_1}$ (see chapter 3, section 3.2.4.1(6)) is not optimum any more since it assumes the populations to be multivariate normal.

If the discriminant score of a company is close to the cut off point, the decision about its level of performance can be withheld. In such a manner, a "grey area" or "zone of ignorance" can be constructed which is constituted by the overlapping of the two samples. Such a "grey area" covers the interval (.23, .58) by setting 90 percent confidence limits. Any company having a discriminant score falling in that interval would not be classified as possibly coming from any of the groups.

The discriminant scores could be used as well by a company to assess its overall performance over the years. If its discriminant score increases from year to year then the company could estimate that its performance is improving. On the contrary, a drop in its discriminant score would mean that the overall efficiency of the company is decreasing. The extent of the drop would measure the seriousness of the problem. A government department could use the discriminant model in such a fashion to monitor the economy. The procedure would consist of computing a discriminant score for all the companies. Their arrangement in descending order would indicate the state of the companies with the best performing at the top and the worst performers at the bottom of the list. An advisory team could be set up and contact the companies with the lowest discriminant score. In collaboration with the management of those companies, it could suggest some measures to improve their performance. The cost of this monitoring procedure would certainly not be prohibitive, if company accounts were supplied to the government in computer readable form. The discriminant score would be a starting point for a more thorough analysis if necessary and would save the time otherwise needed to conduct a financial analysis of every company.

5.4.1.3. High performance and its impact on firm characteristics

This part of the analysis is concerned with the two first years of above average performance covering the period from 1976 to 1977. Its aim is to find out the extent of changes in their financial profile experienced by companies which have just reached an above average level of performance and to discover whether a sustained level of high performance amplifies those changes and whether those companies could be considered as high performers.

The sample of successful companies was constituted of firms that did not experience an above average level of performance during the first four years considered in the study (1972, 1973, 1974 and 1975) and numbered one hundred and three. The second sample comprised the companies that never achieved an above average level of performance during the seven years analysed and numbered three hundred and nine.

A) Univariate analysis

This analysis as in the preceding section was based on the F test for the difference between groups. The variables tested were the same as those considered in the previous analysis.

From the inspection of tables 5.11 and 5.12, we notice that to a certain extent the separation between group although still significant is not so important as for year 1978 (see table 5.2). The number of variables being significant is decreasing as we move back towards the first year of high level of performance. The values of the F statistics are not reported in the tables for reasons of presentation and clarity but their value was decreasing except for few variables. The areas where this is the most striking are the business turnover dimension, the financial leverage dimension and the cash position dimension. This was also noticeable for variables related to stability of performance and for the measures of trend and change.

Such a situation was expected as a sustained above average level performance would strengthen the financial position of a firm and would lead to a better balanced financial structure and qualify that company as well performing.

TABLE 5.11. SIGNIFICANCE OF BETWEEN GROUP DIFFERENCES 1977 (Univariate F - test)

	VARIABLES	MEAN		STANDARD DEVIATION		LEVEL OF SIGNIFICANCE * *
		WELL PERFORMING	LESS WELL PERFORMING	WELL PERFORMING	LESS WELL PERFORMING	
RATIOS:						
R7.	SALES/NW	1.3297	1.4350	0.5900	0.7111	C
R12.	CL/NW	4.5257	4.7108	0.6301	0.6877	B
R18.	NW/TL	4.2580	4.0760	0.5576	0.5546	A
R20.	TA/TL	192.5283	159.6317	50.5291	53.1596	A
R36.	NW/TA	42.0385	37.3558	12.6312	12.4400	A
R8.	WC/SALES	17.3368	12.3577	11.32505	12.4547	A
R11.	CA/CL	5.1096	4.9563	0.3083	0.3230	A
R14.	WC/TA	24.5011	16.8410	13.1990	14.6293	A
R24.	WC/CF	344.7067	391.3833	219.5144	685.0483	C
R31.	St/CL	0.7921	0.7019	0.3812	0.3643	B
R33.	WL/NW	59.4774	44.8578	30.1205	35.8930	A
R34.	WC/NCE	37.6714	27.1103	19.8849	24.8426	A
R1.	EBIT/TA	14.0699	7.7577	2.7831	3.2853	A
R2.	EBIT/NCE	23.9530	14.1290	6.2144	7.4673	A
R3.	EBT/TA	12.0393	5.1612	3.2425	4.0055	A

CONTINUED OVER

TABLE 5.11. SIGNIFICANCE OF BETWEEN GROUP DIFFERENCES 1977 (Univariate F - test) CONTINUED

	VARIABLES	MEAN		STANDARD DEVIATION		LEVEL OF SIGNIFICANCE **
		WELL PERFORMING	LESS WELL PERFORMING	WELL PERFORMING	LESS WELL PERFORMING	
RATIOS:						
R4.	EBIT/NW	36.0226	21.7482	12.2894	12.9334	A
R5.	EBT/SALES	8.4649	3.6691	3.7458	4.0306	A
R22.	CF/TL	14.4070	7.2417	7.8620	6.2524	A
R23.	CF/CL	22.6666	11.7628	13.0625	10.3687	A
R25.	CF/TA	7.7026	4.1852	3.3379	3.5066	A
R6.	SALES/TA	0.4121	0.3814	0.3636	0.4985	C
R10.	CA/SALES	0.4288	0.4083	0.5568	0.7837	C
R26.	DAYS DEBTORS	65.3602	63.2708	23.6817	29.0227	C
R27.	SALES/DEBTORS	0.1790	0.1734	0.0649	0.0795	C
R28.	DAYS CREDITORS	7.6958	7.8098	1.5078	1.6566	C
R16.	QA/CL	9.5056	8.5848	1.6526	1.7819	A
R17.	QA/TA	34.3032	30.4325	10.2226	11.6459	A
R32.	St/CA	44.6938	46.4316	14.1632	17.7263	C
R9.	SALES/FA	1.7262	1.5968	0.1449	0.1690	C
R21.	LTL/NW	0.1974	0.2042	0.0912	0.1212	C
R35.	WC/LTL	0.0169	0.0115	0.0138	0.0138	A
R13.	CASH/CL	1.0948	0.5898	1.8359	1.7932	B
R15.	CASH/TA	0.0979	0.3413	1.8008	1.7315	B

CONTINUED OVER

TABLE 5.11. SIGNIFICANCE OF BETWEEN GROUP DIFFERENCES 1977 (Univariate F - test) CONTINUED

	VARIABLES	MEAN		STANDARD DEVIATION		LEVEL OF SIGNIFICANCE * *
		WELL PERFORMING	LESS WELL PERFORMING	WELL PERFORMING	LESS WELL PERFORMING	
RATIOS:						
R19.	EBIT/T.INT.	31.2691	5.4433	107.0107	7.5360	A
R29.	St/SALES	0.2346	0.4001	0.1194	1.7701	C
STABILITY MEASURES:						
S2.	EBIT/NCE	1.1405	1.1948	0.8664	0.9120	C
S4.	EBIT/NW	1.6186	1.6728	0.7660	0.8848	C
S12.	CL/NW	2.52744	2.68947	0.9843	0.9998	C
S6.	SALES/TA	-2.0943	-2.0702	0.8419	0.7913	C
S7.	SALES/NW	-0.9668	-0.7689	0.8491	0.9771	C
S10.	SALES/CA	-0.5529	-0.4983	0.9060	0.8978	C
S35.	LTL/WC	2.9110	3.4305	1.5460	2.0720	B
S29.	SALES/St.	-2.3408	-2.3327	0.9678	1.1927	C
S30.	St/WC	3.2795	3.8177	1.3221	1.8539	A
S31.	CL/St.	2.7824	2.8863	1.1410	1.1453	C
S27.	DAYS CREDITORS	-0.4850	-0.3519	1.0081	1.0702	C
S28.	DAYS CREDITORS	1.8085	1.8243	0.8132	0.8781	C
S24.	WC/CF	4.7373	5.1837	1.0590	1.5638	A

CONTINUED OVER

TABLE 5.11. SIGNIFICANCE OF BETWEEN GROUP DIFFERENCE 1977 (Univariate F - test) CONTINUED

VARIABLES	MEAN		STANDARD DEVIATION		LEVEL OF SIGNIFICANCE **
	WELL PERFORMING	LESS WELL PERFORMING	WELL PERFORMING	LESS WELL PERFORMING	
TREND AND CHANGE MEASURES:					
1. TRTA	13.5831	9.8927	10.8559	11.1522	A
2. TRSA	20.3499	15.2252	11.4649	12.0220	A
3. TRIN	15.7062	12.8732	19.0132	19.8415	C
4. TRCR	13.4451	11.4829	14.3640	15.2370	C
5. TRDEB	16.5768	14.2971	16.6821	15.8599	C
6. CHTA	18.6054	13.5751	13.7583	14.6415	A
7. CHSA	28.6237	18.1001	14.5318	15.7834	A
8. CHIN	25.9598	19.9668	33.3585	25.0286	C
9. CHCC	19.2950	17.8001	19.7905	22.4396	C
10. CHDEB	26.0353	20.3725	26.5438	25.2265	C
SIZE MEASURES:*					
1. SIZE 1 (TA)	85125	129705	155980.5	338302.7	C
2. SIZE 2 (SALES)	130774	171937	255166.3	370864.7	C

* In thousand pounds.

**A: not significant at $\alpha = 0.01$. B: not significant at $\alpha = 0.05$.
C: significant at $\alpha = 0.05$.

TABLE 5.12: SIGNIFICANCE OF BETWEEN GROUP DIFFERENCES 1976. (Univariate F - test)

	VARIABLES	MEAN		STANDARD DEVIATION		LEVEL OF SIGNIFICANCE **
		WELL PERFORMING	LESS WELL PERFORMING	WELL PERFORMING	LESS WELL PERFORMING	
RATIOS:						
R7.	SALES/NW	1.3116	1.3634	0.6215	0.7109	C
R12.	CL/NW	4.5369	4.6322	0.6695	0.7313	C
R18.	NW/TL	4.2387	4.1079	0.5993	0.6025	C
R20.	TA/TL	171.6178	163.2197	54.0515	55.3856	B
R36.	NW/TA	41.7310	38.7329	13.1433	13.1433	B
R8.	WC/SALES	16.8297	12.5773	12.0802	12.5361	A
R11.	CA/CL	5.1019	4.9584	0.3077	0.3195	A
R14.	WC/TA	23.0511	16.3189	13.5563	14.4934	A
R24.	WC/CF	386.1106	444.7567	347.3476	1230.0336	C
R31.	St/CL	0.7679	0.7068	0.3643	0.3728	C
R33.	WC/NW	54.8220	42.0134	28.7336	38.6716	A
R34.	WC/NCE	40.6908	29.6157	19.3200	23.8923	A
R1.	EBIT/TA	12.1232	6.4355	2.8819	4.4001	A
R2.	EBIT/NCE	20.4976	11.3330	6.7659	8.3677	A
R3.	EBT/TA	9.7523	3.8691	3.5105	4.8665	A
R4.	EBIT/NW	30.7427	17.9762	13.0160	14.3348	A

CONTINUED OVER

TABLE 5.12: SIGNIFICANCE OF BETWEEN GROUP DIFFERENCES 1976. (Univariate F test) continued.

	VARIABLES	MEAN		STANDARD DEVIATION		LEVEL OF SIGNIFICANCE **
		WELL PERFORMING	LESS WELL PERFORMING	WELL PERFORMING	LESS WELL PERFORMING	
R5	EBT/SALES	6.7876	2.8065	3.5111	4.2546	A
R22	CF/TL	11.0082	6.2762	6.0370	5.6300	A
R23	CF/CL	17.5115	10.5528	10.5108	11.4650	A
R25	CF/TA	6.1469	3.5465	2.9188	3.0293	A
R6	SALES/TA	0.39241	0.3460	0.3597	0.5258	C
R10	CA/SALES	0.43621	0.4074	0.5989	0.8268	C
R26	DAYS/DEBYORS	68.0330	63.0420	25.1401	29.3276	C
R27	SALES/DEBTORS	0.1864	0.1727	0.0689	0.0804	C
R28	DAYS/CREDITORS	7.6646	7.7911	1.4774	1.6667	C
R16	QA/CL	9.4768	8.6017	1.8242	1.0248	A
R17	QA/TA	33.0511	28.8288	9.6050	11.2319	A
R32	St/CA	44.8400	42.0134	14.1723	17.4596	C

TABLE 5.12:SIGNIFICANCE OF BETWEEN GROUP DIFFERENCES 1976. (Univariate F Test) continued.

	VARIABLES	MEAN		STANDARD DEVIATION		LEVEL OF
		WELL PERFORMING	LESS WELL PERFORMING	WELL PERFORMING	LESS WELL PERFORMING	SIGNIFICANCE**
R9	SALES/FA	1.6403	1.4981	0.1514	0.1804	C
R21	LTL/NW	0.1874	0.2049	0.0967	0.1223	C
R35	WC/LTL	0.0153	0.0113	0.0120	0.0144	A
R13	CASH/CL	0.8459	0.5607	1.0177	1.7534	C
R15	CASH/TA	-0.1563	-0.4201	1.8942	1.6516	C
R19	EBIT/T.INT	11.8622	4.4127	20.0465	7.2821	A
R29	St/SALES	0.3276	0.3534	0.2735	1.0846	C
STABILITY MEASURES						
S2	EBIT/NCE	1.0625	1.2467	0.9334	0.9328	C
S4	EBIT/NW	1.5832	1.6742	0.9538	0.9119	C
S12	CL/NW	2.6892	2.6954	0.9574	0.9783	C
S6	SALES/TA	-2.0685	-2.0308	0.7570	0.7806	C
S7	SALES/NW	-0.8390	-0.7426	0.8944	0.9534	C
S10	SALES/CA	-1.6158	-1.4326	0.8128	0.8474	C

TABLE 5.12: SIGNIFICANCE OF BETWEEN GROUP DIFFERENCES 1976. (Univariate F Test) continued

	VARIABLES	MEAN		STANDARD DEVIATION		LEVEL OF
		WELL PERFORMING	LESS WELL PFRFORMING	WELL PERFORMING	LESS WELL PERFORMING	SIGNIFICANCE **
S29	SALES/St	-2.3504	-2.0433	1.0200	1.2123	B
S30	St/WC	3.5766	3.9474	1.5027	1.8088	C
S31	CL/St	2.9610	3.0463	1.0728	1.3507	C
S35	LTL/WC	3.1480	3.5564	1.8599	2.0575	C
S27	DAYS/DEBTORS	-0.5240	-0.4466	0.7815	0.9759	C
S28	DAYS/CREDITORS	1.8416	1.8777	0.7566	0.8750	B
S24	WC/CF	4.6447	5.2746	1.0393	1.5307	A
TREND AND CHANGE MEASURES						
1	TRTA	11.1580	9.6719	11.7106	10.9256	B
2	TRSA	19.8090	15.6363	13.9404	13.3613	C
3	TRIN	20.1150	17.8865	21.9225	20.1168	C
4	TRCR	11.5429	8.7812	14.6972	14.7958	C
5	TRDEB	18.11734	16.0000	16.96144	16.0598	C
6	CHTA	8.6861	6.0043	12.8771	12.4019	B

TABLE 5.12: SIGNIFICANCE OF BETWEEN GROUP DIFFERENCES 1976 (Univariate F Test) continued

	VARIABLES	MEAN		STANDARD DEVIATION		LEVEL OF SIGNIFICANCE **
		WELL PERFORMING	LESS WELL PERFORMING	WELL PERFORMING	LESS WELL PERFORMING	
7	CHSA	15.7929	11.3415	15.3290	16.1569	C
8	CHIN	11.4479	8.6425	29.1575	27.4415	C
9	CHCR	7.4527	6.4438	18.2035	20.8649	C
10	CHDEB	10.3907	10.5151	25.7846	23.7874	C
SIZE MEASURES *						
1	SIZE 1 (TA)	73080	112328	135843.9	282027.7	C
2	SIZE 2 (SALES)	106589	141298	209079.7	301160.2	C

* in thousand pounds

** A : not significant at $\alpha = 0.01$

B : not significant at $\alpha = 0.05$

C : significant at $\alpha = 0.05$

B. Multivariate Analysis.

Using the variables that were selected to enter the discriminant function, a multivariate F test for the difference between groups was performed for the years 1977 and 1976. Wilks' Λ s were equal to:

Year 1977 $\Lambda = 0.6339$

Year 1976 $\Lambda = 0.7462$

and their corresponding F statistics:

Year 1977 $F = 25.795$

Year 1976 $F = 15.191$

Those two values are still highly significant but they show a drastic decrease from the value of 76.801 corresponding to year 1978. This is even more remarkable for year 1976 where the value drops to 15.191.

This confirms the above univariate analysis and adds weight to the argument that to be considered as successful a firm should sustain a high level of performance for a long period of time.

C. Classification using the Discriminant Function Developed in the Previous Section.

Using the discriminant function developed in the preceding section, the companies belonging to the well performing sample in years 1977 and 1976 were classified. According to the results presented in table 5.13, more than twenty five percent of the companies included in the 1977 sample of successful firms are misclassified as not successful. This proportion concerning the 1976 sample is just below forty five percent.

TABLE 5.13. PROPORTION OF MISCLASSIFICATION

(YEARS 1977 and 1976)

	Year 1977	Year 1976
Proportion of Misclassification	25.24%	44.66%

This increase in misclassification corroborates the results of the above univariate and multivariate analyses and indicates that the criteria for selection as a well performing company of at least three years of above average performance was fully justified.

From the above findings, it can be concluded that the companies included in the well performing sample in year 1976 can not be considered as successful since nearly half of them are misclassified by the discriminant model. Since such a result could have been reached by simply picking those companies at random, it appears that those companies could rather be considered as potential well performers. Therefore, year 1976 will be included in the analysis concerning the identification of potential well performers. The non inclusion of year 1977 stems from the fact that nearly seventy five percent of the well performing firms are correctly classified indicating that such companies very much resemble the successful companies (year 1978) and could be considered as such.

5.4.2. IDENTIFICATION OF POTENTIAL HIGH PERFORMERS.

The aim of this paragraph is to establish whether companies rising from a low performing state to a successful state could be identified with a certain confidence and so as far away as possible in time. If such was the case, then results could be employed in relation to the discriminant model constructed to identify well performing companies. Any company classified as less well performing could be analysed to estimate whether it has potential to reach a successful state in the near future.

Firstly, the year 1977 will be studied as parts of the analysis have already been completed. Then the years 1975, 1974, 1973, and 1972 will be analysed. Discriminant analyses will be performed for each year. Following Betts and Belhoul(1982b) approach the discriminant model obtained in each year will be used to classify companies in the other years. The discriminant function, that will on average achieve the best performance will be retained.

5.4.2.1. Discriminant Analysis of Year 1976.

The two samples used are the same as those in the univariate analysis. Discriminant runs will be performed in order to obtain the "best" discriminant model. The same procedure as that of the preceding section will be followed.

The first discriminant run resulted in eleven variables being selected but some had the sign of their coefficients opposed to the sign of the difference between their group means. Removing those variables led to the selection of the following variables:

- R1:Earnings before taxes and interest over total assets.
- R16:Quick assets over current liabilities.
- R21:Long term liabilities over net worth.
- R25:Cash flow over total assets.

The corresponding linear discriminant function was:

$$z(1) = -3.90599 + 0.30806\ R1 + 0.13812\ R16$$

$$- 3.16536\ R21 + 0.08659\ R25$$

The separation between the groups is highly significant since the computed F statistic was

$$F = 41.285$$

with 4 and 407 degrees of freedom ($F_{4,\infty} = 4.62$ for $\alpha = 0.001$)

The corresponding

$$D^2 = 2.1535$$

and

$$\Lambda = 0.7114$$

For year 1976, a large separation between the two groups is therefore observed, which would indicate that differences exist in the financial profile of potential high performers and low performers. This indicates that at this stage an identification of a potential performer is possible.

From Table 5.14 we notice that about eighty percent of the companies are correctly classified according to the resubstitution method and Lachenbruch's Jackknife method respectively using a cut-off point of zero.

TABLE 5.14. CLASSIFICATION MATRICES (YEAR 1976)

RESUBSTITUTION METHOD		PREDICTED MEMBERSHIP	
		POTENTIAL HIGH PERFORMERS	LOW PERFORMERS
ACTUAL MEMBERSHIP	POTENTIAL HIGH PERFORMERS	87.4	12.6
	LOW PERFORMERS	27.2	72.8

JACK KNIFE METHOD		PREDICTED MEMBERSHIP	
		POTENTIAL HIGH PERFORMERS	LOW PERFORMERS
ACTUAL MEMBERSHIP	POTENTIAL HIGH PERFORMERS	86.4	13.6
	LOW PERFORMERS	27.5	72.5

A better rate of correct classification is apparent for the potential well performing group. By setting the cut-off point at 0.11 a more even rate of correct classification (Table 5.15) is obtained, with a slight increase in the overall rate of correct classification which is eighty one percent and eighty percent according to the resubstitution and Lachenbruch's Jackknife method respectively.

As far as year 1976 is concerned, table 5.15 indicates that a potential high performer can be identified with more than eighty percent accuracy.

5.4.2.2. Analyses of years 1975, 1974, 1973 and 1972.

The period studied covers the years 1975, 1974, 1973 and 1972. It is a continuation in time of the analysis carried out in the previous paragraph. Along the same lines, the companies are divided into two groups: the potential high performers and the low performers, numbering one hundred and three and three hundred and nine respectively. The analysis was firstly on an univariate basis then discriminant runs were performed to select the significant variables. However, before proceeding with the analysis, the difference between group means of each variable was examined in order to establish whether it was having the same direction as that

TABLE 5.15. CLASSIFICATION MATRICES (YEAR 1976)

RESUBSTITUTION METHOD		PREDICTED MEMBERSHIP: POTENTIAL HIGH PERFORMERS	PREDICTED MEMBERSHIP: LOW PERFORMERS
ACTUAL MEMBERSHIP	POTENTIAL HIGH PERFORMERS	81.6	18.4
	LOW PERFORMERS	18.8	81.2

JACK KNIFE METHOD		PREDICTED MEMBERSHIP: POTENTIAL HIGH PERFORMERS	PREDICTED MEMBERSHIP: LOW PERFORMERS
ACTUAL MEMBERSHIP	POTENTIAL HIGH PERFORMERS	79.6	20.4
	LOW PERFORMERS	19.4	80.6

observed for the years, 1978, 1977 and 1976 and therefore indicates its relevance to the present analysis.

A) <u>Examining the direction of the group mean differences</u>.

Concerning the financial ratios, table 5.16. indicates a good consistency in the direction of the differences between group means over the period studied. The only exceptions are presented in the table below:

FINANCIAL RATIO WITH OPPOSITE DIFFERENCE	YEAR
SALES/TA	1974, 1972.
CASH/CL	1974, 1973, 1972.
CASH/TA	1974,1973, 1972.
EBIT/T.INT.	1973
WC/CF	1975, 1974, 1972.
SALES/St	1973
St/CA	1973, 1972.

TABLE 5.16. GROUP MEAN DIFFERENCES

VARIABLE NAME	OVERALL (78,77,76)		1975		1974		1973	1972
	RATIOS	ST. DEV.	RATIOS	ST. DEV.	RATIOS	ST. DEV.	RATIOS	RATIOS
1. EBIT/TA	+	C	+	+	+	–	+	+
2. EBIT/NCE	+	–	+	+	+	–	+	+
3. EBT/TA	+	C	+	+	+	–	+	+
4. EBIT/NW	+	–	+	+	+	–	+	+
5. EBT/TA	+	C	+	+	+	–	+	+
6. SALES/TA	+	–	+	–	–	–	+	–
7. SALES/NW	–	–	–	–	–	–	–	–
8. WC/SALES	+	C	+	+	+	+	+	+
9. SALES/FA	+	C	+	–	+	–	+	+
10. CA/SALES	+	–	+	+	+	–	+	+
11. CA/CL	+	+	+	+	+	+	+	+
12. CL/NW	–	–	–	+	–	–	–	–
13. CASH/CL	+	+	+	+	–	–	–	–
14. WC/TA	+	+	+	+	+	+	+	+
15. CASH/TA	+	+	+	+	–	+	–	–
16. QA/CA	+	+	+	+	+	–	+	+
17. QA/TA	+	+	+	+	+	–	+	+

CONTINUED OVER

TABLE 5.16. GROUP MEAN DIFFERENCES (CONTINUED)

VARIABLE NAME	OVERALL (78,77,76)		1975		1974		1973	1972
	RATIOS	ST. DEV.	RATIOS	ST. DEV.	RATIOS	ST. DEV.	RATIOS	RATIOS
18. NW/TL	+	+	+	+	+	-	+	+
19. EBIT/T.INT.	+	+	+	+	+	+	-	+
20. TA/TL	+	C	+	+	+	-	+	+
21. LTL/NW	-	C	-	+	-	-	-	-
22. CF/TL	+	+	+	+	+	+	+	+
23. CF/CL	+	+	+	+	+	+	+	+
24. WC/CF	-	-	+	-	+	+	-	+
25. CF/TA	+	C	+	+	+	+	+	+
26. DAYS DEBTORS	+	C	+	+	+	-	+	+
27. SALES DEBTORS	+	-	+	-	+	-	+	+
28. DAYS CREDITORS	-	-	+	+	+	-	-	-
29. St/SALES	-	-	-	-	-	-	+	-
30. St/WC	C	-	-	+	-	-	+	+
31. St/CL	+	-	+	-	+	-	+	+
32. St/CA	-	C	-	+	-	+	+	+
33. WC/NW	+	C	+	-	+	-	+	+
34. WC/NCE	+	C	+	-	+	-	+	+
35. WC/LTL	+	-	+	-	+	-	+	-
36. NW/TA	+	C	+	+	+	-	+	+

TABLE 5.16. GROUP MEAN DIFFERENCES (CONTINUED)

VARIABLE NAME	OVERALL (78,77,76)	1975	1974	1973	1972
BSDM1	C	+	-	+	
TADM1	C	+	-	+	
TLDM	C	+	-	-	
BSDM3	C	+	+		
TADM3	C	+	-		
TLDM3	C	+	-		
TRAT	+	-	-		
TRSA	+	-	-		
TRIN	+	-	-		
TRDEB	+	+	-		
TRCR	+	+	-		
CHAT	+	+	-	-	
CHSA	+	+	-	+	
CHIN	+	+	-	-	
CHDEB	+	+	-	-	
CHCR	+	+	-	-	
SIZE 1 (TA)	C	-	-	-	-
SIZE 2 (SALES)	C	-	-	-	-

+ = positive difference

− = negative difference

C = conflicting signals

Regarding the stability measures and measures of trend and change, the same consistency was not observed. Most of the stability measures have positive differences, likewise, most of the measures of trend and change have different signs opposite to those observed during the period 1976 to 1978. These findings indicate that the stability concept appears not to be as much relevant in identifying potential high performers as it was thought at the beginning of the analysis.

B) Univariate Analysis

An F - test for the difference between group means was performed on the variables that showed some consistency with those retained in the analysis of well performing companies.

The trend already observed in the preceding univariate analysis is accentuated. The further away from the well performing year, the less significant the variables become. The number of significant financial ratios was:

- fifteen: year 1975.
- eight: year 1974.
- seven: year 1973.
- three: year 1972.

A decrease in their significance was also noticeable. Regarding the stability measures for years 1975 and 1974, only one of them was significant. This indicates that it becomes more and more difficult to notice specific characteristics in the financial profile of potential high performers as the period

TABLE 5.17. SIGNIFICANCE OF BETWEEN GROUP DIFFERENCE 1975 (Univariate F test)

VARIABLES		MEAN		STANDARD DEVIATION		LEVEL OF
		WELL PERFORMING	LESS WELL PERFORMING	WELL PERFORMING	LESS WELL PERFORMING	SIGNIFICANCE**
RATIOS:						
R7.	SALES/NW	1.2504	1.2743	0.6368	0.6679	C
R12.	CL/NW	4.6407	4.6709	0.6893	0.6965	C
R18.	NW/TL	4.2012	4.0952	10.6350	0.5988	C
R20.	TA/TL	169.1650	163.1194	57.4728	55.3039	C
R36.	NW/TA	40.8861	38.6952	13.8908	13.1192	C
R8.	WC/SALES	14.8598	12.3440	12.8143	12.7370	C
R11.	CA/CL	4.9859	4.8958	0.3360	0.3365	B
R14.	WC/TA	18.8315	15.2372	13.2791	13.4657	B
R31.	St/CL	0.7232	0.6901	0.3401	0.3637	C
R33.	WC/NW	46.4878	39.0494	31.1938	36.4513	C
R34.	WC/NCE	32.4803	26.2930	21.1809	23.3977	B
R1.	EBIT/TA	10.0017	7.8435	4.3327	4.2142	A
R2.	EBIT/NCE	17.8014	14.2789	9.4727	8.7223	A
R3.	EBT/TA	7.3844	5.2090	5.0946	4.5917	A
R4.	EBIT/NW	26.2609	22.1524	22.2105	14.2265	B

CONTINUED OVER

TABLE 5.17. SIGNIFICANCE OF BETWEEN GROUP DIFFERENCE 1975 (Univariate F test) CONTINUED

	VARIABLES	MEAN		STANDARD DEVIATION		LEVEL OF SIGNIFICANCE**
		WELL PERFORMING	LESS WELL PERFORMING	WELL PERFORMING	LESS WELL PERFORMING	
RATIOS:						
R5.	EBT/SALES	6.1156	4.1997	5.7439	4.3184	A
R22.	CF/TL	9.0823	6.8545	9.6338	5.6258	A
R23.	CF/CL	14.6962	11.2596	19.1325	10.7201	B
R25.	CF/TA	4.8473	4.0944	4.84746	2.8868	C
R6.	SALES/TA	0.2898	0.2698	0.4032	0.4990	C
R10.	CA/SALES	1.5474	1.4468	0.6180	0.2187	C
R26.	DAYS/DEBTORS	74.6137	67.0399	28.7399	33.1277	B
R27.	SALES/DEBTORS	0.2044	0.1904	0.0788	0.1131	C
R16.	QA/CL	8.9091	8.3638	1.7184	1.7512	A
R17.	QA/TA	32.2977	28.9539	11.2730	10.9793	A
R32.	St/CA	45.8186	46.6540	14.5613	17.5608	C
R9.	SALES/FA	0.4668	0.4550	0.1692	0.2343	C
R21.	LTL/NW	0.1717	0.1927	0.0991	0.1206	C
R35.	WC/LTL	2.0391	1.3421	3.1956	1.9121	A
R13.	CASH/CL	0.4254	0.3279	1.7013	1.6458	C
R15.	CASH/TA	-0.5003	-0.6128	1.6841	1.5669	C

TABLE 5.17. SIGNIFICANCE OF BETWEEN GROUP DIFFERENCE 1975 (Univariate F test) CONTINUED

	VARIABLES	MEAN		STANDARD DEVIATION		LEVEL OF SIGNIFICANCE**
		WELL PERFORMING	LESS WELL PERFORMING	WELL PERFORMING	LESS WELL PERFORMING	
RATIOS:						
R19.	EBIT/T.INT	14.8585	5.1853	63.8501	8.1567	A
R29.	St/SALES	0.3648	0.4046	0.7940	1.5755	C
R30.	St/WC	162.5159	230.1284	222.3712	444.7529	C
STABILITY MEASURES:						
S33.	WC/NW	1.9443	2.0009	0.8888	0.8827	C
S34.	WC/NCE	1.4073	1.4258	0.9081	0.8451	C
S6.	SALES/TA	-2.2744	-2.1820	0.8951	0.8805	C
S7.	SALES/NW	-0.8504	-0.8072	0.9442	0.9798	C
S9.	SALES/FA	-1.7356	-1.5201	0.9916	0.8854	B
S27.	SALES/DEBTORS	-0.6061	-0.4630	0.9544	1.0269	C
S29.	SALES/st.	-2.1624	-2.0556	1.1314	1.1533	C
S31.	CL/St.	2.9825	3.0654	1.3228	1.2078	C
S35.	LTL/WC	3.1658	3.4108	2.1240	1.9375	C

** A = not significant at 0.01. B = not significant at 0.05. C = significant at 0.05.

TABLE 5.18. SIGNIFICANCE OF BETWEEN GROUP DIFFERENCES 1974 (Univariate F test)

	VARIABLES	MEAN		STANDARD DEVIATION		LEVEL OF SIGNIFICANCE **
		WELL PERFORMING	LESS WELL PERFORMING	WELL PERFORMING	LESS WELL PERFORMING	
RATIOS:						
R7.	SALES/NW	1.0920	1.1822	0.5994	0.7275	C
R12.	CL/NW	4.4895	4.5443	0.6039	0.7501	C
R18.	NW/TL	4.3123	4.2400	0.5919	0.6164	C
R20.	TA/TL	177.1956	171.0419	56.1215	58.4692	C
R36.	NW/TA	43.5652	41.5348	13.7980	14.1983	C
R8.	WC/SALES	16.0954	13.4722	13.0653	13.1695	C
R11.	CA/CL	4.9889	4.9630	0.3253	0.3106	C
R14.	WC/TA	18.6307	15.5730	13.3118	13.4059	B
R31.	St/CL	0.6681	0.6195	0.3276	0.3289	C
R33.	WC/NW	42.4083	38.6893	29.3138	36.1370	C
R34.	WC/NCE	29.5296	26.0030	18.6542	22.9963	C
R1.	EBIT/TA	9.8486	8.7548	2.9466	3.2038	A
R2.	EBIT/NCE	17.2142	15.6328	7.4754	7.8094	C
R3.	EBT/TA	7.7371	6.7715	3.2430	3.4499	B
R4.	EBIT/NW	24.7218	23.2597	11.5152	11.9465	C
R5.	EBT/SALES	6.3607	5.6170	4.0681	3.8035	C

CONTINUED OVER

TABLE 5.18. SIGNIFICANCE OF BETWEEN GROUP DIFFERENCES 1974 (Univariate F test) CONTINUED

	VARIABLES	MEAN		STANDARD DEVIATION		LEVEL OF SIGNIFICANCE **
		WELL PERFORMING	LESS WELL PERFORMING	WELL PERFORMING	LESS WELL PERFORMING	
RATIOS:						
R22.	CF/TL	11.0610	9.4083	6.9864	5.7254	B
R23.	CF/CL	18.0186	15.2779	13.9429	11.3053	B
R25.	CF/TA	5.6893	5.1237	2.9342	2.6176	C
R10.	CA/SALES	1.4435	1.3750	0.5974	0.8574	C
R26.	DAYS DEBTORS	78.4788	71.9636	31.3116	34.3462	C
R27.	SALES/DEBTORS	0.2216	0.1971	0.0888	0.0941	B
R16.	QA/CL	9.2133	8.8818	1.7947	2.0635	C
R17.	QA/TA	33.3666	30.2783	12.1911	11.8300	B
R32.	St/CA	40.0799	42.9427	15.2163	17.9481	C
R9.	SALES/FA	0.4811	0.4441	0.1754	0.1892	C
R21.	NW/LTL	0.1161	0.1889	0.1124	0.1332	C
R35.	LTL/WC	2.5131	1.8543	4.6598	4.5601	C
R19.	EBIT/T.INT.	8.7491	7.1902	15.6487	9.2255	C
R29.	St/SALES	0.3205	0.3092	0.3156	1.7516	C
R30.	St/WC	156.7142	195.1902	267.9744	378.5433	C

CONTINUED OVER

TABLE 5.18. SIGNIFICANCE OF BETWEEN GROUP DIFFERENCES 1974 (Univariate F test) CONTINUED

	VARIABLES	MEAN		STANDARD DEVIATION		LEVEL OF SIGNIFICANCE **
		WELL PERFORMING	LESS WELL PERFORMING	WELL PERFORMING	LESS WELL PERFORMING	
STABILITY MEASURES:						
S33.	WC/NW	1.8881	1.9620	0.8479	0.9274	C
S34.	WC/NCE	1.4339	1.4463	0.8474	0.9509	C
S6.	SALES/TA	-2.4432	-2.1879	0.9316	0.9537	C
S7.	SALES/NW	-1.2660	-0.9864	0.8937	1.0996	C
S9.	SALES/FA	-1.7322	-1.4818	0.8840	0.9804	C
S27.	SALES/DEBTORS	-0.8231	-0.5528	1.1177	1.0989	C
S29.	SALES/St.	-1.6705	-1.6147	0.9143	1.2442	C
S31.	CL/St.	2.9985	3.0418	1.1181	1.2393	C
S35.	LTL/WC	3.0179	3.3820	2.0302	2.1005	C

** A = not significant at α = 0.01.

B = not significant at α = 0.05

C = significant at α = 0.05

TABLE 5.19. SIGNIFICANCE OF BETWEEN GROUP DIFFERENCES 1973 (Univariate F test)

RATIOS:	VARIABLES	MEAN		STANDARD DEVIATION		LEVEL OF SIGNIFICANCE **
		WELL PERFORMING	LESS WELL PERFORMING	WELL PERFORMING	LESS WELL PERFORMING	
R7.	SALES/NW	1.0454	1.0649	0.6550	0.6885	C
R12.	CL/NW	4.3559	4.3654	0.6362	0.7221	C
R18.	NW/TL	4.4450	4.3575	0.6048	0.6181	C
R20.	TA/TL	186.3506	180.9153	56.1806	58.4808	C
R36.	NW/TA	46.3377	44.7255	13.9698	14.4575	C
R8.	WC/SALES	17.8275	14.8122	13.7527	13.7579	C
R11.	CA/CL	5.0764	4.9900	0.3152	0.3722	B
R17.	WC/TA	20.5914	17.3614	12.7958	14.9566	B
R24.	WC/CF	453.8257	437.2590	303.4210	484.6335	C
R31.	St/SALES	0.7125	0.6827	0.3721	0.4047	C
R33.	WC/NW	44.6616	39.3988	26.86476	31.83751	C
R34.	WC/NCE	32.2973	28.5236	19.5041	22.2806	C
R1.	EBIT/TA	9.2674	8.11362	3.3893	3.6784	A
R2.	EBIT/NCE	14.9588	13.8744	6.9819	7.7908	C

CONTINUED OVER

TABLE 5.19. SIGNIFICANCE OF BETWEEN GROUP DIFFERENCES 1973 (Univariate F test) CONTINUED

	VARIABLES	MEAN		STANDARD DEVIATION		LEVEL OF SIGNIFICANCE **
		WELL PERFORMING	LESS WELL PERFORMING	WELL PERFORMING	LESS WELL PERFORMING	
RATIOS:						
R3.	EBT/TA	7.7132	6.5243	3.4419	3.8100	A
R4.	EBIT/NW	21.0991	19.8190	11.3281	11.3198	C
R5.	EBT/SALES	6.4368	5.4319	4.3246	3.9464	B
R22.	CF/TL	12.2946	10.4427	6.9008	6.0821	A
R23.	CF/CL	19.0522	16.9502	12.6097	11.0487	C
R25.	CF/TA	8.0239	5.3659	3.1687	2.7825	B
R6.	SALES/TA	0.2430	0.2061	0.4256	0.5089	C
R10.	CA/SALES	0.4620	0.4494	0.1752	0.2161	C
R26.	DAYS DEBTORS	77.3693	71.1349	29.5057	33.9956	C
R27.	SALES/DEBTORS	0.2119	0.2013	0.0808	0.1176	C
R16.	QA/CL	9.5992	9.8863	1.9479	2.1199	C
R17.	QA/TA	31.8813	30.4093	10.4535	12.1713	C
R9.	SALES/FA	0.4620	0.4494	0.6149	0.8132	C
R21.	LTL/NW	0.1642	0.1829	0.1205	0.1349	C
R35.	WC/LTL	2.9321	3.8272	2.8476	1.1918	C
R28.	DAYS CREDITORS	7.3905	7.4160	1.4455	1.6402	C

** A = not significant at $\alpha = 0.01$. B = not significant at $\alpha = 0.05$. C = significant at $\alpha = 0.05$

TABLE 5.20. SIGNIFICANCE OF BETWEEN GROUP DIFFERENCES 1972 (Univariate F test)

	VARIABLES	MEAN		STANDARD DEVIATION		LEVEL OF SIGNIFICANCE **
		WELL PERFORMING	LESS WELL PERFORMING	WELL PERFORMING	LESS WELL PERFORMING	
RATIOS:						
R7.	SALES/NW	1.0155	1.0699	0.6208	0.6871	C
R12.	CL/NW	4.3050	4.3519	0.6303	0.7383	C
R18.	NW/TL	4.4462	4.3768	0.6099	0.6484	C
R20.	TA/TL	186.5606	182.5810	58.088	60.6896	C
R36.	NW/TA	46.3981	45.2298	14.4452	15.0343	C
R8.	WC/SALES	17.2367	14.5843	12.4140	14.0042	C
R11.	CA/CL	5.0540	4.9840	0.3646	0.3855	C
R14.	WC/TA	20.4555	17.3542	13.1548	14.6181	C
R31.	WC/CF	0.7601	0.6929	0.3941	0.4424	C
R33.	WC/NW	43.1908	39.6998	32.5924	32.3136	C
R34.	WC/NCE	30.0998	27.8678	23.8609	22.5601	C
R1.	EBIT/TA	8.34598	7.4533	3.5211	3.5197	B
R2.	EBIT/NCE	13.3608	12.8177	7.2375	7.5362	C
R3.	EBT/TA	6.3958	5.6906	4.2923	3.8123	C
R4.	EBIT/NW	19.3296	18.2686	10.4693	11.9053	C
R5.	EBT/SALES	5.2842	4.7676	4.7353	4.0230	C

CONTINUED OVER

TABLE 5.20. SIGNIFICANCE OF BETWEEN GROUP DIFFERENCES 1972 (Univariate F test) CONTINUED

	VARIABLES	MEAN		STANDARD DEVIATION		LEVEL OF SIGNIFICANCE **
		WELL PERFORMING	LESS WELL PERFORMING	WELL PERFORMING	LESS WELL PERFORMING	
RATIOS:						
R22.	CF/TL	10.3599	8.7185	8.0005	5.8777	B
R23.	CF/CL	16.5053	14.0884	13.529	12.0721	C
R25.	CF/TA	5.0348	4.4749	2.7825	2.8243	C
R10.	SALES/CA	0.4640	0.4460	0.1803	0.2438	C
R26.	DAYS DEBTORS	77.9581	71.1349	30.0203	32.6586	B
R27.	SALES/DEBTORS	0.2199	0.2000	0.0940	0.1110	C
R16.	QA/CL	9.4697	9.1563	1.8797	2.0390	C
R17.	QA/TA	30.8309	31.8813	11.3028	12.0471	C
R9.	SALES/FA	0.4640	0.4460	0.5703	0.8140	C
R21.	NW/LTL	0.1821	0.1841	0.1245	0.1321	C
R29.	SALES/St.	0.4194	0.2874	2.5222	0.7811	C
R28.	DAYS CREDITORS	7.3088	7.3894	1.4594	1.7424	C

**A = not significant at $\alpha = 0.01$.
B = not significant at $\alpha = 0.05$.
C = significant at $\alpha = 0.05$.

of time between the year analysed and the year of eventual high performance is increased. However, from the results of tables 5.17 to 5.20, some differences between the financial profile of potential high performers and low performers exist. A significant dimension common to all years is return on investment. The working capital management dimension has as well a financial ratio significant in every year except for 1972. The other dimensions showing some sort of significance were:

- 1975: Business turnover, liquidity and debt position
- 1974: Business turnover and liquidity
- 1972: Business turnover

The return on investment ratios appear, therefore, to be of importance in the identification of potential high performers and so up to five years before a level of high performance is reached. The other dimensions relevant to the problem on a purely univariate basis are liquidity and business turnover and although they do not demonstrate the same level of significance and become less important as we move backwards in time.

The classification of potential high performers using the discriminant model constructed to identify well performing companies resulted in a high rate of misclassification for years 1975 and 1974 (years for which stability measures are available) with more than fifty percent of the companies being misclassified. This again demonstrates the non-relevance of this model to identify potential high performers and that a different model should be developed.

c) Discriminant runs.

A discriminant function was developed for each year from 1975 to 1972. The variables included in the discriminant analysis are those listed in tables 5.17 to 5.20. The same procedure in selecting the variables as that previously used was followed.

The discriminant results are reported in table 5.21 along with those of year 1976. The significance of the between group differences is decreasing as we move backwards in time. The computed F statistic to test for the difference between group are still significant but their value is decreasing. In year 1972, its significance is just above the 0.05 level. The decrease in the discriminatory power of the functions ends in poorer performances. Although the rate of the correct classification is more or less the same from 1975 to 1972, its level is quite low, around sixty percent. This represents a significant drop from the eighty percent of correct classification obtained in 1976.

The discriminant functions were as follows:

- year 1975: $z(2) = -2.21762 + 0.05735R1 + 0.04893R5 + 0.03088R17 + 0.01120R23 + 0.52516R31$

TABLE 5.21 : DISCRIMINANT ANALYSIS RESULTS

YEAR OF ANALYSIS	VARIABLES IN THE MODEL	PERCENTAGE OF CORRECT CLASSIFICATION						SIGNIFICANCE			
		RESUBSTITUTION METHOD			JACK KNIFE METHOD						
		POTENTIAL	LOW	TOTAL	POTENTIAL	LOW	TOTAL	D^2	WILKS' Λ	F STAT.	DEGREES OF FREEDOM
1976	R1,R16,R21,R25.	81.6	81.2	81.3	79.6	80.6	80.4	2.1535	0.7114	41.285	4,407
1975	R1,R5,R17,R23,R31.	61.2	60.5	60.7	57.3	60.2	59.5	0.3879	0.9317	5.949	5,406
1974	R1,R1t,S7.	60.2	57.3	58.0	59.2	57.3	57.8	0.2910	0.9480	7.457	3,408
1973	R1,R14,R24,R26,R31.	59.2	59.9	59.7	57.3	59.2	58.7	0.2617	0.9530	4.003	5,406
1972	R1,R22,R26,R31.	58.3	56.6	57.0	56.3	55.3	55.6	0.1827	0.9667	3.502	4,407

$F(4;\infty) = 4.62;\ \alpha = 0.001$

$F(5;\infty) = 4.10;\ \alpha = 0.001$

$F(3;\infty) = 5.42;\ \alpha = 0.001$

$F(5;\infty) = 3.02;\ \alpha = 0.01$

$F(4;\infty) = 2.37;\ \alpha = 0.05$

- year 1974 : $z(3) = -2.11085 + 0.11295R1 + 0.02214R17 -0.31330\ln S7.$

- year 1973: $z(4) = -1.63259 + 0.08384R1 + 0.08054R14 - 0.00120R24 + 0.00814R26 + 0.47469R31$

- year 1972 : $z(5) = -1.58179 + 0.05547R1 + 0.02654R22 + 0.00786R26 + 0.42275R31$

Year 1976 was given in the preceding section.

d) Selection of the "best" discriminant model

The five discriminant functions presented in table 5.21 could be used to identify potential high performers. Ideally, the results of each linear discriminant function should be interpreted in relation to time. Hence a score indicating a potential high performer utilizing, say, the discriminant model corresponding to year 1976 (z(1)) means that this company should reach a high level of performance in one year's time. Such a score obtained with the discriminant model corresponding to year 1975 (z(2)) means that the high performance level would be reached in two year's time and so on for z(3), z(4), z(5).

However, the accuracy of the results as the two years' time lead is reached decreases significantly. Besides, a company identified as a potential high performer, say, by z(2) would certainly be so by z(1). It would be expected that the further in time a company is identified as a potential high performer, the more likely it would be classified as so by the other discriminant models. Therefore it would be of more practical use to retain only one discriminant model if the classification results are not too badly affected. The linear discriminant function which on average perform best over the five years, will be selected as the "best" discriminant model.

The retention of only one discriminant model is, as well, reinforced by the fact that those models cannot be used to predict the future state of a company but to identify a company with certain characteristics. Thus a firm that is classified as a potential high performer by, say, z(1) does not indicate for certain that it will reach a level of high performance in a year's time but that this company is very similar to companies that reached a level of high performance a year later. It is an indication of potentiality. Whether they will be fully exploited is not certain.

Table 5.22 is a summary of the performances of the different discriminant functions worked out by using a combination of the variables selected in the five initial discriminant models and of the data available for the different years. Z(1,1) refers to the discriminant function previously noted as z(1) which is derived from the data of year 1976. z(1,2) refers to the discriminant function

FUNCTION	YEAR (J)	CORRECT CLASSIFICATION OF PERCENTAGE						SIGNIFICANCE		
		RESUBSTITUTION			JACKNIFE					
		Potential	Low	Total	Potential	Low	Total	Wilks' Λ	F.Statistic	Degrees of Freedom
z (1,J)	1	81.6	81.2	81.7	81.6	80.6	80.6	0.7114	41.285	4,407
	2	64.7	66.7	66.2	62.0	66.0	65.0	0.9401	6.490	4,407
	3	60.2	55.7	56.8	56.3	55.3	55.6	0.9651	3.678	4,407
	4	59.2	56.6	57.3	57.3	56.3	56.6	0.9751	2.598	4.407
	5	56.3	54.7	55.1	54.4	53.1	53.4	0.9826	1.798	4,407
z (2,J)	1	80.6	80.9	80.8	80.6	80.6	80.6	0.7252	30.762	5,406
	2	61.2	60.5	60.7	57.3	60.2	59.5	0.9317	5.949	5,406
	3	59.2	57.9	58.3	53.4	57.6	56.6	0.9581	3.552	5,406
	4	59.2	56.6	57.3	58.3	55.7	56.3	0.9721	2.328	5,406
	5	54.2	57.3	57.8	53.4	54.7	54.4	0.9763	1.974	5,400
z (3,J)	1	80.5	81.2	81.0	78.5	80.6	79.9	0.7221	52.340	3,408
	2	62.1	64.4	63.8	59.2	63.8	62.6	0.9427	8.269	3,408
	3	60.2	57.3	58.0	59.2	57.3	57.8	0.9480	7.457	3,408
z (4,J)	1	81.6	81.6	81.6	79.6	79.9	79.9	0.7217	31.354	5,406
	2	69.9	63.3	65.3	65.0	62.8	63.3	0.9389	5.289	5,406
	3	60.2	60.5	60.4	57.3	60.2	59.5	0.9586	3.508	5,406
	4	59.2	59.7	59.7	57.3	59.2	58.7	0.9530	4.003	5,406
	5	57.3	58.3	58.0	57.3	57.9	57.8	0.9681	2.671	5,406
z (5,J)	1	79.6	80.9	80.6	79.9	79.9	79.9	0.7223	39.115	4,407
	2	63.1	64.1	63.8	60.2	63.1	62.4	0.9414	6.336	4,407
	3	57.3	60.2	59.5	56.3	59.2	58.5	0.9592	4.325	4,407
	4	56.3	61.5	60.2	54.4	60.8	59.2	0.9612	4.107	4,407
	5	58.3	56.6	57.0	56.3	55.3	55.6	0.9667	3,502	4,407

TABLE 5.22: CLASSIFICATION RESULTS

derived using the same variables as z(1,1) but data corresponding to year 1975 so that a new set of coefficients are estimated. The same procedure is followed for each discriminant function and for each year resulting in a total twenty three discriminant functions. Only three discriminant functions could be determined using the variable of z(3) since among the variable a stability measure is included and could not be calculated for the years 1973 and 1972.

The linear discriminant functions z(1,J), J = 1,5, were giving the best results. A slightly better performance can be noticed for year 1975 where the total correct classification rate is about sixty five percent which is still quite low. These five discriminant functions were used to classify companies in other years. The results are given in table 5.23. Their coefficients are as follows:

$$z(1,1) = -3.90599 + 0.30806R1 + 0.13812\sqrt{R16} - 3.16536R21 + 0.08659R25$$

$$z(1,2) = -1.8766 + 0.10891R1 + 0.13998\sqrt{R16} - 1.83364R21 + 0.00506R25$$

$$z(1,3) = -1.45667 + 0.1095R1 + 0.06251\sqrt{R16} - 1.41366R21 + 0.01984R25$$

$$z(1,4) = -1.20276 + 0.06684R1 + 0.06249\sqrt{R16} - 0.99593R21 + 0.03548R25$$

$$z(1,5) = -1.31638 + 0.05859R1 + 0.07773\sqrt{R16} - 0.09057R21 + 0.0306R25$$

TABLE 5.23. FINAL DISCRIMINANT FUNCTIONS

FUNCTION	CORRECT CLASSIFICATION (%)	1976	1975	1974	1973	1972
z(1,1)	POTENTIAL	81.6	61.2	61.2	55.3	58.3
	LOW	81.2	69.9	53.1	60.5	58.4
	TOTAL	81.3	67.7	55.1	59.2	58.4
z(1,2)	POTENTIAL	79.6	61.2	60.2	59.2	59.2
	LOW	74.8	60.5	53.1	54.0	55.3
	TOTAL	76.0	60.7	54.9	55.3	56.3
z(1,3)	POTENTIAL	81.6	69.9	60.2	57.3	57.3
	LOW	71.7	63.4	57.3	57.3	55.7
	TOTAL	78.7	65.1	58.0	57.3	56.1
z(1,4)	POTENTIAL	82.5	65.1	59.2	59.2	58.3
	LOW	77.0	66.7	53.4	59.9	53.4
	TOTAL	78.4	66.3	54.9	59.7	54.6
z(1,5)	POTENTIAL	81.6	66.0	58.3	59.2	58.3
	LOW	78.3	62.5	52.1	58.3	56.6
	TOTAL	79.1	63.4	53.6	58.5	57.0

The classification rate are more or less the same using the different linear discriminant function. Any of them could be used with more or less the same results. However it was preferred to retain z(1,1) for two reasons:

1) the correct classification rates are quite high
2) its significance in relation to the F statistic is the highest of the five. (table 5.22)

e) <u>Financial dimensions related to the discriminant model</u>

The four financial ratios selected to enter the final discriminant function are related to the Return on Investment dimensions, Liquidity and Debt Position dimensions. Only one of these was represented in the discriminant model developed to identify high performers which was Return on Investment, but here again the three basic dimensions of Courtis' framework are represented. Therefore it would seem that every basic financial characteristic is of importance if a firm is to become a high performer.

The ranking of the variables according to their contribution to the discriminatory power of the linear discriminant function indicates that earnings before taxes and interest over total assets is the major contributor. Then comes long term liabilities to net worth and quick assets to current liabilities. Finally the contribution cash flow to total assets is the least significant. Therefore it appears that the

TABLE 5.24. RANKING OF THE VARIABLES ACCORDING TO THEIR CONTRIBUTION TO THE DISCRIMINANT MODEL

VARIABLES	RANKING					
	F-TEST	STANDARD COEFFICIENT	MOSTELLER AND WALLACE MEASURE	F DELETION	FORWARD STEPPING	BACKWARD STEPPING
R1:EBIT/TA	1	1	1	1	1	1
R16:QA/CL	3	3	3	3	3	3
R21:LTL/NW	4	2	4	2	2	2
R25:CF/TA	2	4	2	4	4	4

most important dimension in relation to problem is Return on Investment. However, from the financial dimensions represented in the discriminant model, it can be concluded that a firm needs to have a well balanced structure if it is to achieve a high level of performance in the near future. Not only should a firm have a high return on investment but it should satisfactorily perform in areas such as liquidity and capital structure if it is to see the fruit of its efficiency regarding its profitability.

f) Testing the underlying assumption of the Model.

The same tests as previously were used to test multivariate normality and equality of variance covariance matrices.

Concerning the potential high performer group, the test for skewness and kurtosis were:

$$b_{1,4} = 3.722$$

$$b_{2,4} = 31.953$$

and their corresponding A and B statistics were:

$$A = 63.894$$

$$B = 5.825$$

Regarding the low performing group the results were as follows:

$$b_{1,4} = 1.357$$

$$b_{2,4} = 32.208$$

$$A = 69.886$$

$$B = 10.413$$

Both distributions showed some skewness as the null hypothesis would be rejected at 0.01 level of significance (χ^2 = 41.417, a = 0.01). The same was true about their kurtosis as both values were significant at 0.01 level of significance.

The observed departure from multivariate normality affects the results of Box's test for equality of variance covariance matrices. However, if the test is performed, the following results are obtained:

Group	Rank	Log Determinant
Potential High Performers	4	0.582
Low Performers	4	1.741
Pooled within group variance covariance matrix	4	1.556

Box's M criterion is equal:

$$M = 42.117$$

with the corresponding F statistic equal to:

$$F = 4.1474$$

which is not significant at 0.001 level ($F_{4,\infty}$ = 4.62, α =0.001) but which is significant at the 0.05 level ($F_{4,\infty}$ = 2.47, α =0.05) Therefore the certainty with which the equality of the variance covariance matrices are rejected is not very high taking into consideration the influence of the departure from multivariate normality on the test. The null hypothesis can not be rejected with total confidence and the fitting of a linear discriminant function is then entirely justified.

5.5. CONCLUSION

In this chapter it was attempted to formulate a model that could identify companies that had a high level of overall performance and investigate whether those firms presented specific traits in their financial profile that could be employed to identify them some time before they were successful. The first part of this study was carried out with a certain success since the "best" discriminant model obtained includes besides measures of resources utilisation efficiency, variables associated with other financial dimensions. Therefore, to be classified as well performing a firm should, as well as being efficient, show areas of financial strengths.

The second part concerned with the identification of potential high performers, was not so fruitful. The accuracy of the discriminant model drops considerably as the period considered was further and further away from the period of high level of performance. However, it was demonstrated that as far back as five years before a company reach a high level of performance, it displays specific financial characteristics and that the concept of performance stability is not so important in relation to the identification of potential high performing companies.

CHAPTER 6

INDEX OF PERFORMANCE AND STRUCTURAL CHANGE

CHAPTER 6

The model developed in the preceding chapter to identify well performing companies can be used to classify companies as coming from the well performing or the less well performing groups. However, the Z-score given by the model does not precisely indicate the firm's level of performance. It does not reveal how bad or how well the firm is performing. The only information that can be derived from the Z-score besides the classification of the firm is in relation to other Z-scores computed from the same discriminant function. Thus, a company Z-score can only be compared to:

- the Z-scores of the same firm from previous years (intrafirm comparison)
- the Z-scores of other firms calculated on the data from the same year (interfirm comparison)

Both the intrafirm and interfirm analyses may be useful to the financial analyst or to the management of a firm as they depict the past behaviour of a firm or its position vis a vis other companies that may be direct competitors. But unless the number of companies included in the interfirm analysis is very large, these types of analysis are of little help in answering the exact level of performance of a firm. The aim of the present chapter is to assign to the Z-score computed from the discriminant model a more comprehensive meaning besides its role as a classification criterion. Such an index would have the advantage of having the weights and the variables selected on a statistical basis as opposed to the quite artitrary manner in which they are chosen in the indices of performance elaborated so far.

Some of the multi-variate models that have been developed up to now to assess the performance of firms will be presented. Then, the methodology used will be described and the model constructed. In a second part, the internal transformation of the financial structure experienced by firms that reached a high level of performance will be analysed in order to get a better understanding of the performance problem.

6.1. DISCRIMINANT CRITERION AS AN INDEX OF PERFORMANCE

6.1.1. INDICES OF PERFORMANCE

Although, early developments of financial ratios analysis emphasised the use of single ratios, the need to use several weighted financial ratios to produce a single index was soon to become apparent in order to overcome the main shortcomings of univariate financial ratio analysis such as:

- the ignorance of intercorrelation among the financial ratio
- the possible emission of conflicting signals

A) WALL AND DUNNING INDEX OF CREDIT STRENGTH

This index proposed by Wall and Dunning (1928) is described by Lev (1974) as follows:

$$I = \sum_{i=1}^{7} w_i \left[1 + (1 - R_i/\bar{R}_i)\right]$$

where

W_i is the weight of ratio i

R_i is the value of ratio i for the specific firm

$\bar{R}_i$ is the standard or base ratio for the industry

The financial ratios and their corresponding weights are:

	RATIOS (Ri)	WEIGHTS (Wi)
1	Current Ratio	.25
2	Net worth to fixed assets	.15
3	Net worth to debt	.25
4	Sales to account receivables	.10
5	Sales to inventories	.10
6	Sales to fixed assets	.10
7	Sales to net worth	.05

The index score would be compared to a reference scale to evaluate the credit standing of the company under investigation.

B) TAMARI INDEX OF FINANCIAL SOLVENCY

This index was developed by Tamari (1966) with the aim of forecasting bankruptcy. The index includes the following indicators:

1. Equity capital + reserves to total liabilities
2. Profit trend
3. Current ratio
4. Value of production to inventory

5. Sales to receivables
6. Value of production to working capital

Each item is given a certain number of points according to its value so that the index score of any firm can be calculated. The values that the index can take range from zero to one hundred.

To test the validity of his index, Tamari applied it to a sample of companies of which some went bankrupt. He found that companies presenting a low index score (between 0 and 30) were likely to fail in the near future while the chances of failure of companies with a medium (between 31 and 60) and high (61 to 100) index score were very small. Another point he noticed was the tendency for firms with medium and high scores to retain such a rating in the following years.

C) BURCH INDEX OF PERFORMANCE

Burch (1972) suggested this index to rank seven chemical companies according to their overall performance. His definition of performance was : "the effectiveness with which company resources are utilized." The period of time for which the study was carried out was 1947 - 1957. Ten variables were selected to constitute the index. They were:

1. Sales growth 1947 - 1957
2. Return on capital 1957

3. Return on capital 1953 - 1957
4. Return on capital before depreciation 1953 - 1957
5. Earnings margin 1957
6. Earnings margin 1953 - 1957
7. Capital turnover 1957
8. Capital turnover 1953 - 1957
9. Increase in earnings per share 1953 - 1957 Vs. 1947 - 1951
10. Increase in earnings 1957 Vs. 1947 - 1951

The weight corresponding to each variable was determined by performing a principal component analysis on the data from those seven companies. The first principal component was interpreted as a factor of general performance since most of the variables had significant loading on it. Accordingly, the factor score of the first principal component was retained as the index of performance. The ranking of the seven chemical companies using the index were consistent with the results based on conventional financial techniques.

D) SHASHUA AND GOLDSCHMIDT INDEX OF FINANCIAL PERFORMANCE

Shashua and Goldschmidt (1974) based their index on the utility theory. They defined the utility function of the evaluator of a firm as:

$$U(.) = U(X_1, X_2, \ldots\ldots, X_k) \pm I$$

Then assuming that $U(.)$ can be approximated by an additive relationship and that each additive utility can be expressed as a probability,

$$U(.) = \sum_{i=1}^{k} W_i P_i$$

where w_is are the weighting constants and P_is the associated probabilities.

They considered three methods of evaluation of the weights:

- egalitarian method where all the weights are equal.
- value judgment method where the weights are determined by financial experts.
- statistical method where the weights are evaluated using principal component analysis.

In addition, arbitrary extreme weights were used to compare the different methods.

The variables ($X_i; i=1,..,k$) that were selected were:

X_1 profit margin

X_2 capital margin

X_3 returns to owners

X_4 equity ratio

X_5 working capital ratio

X_6 activity ratio

The computed index scores represent the probability of success of firms and range from zero to one hundred. The ratings according to the different methods of weights determination were similar. Therefore, the eqalitarian method which is also the simplest was retained.

To avoid the estimation of the probability for each variable and to simplify the use of the index, the ratings were approximated through regression analysis giving the following function:

$$I=15+0.41X_1+0.83X_2+0.15X_3+0.11X_4+0.15X_5+0.20X_6$$

The ratings given by the model were found to be in agreement with ratings given by a financial expert.

These four indices of performance are some of the main indices constructed uptonow. They give a good picture of the developments that have taken place in this area but they present some limitations that will be examined in the next paragraph.

6.1.2 LIMITATION OF THE ABOVE INDICES OF PERFORMANCE

The major deficiency presented by the type of indices described above is related to the somehow arbitrary fashion in which the variables and their associated weights are chosen. This is particularly true of the Wall and Dunning, and the Tamari indices where the choices of ratios and weights are based on the author's experience or on their importance in the eyes of persons involved in evaluating companies financial position (financial analysts, bankers,economists, credit men, etc). Such a limitation is generally recognised by their authors and is somewhat stressed when they state that the importance to attach to any financial ratios must be selected by each separate analyst (Wall and Dunning, 1928). Such a highly subjective nature due to the lack of a conceptual or empirical support results in indices that are too specific and of which the generalization of their use is questionable.

Although Burch, and Shashua and Goldschmidt's indices do not suffer from the same deficiency concerning the selection of the weights, the manner in which the variables are chosen remains arbitrary. In both cases, the variables have been used by persons dealing with the same problem or recommended by financial analysts. They do not cover every aspect of a company financial profile but only those that are thought by the writers to be of importance. This is particularly noticeable in Burch's study where all the variables are associated with the profitability and capital turnover financial dimensions. This leads again to indices that cannot be generalized and may imply the selection of a different set of indicators if the same analysis is to be carried out on a different set of companies (Burch,1972).

Some criticisms can as well be raised regarding the method used to calculate the weights in the last two indices (Burch, and Shashua and Goldschmidt). The consideration of the first factor only in evaluating the weights of the index results in the loss of a significant amount of information since only part of the total variance of the data is explained by the first component, about sixty two percent in Burch's case.

As a consequence, the agreement found between this method and the egalitarian method of determining weights is not so surprising and may question the validity of their approach of considering only the first principal component.

6.1.3 THE Z-SCORES AS AN INDEX OF PERFORMANCE.

If the "z-scores" of the discriminant function constructed to identify well performing companies could be assigned a more specific meaning, the index of performance so derived would not suffer from the major deficiencies presented by the indices described above. Both variables and weights would be selected on a statistical basis giving if not analytical at least empirical support to the index.

Finding the distribution of the "z-scores" would allow us to associate to each "z-score" a probability. Therefore, the proportion of companies having a "z-score" as high (low) as a certain value could be determined giving the discriminant criterion the meaning that is looked for.

As seen in chapter 2, the distribution of the "z-scores" is quite straightforward if the population parameters are known.

$$z = X'\Sigma^{-1}(\mu_1 - \mu_2) - \tfrac{1}{2}(\mu_1 + \mu_2)'\Sigma^{-1}(\mu_1 - \mu_2)$$

is distributed as $N(\delta^2/2, \delta)$ if X comes from population 1 and $N(-\delta^2/2, \delta^2)$ if X comes from population 2. However, the distribution of Z is not so simply derived when the population parameters are not known as in the present case.

Complications in finding the distribution of the "Z-scores" arise leading to distributions that are too complicated to be useful (Okamoto , 1963; Giri, 1977). The limiting distribution theory (Wald 1944) could be applied in our case since the samples are fairly large but this requires the assumptions of multi-variate normality and equality of variance covariance matrices to hold. Yet evidence from chapter 4 suggests a certain departure from those assumptions.

Since it is too complicated if not impossible to derive the distribution of the discriminant criterion on apriori analytical grounds, it would seem appropriate to approximate the "z-score" distribution by one of the probability distributions used in statistics and engineering.

The Regina Computer package (1982) was used to this effect. Seven continuous distributions can be tested for goodness of fit namely:

1. Weibull
2. Bimodal Weibull
3. Exponential
4. Normal
5. Lognormal
6. Gamma
7. Extreme value (type 1)

However, owing to the nature of the data the exponential and Bimodal Weibull will not be included in the analysis. As the exponential distribution is often taken as a reference to explain the behaviour of other distributions, it will be described in Appendix VI.

6.1.4 CONTINUOUS DISTRIBUTIONS USED TO APPROXIMATE THE DISCRIMINANT CRITERION DISTRIBUTION

A succint description of the continuous distribution used later in the analysis is given as they may not be very familiar to people involved in the field of financial analysis. Some references will be given for a more detailed analysis of their characteristics.

a) Normal Distribution

Only a very brief description of the normal distribution will be given below since this is a very familiar distribution due to its important role in the theory of inductive statistics and to its requirement for the application of certain statistical techniques (Analysis of variance, t - test, regression analysis ..etc.).

The normal distribution is a two parameter distribution. Its probability density function is given by:

$$f(x) = \frac{1}{\sqrt{2\pi 6^2}} e^{-\frac{1}{2}\left(\frac{x-\mu}{6}\right)^2}, \quad -\infty < x < +\infty$$

where

μ is the mean

and

6 is the standard deviation.

The values that the parameters can take vary from $-\infty$ to $+\infty$ for μ and o to $+\infty$ for 6.

The mean and variance of the normal distribution are calculated as follows:

$$E(x) = \mu = \int_{-\infty}^{+\infty} x \frac{1}{\sqrt{2\pi 6^2}} e^{-\frac{1}{2}\left(\frac{x-\mu}{6}\right)^2} dx$$

$$Var(X) = E\{(x-\mu)^2\} = 6^2$$

b) Lognormal Distribution

The lognormal distribution is a two parameter distribution. Its probability density function is given by:

$$f(x) = \frac{1}{\beta x\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\ln x - \delta}{\beta}\right)^2}, \quad x > o,\ \beta > o,\ \infty > \delta > \infty$$

$$= o \quad , \text{ elsewhere}$$

where

δ is the scale parameter

and

β is the shape parameter

The mean and variance of the distribution are respectively computed as follows:

$$E(x) = e^{\delta + \beta^2/2}$$

$$Var(x) = (e^{\beta^2} - 1)\ e^{(2\delta + \beta^2)}$$

The lognormal distribution is unimodal. It is skewed to the right with skewness decreasing as the value of β decreases to approximate the normal distribution when β equals zero.

The lognormal distribution has been found to give a good description of observations used in as varied fields as economics, biology and engineering by Hahn and Shapiro 1967, among others.

c) Extreme Value (Type 1) Distribution

The extreme value (type 1) distribution may be used to characterise external phenomena dependent directly on the largest value in a sample from an exponential type distribution. This implies that distributions such as the Gamma, normal and log-normal could be possible initial distributions.

The probability density function of the extreme value (type 1) distribution is given by:

$$f(x) = \frac{1}{6} e^{\{-\frac{1}{6}(x-\mu) - e^{\frac{-1}{6}(x-\mu)}\}}, \infty < x < +\infty$$

where

μ is the location parameter

and

6 is the scale parameter

The values that the parameters can take vary from $-\infty$ to $+\infty$ for μ and from o to $+\infty$ for 6.

Just as for the normal distribution, the extreme value (type 1) distribution has no shape parameter and is characterised by a bell shaped curve slightly skewed to the right.

The mean and variance of the distribution are related to the parameters as follows:-

$$E(x) = \mu + 0.557 \cdot 6$$

$$Var(x) = 1.645 \cdot 6^2$$

Note, however, that μ is the mode of the distribution. The extreme value (type 1) distribution is thoroughly described in Gumbel (1958), and Hahn and Shapiro (1967). It gives a good representation of phenomena such as extinction times for bacteria, depths of corrosion pits, maxima of stock market indices in a given year etc.

d) Gamma Distribution

The gamma distribution is a two parameters distribution. Its density function is given by:-

$$f(x) = \frac{\beta^{\alpha}}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x} \quad , \quad x > 0, \alpha > 0, \beta > 0$$

$$= 0 \quad , \quad \text{elsewhere}$$

where

α is the shape parameter

β is the scale parameter

and

$\Gamma(\alpha)$ is a value of the gamma function

The gamma function is defined as:-

$$\Gamma(\alpha) = \int_0^{\infty} x^{\alpha-1} e^{-x} dx \text{ for } \alpha > 0$$

which is equal, if α has a positive integer value, to

$$\Gamma(\alpha) = (\alpha - 1)!$$

This distribution is characterised by a reverse J shaped curve for $\alpha < 1$. For $\alpha = 1$ the distribution is exponentionably distributed and for $\alpha > 1$ the distribution has a single mode at $x = (\alpha-1)/\beta$ and is skewed to the right. As α tends to infinity, the distribution tends to normality.

The mean and variance of the gamma distribution are calculated as follows:-

$$E(x) = \frac{\beta^{\alpha}}{\Gamma(\alpha)} \int_0^{\infty} x^{\alpha-1} e^{-\beta x} \, dx$$

$$= \alpha/\beta$$

and

$$\mathrm{Var}(x) = \alpha/\beta^2$$

For further applications and description of the gamma distribution one may refer to Hahn and Shapiro (1967) and Kendall and Stuart (1958).

e) <u>Weibull Distribution</u>

The Weibull distribution is very popular in the field of reliability engineering and has recently been found to provide a good representation for financial variables (Roosta, 1979; Mulando, 1981; Urea, 1981).

The Weibull distribution is a two parameter distribution and its probability density function is given by:

$$f(x) = \frac{\alpha}{\beta^{\alpha}} x^{\alpha-1} e^{-(x/\beta)^{\alpha}}, \quad x > o, \alpha > o, \beta > o$$

$$= o \qquad , \quad \text{elsewhere}$$

where

α is the shape parameter

and

β is the scale parameter

For $\alpha = 1$ the Weibull distribution reduces to the exponential distribution. As α increases above one, it takes a bell-shaped form to approximate the lognormal distribution at $\alpha = 2$ and the normal distribution at values of α between 3.26 and 3.46. (Tia, 1975).

The mean and variance of the Weibull distribution are:-

$$E(x) = \beta\Gamma\ (1 + 1/\alpha)$$

and

$$Var(x) = \beta^2\{\Gamma(1 + 2/\alpha) - \{\Gamma(1 + 1/\alpha)\}^2\},$$

respectively.

6.1.5 ESTIMATION OF PARAMETERS

Several methods exist to estimate parameters. The simplest techniques of estimation are the graphical methods but they are dependent on visual inspection. Others analytical methods are:-

- the method of moments
- the method of least square
- the method of maximum likelihood
- the Bayesian method.

The method of least square and maximum likelihood will be described later as they are the methods of estimation utilized by the REGINA Computer package. The Gamma distribution not being yet fully implemented in the REGINA Computer package drawing gamma probability plots was impossible and resulted in utilizing the simpler method of matching moments for the estimation of the parameters which is described in Appendix VI.

a) Method of Least Square

The method of least square is easy to implement and as a consequence is widely employed. It consists of choosing the parameters $\hat{\theta}j$ $(j = 1,\ldots, p)$ of a distribution so that the sum of the squared differences (residuals) between the observed values and the estimated values is minimised.

Consider a set of observations, y_i $(i = 1, \ldots, n)$ and a model that is assumed to best represent the behaviour of the data set, $f(x, \theta j ; j = 1, \ldots, p)$, the method obtains the estimates of θj such that:

$$\text{Residuals} = R = \sum_{i=1}^{\mu} \{ y_i - f(x, \theta j ; j = 1, \ldots, p)\}^2$$

is minimum.

In order to find the values of θj ($j = 1, .., p$), R is differentiated with respect to each θj and equated to zero. The resulted set of p equations is solved to obtain the p parameters.

Further discussion of the method of least square can be found in Linnik (1961).

b) Method of Maximum Likelihood

This method of obtaining estimates of the parameters of a population from a random sample has been proposed by Fisher (1922). It chooses among all the possible estimates of the parameters θj those which make the probability of obtaining the observed sample as large as possible.

The maximum likelihood method may be outlined as follows:- Assuming that $x_1, x_2 \ldots\ldots x_m$ is a random sample and that $\{f(x; \theta_j); (j = 1, .., p)\}$ is the probability density function that it follows, the likelihood function of the variable x which defines the joint probability of the sample being analysed is:

$$
\begin{aligned}
L &= L(x_1, x_2, \ldots, x_m; \theta j) \quad j = 1, \ldots, p \\
&= f(x_1; \theta j) \cdot f(x_2; \theta j) \ldots\ldots f(x_m; \theta j) \\
&= \prod_{i=1}^{m} f(x_i; \theta j)
\end{aligned}
$$

The next stage is to maximize the likelihood function. Differentiating with respect to each parameter and equating each derivative to zero, gives the values of the parameters (maximum likelihood estimates) for which the likelihood function is maximized. As the likelihood function is a product, the procedure is simplified if the logarithm of the likelihood function (log likelihood function) is considered.

Klein (1953) and Kamath (1978) among others give a good description of the properties and applications of the method of maximum likelihood.

6.1.6. TESTING THE GOODNESS OF FIT.

The Kolmogorov-Smirnov test of goodness of fit described in Chapter 3 paragraph 3.3.1 will be used to reject or accept a model as a good approximation of the distribution of the discriminant criterion.

6.1.7. CHOOSING AMONG COMPETING MODELS

A case may arise where several models are accepted on the basis of the goodness of fit test. In this situation, Akaike's information criterion (1973) can be used to discriminate between the distributions.

AKAIKE INFORMATION CRITERION (AIC)

The A.I.C. is an extension of the maximum likelihood principle. Its aim is to identify an optimal model from a group of competing models. Akaike (1973) defines the information criterion as follows:

AIC = -2 log (maximum likelihood)

+2 (number of independent parameters)

The AIC can readily be interpreted in matter of model fitting. The first term reflects the badness of fit and the second term indicates the increased unreliability due to the increase in number of parameters.

The model with the minimum value of the AIC will then be retained as achieving the most satisfactory compromise.

6.1.8.ANALYSIS OF THE DISCRIMINANT CRITERION

Since the lognormal, gamma and Weibull distributions require the dependent variable to take positive values a constant was added to all the z-scores so that they would take positive values only. The value of the constant was fifteen. It should be noted that this does not affect the classification rule or the randomness of the z-scores as the cut-off point is merely shifted from its optimum value of 0.11 to the value of 15.11.

The analysis of the z-scores of the well performing companies resulted in the rejection of the extreme value, gamma and weibull distributions. Both the normal and lognormal distributionsgave a good fit to the empirical data and showed little difference between themselves.

Concerning the z-scores of the less well performing companies, both the normal and the weibull distribution proved to give a good representation of the data with the weibull distribution showing a somewhat better fit since the D-Max value of the normal distribution was significant at the five percent level.

The analyses of both sets of data indicates that the maximum likelihood estimates give lower values of D-Max than their least square counterparts. The parameter estimates presented in tables 6.1 and 6.2 are therefore those obtained using the maximum likelihood method of estimation except for the gamma distribution for reasons given above.

The probability plots of the distributions are given in figures 6.2 to 6.5 for the well performing group and in figures 6.7 to 6.10 for the less well performing group.

The selection of the best representative model based on the log likelihood and on the Akaike's information criterion would result in selecting the lognormal distribution for the well performing group and the weibull distribution for the less well performing group.

TABLE 6.1 RESULTS OF FITTING DISTRIBUTIONS TO THE Z-SCORES OF THE WELL PERFORMING GROUP

DISTRIBUTION	PARAMETERS		D-MAX	K-S RESULTS	L-L VALUE	AIC VALUE
Normal	Location	16.70	0.0589	NS	-788.6	1581.2
	Scale	1.66				
Lognormal	Shape	0.10	0.0583	NS	-787.3	1578.6
	Scale	2.81				
Extreme Value	Location	15.91	0.1002	S	-817.6	1639.2
	Scale	1.69				
Gamma	Shape	6.07	0.1061	S		
	Scale	101.49				
Weibull	Shape	9.60	0.1038	S	-829.1	1662.2
	Scale	17.48				

K-S results: Kolmogorov-Smirnov test statistic

L-L value: Log-Likelihood

AIC value: Akaike's information criterion

NS: not significant

S: significant

TABLE 6.2 RESULTS OF FITTING DISTRIBUTIONS TO THE Z-SCORES OF THE LESS WELL PERFORMING GROUP

DISTRIBUTION	PARAMETERS		D-MAX	K-S RESULTS	L-L VALUE	AIC VALUE
Normal	Location	13.30	0.0788	NS	-876.6	1757.2
	Scale	2.04				
Lognormal	Shape	0.18	0.1105	S	-924.4	1852.8
	Scale	2.57				
Extreme Value	Location	12.20	0.1533	S	-988.5	1981.0
	Scale	2.53				
Gamma	Shape	3.19	0.1201	S		
	Scale	44.34				
Weibull	Shape	7.92	0.0437	NS	-858.8	1721.6
	Scale	14.11				

K-S. results: Kolmogorov-Smirnov test statistic.

L-L value: Log-Likelihood.

AIC value: Akaike's information criterion

NS: not significant

S: Significant

HISTOGRAM

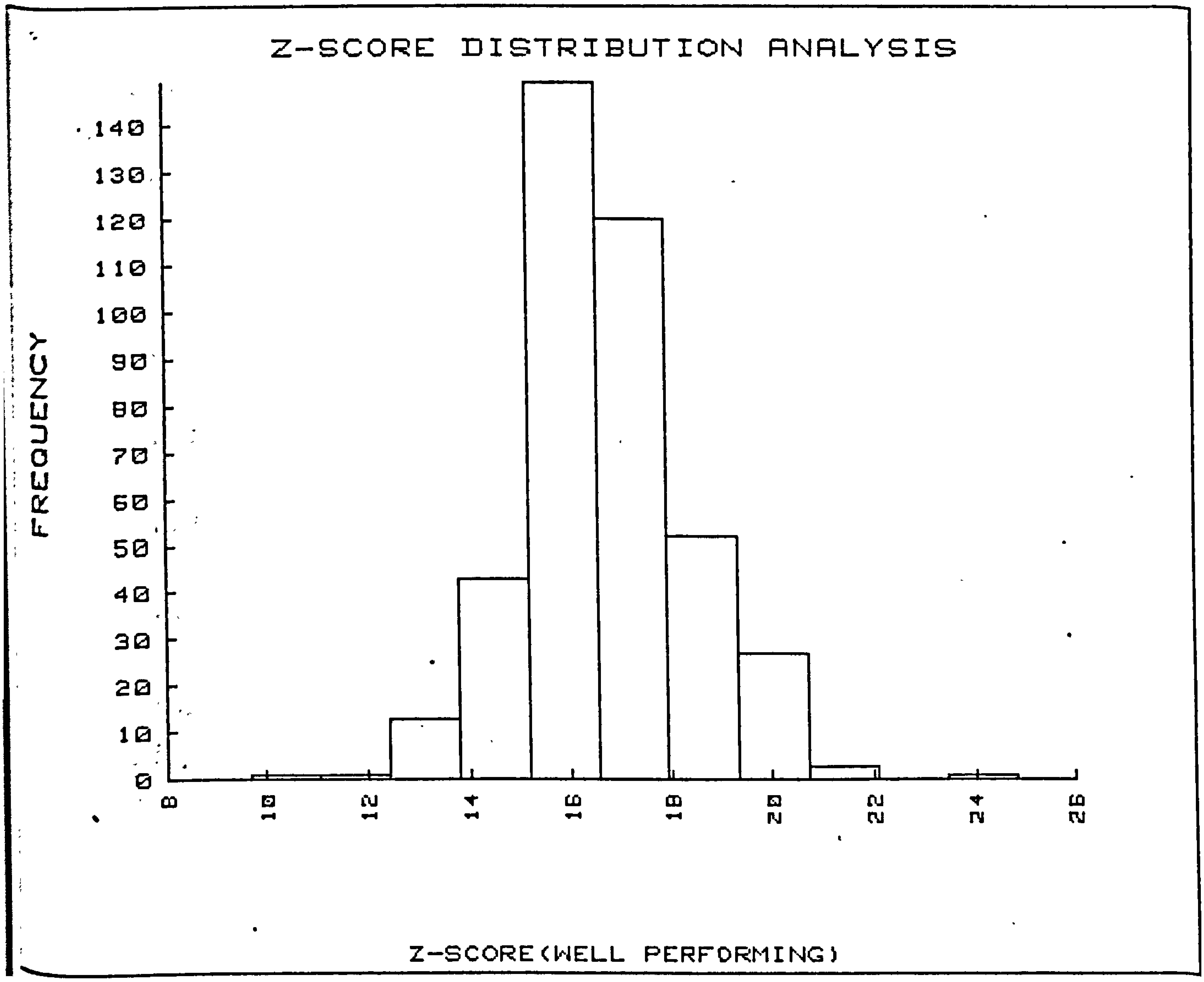


Figure 6.1. Histogram of the Z-Scores of the Well Performing Companies.

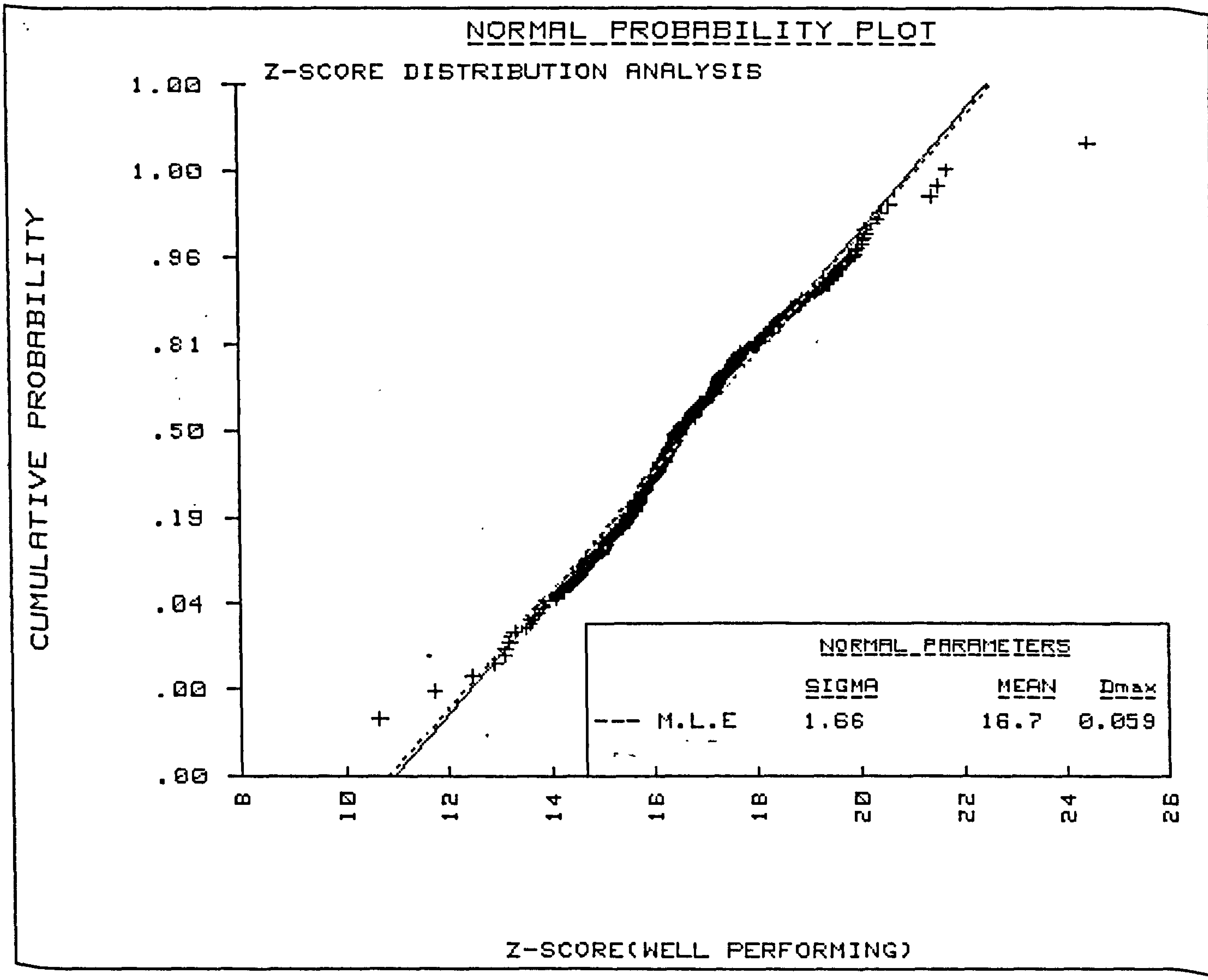


Figure 6.2. Normal Probability Plot (Well Performing Companies)

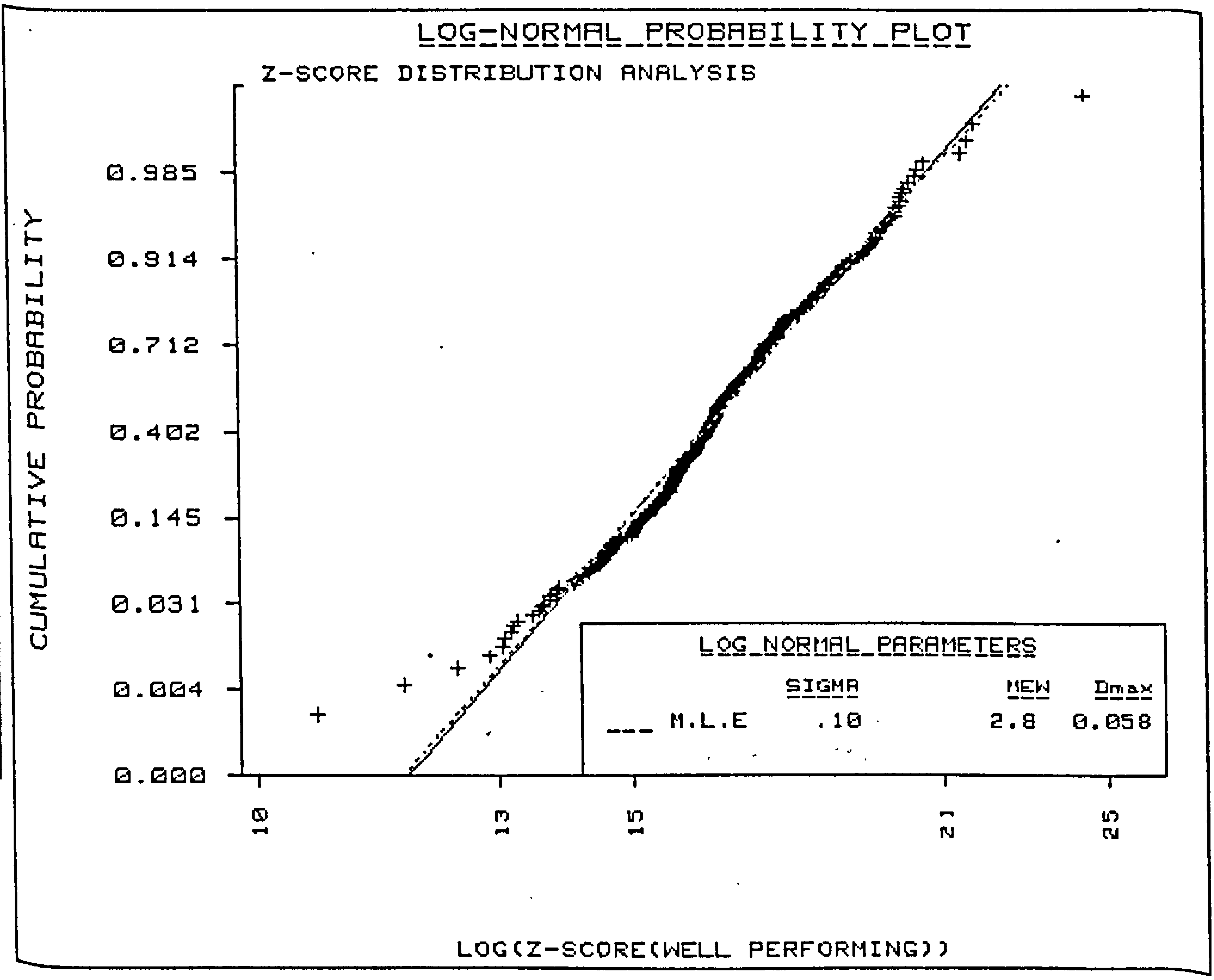


Figure 6.3. Log-Normal Probability Plot

(Well Performing Companies)

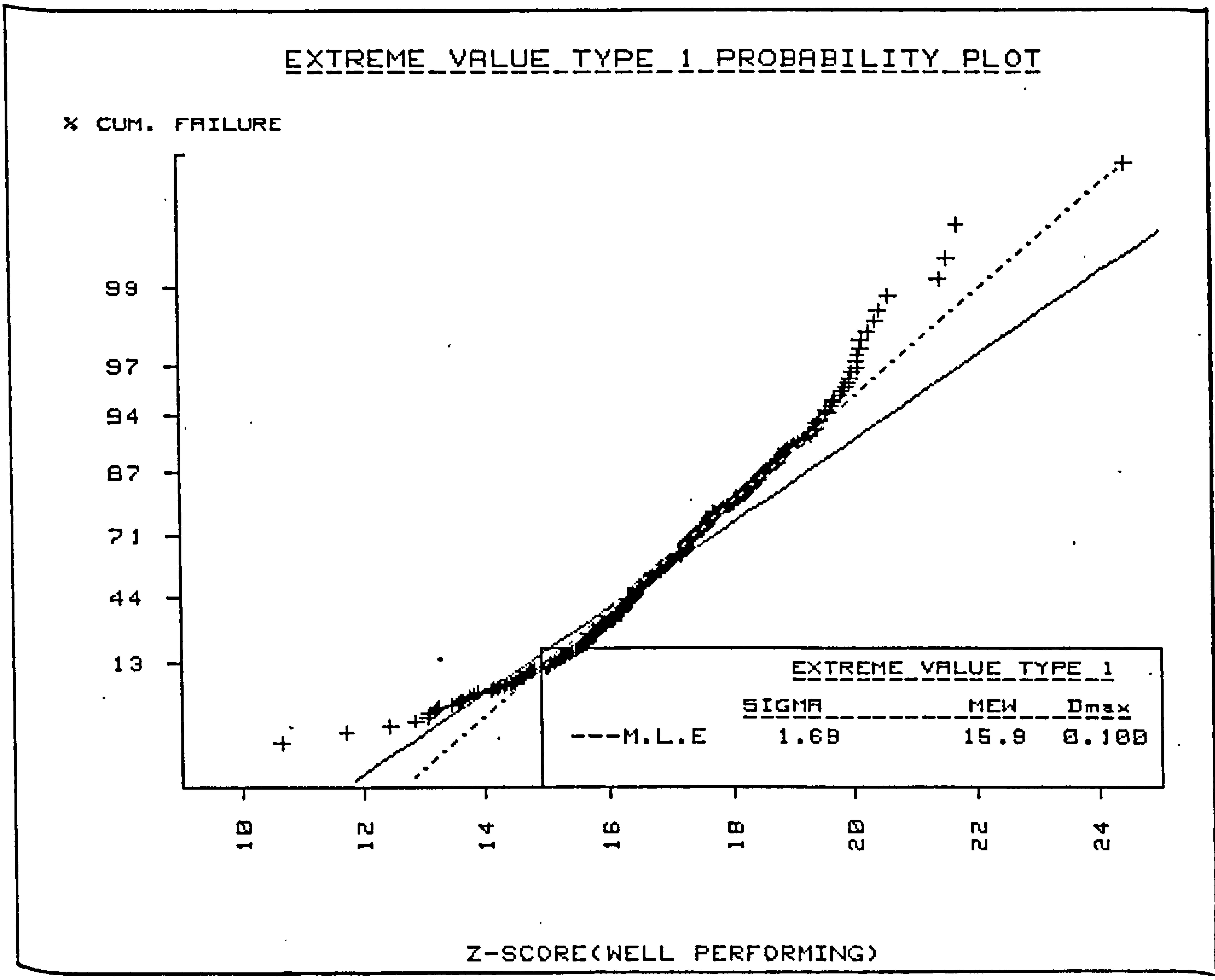


Figure 6.4. Extreme Value Type 1 Probability Plot

(Well Performing Companies)

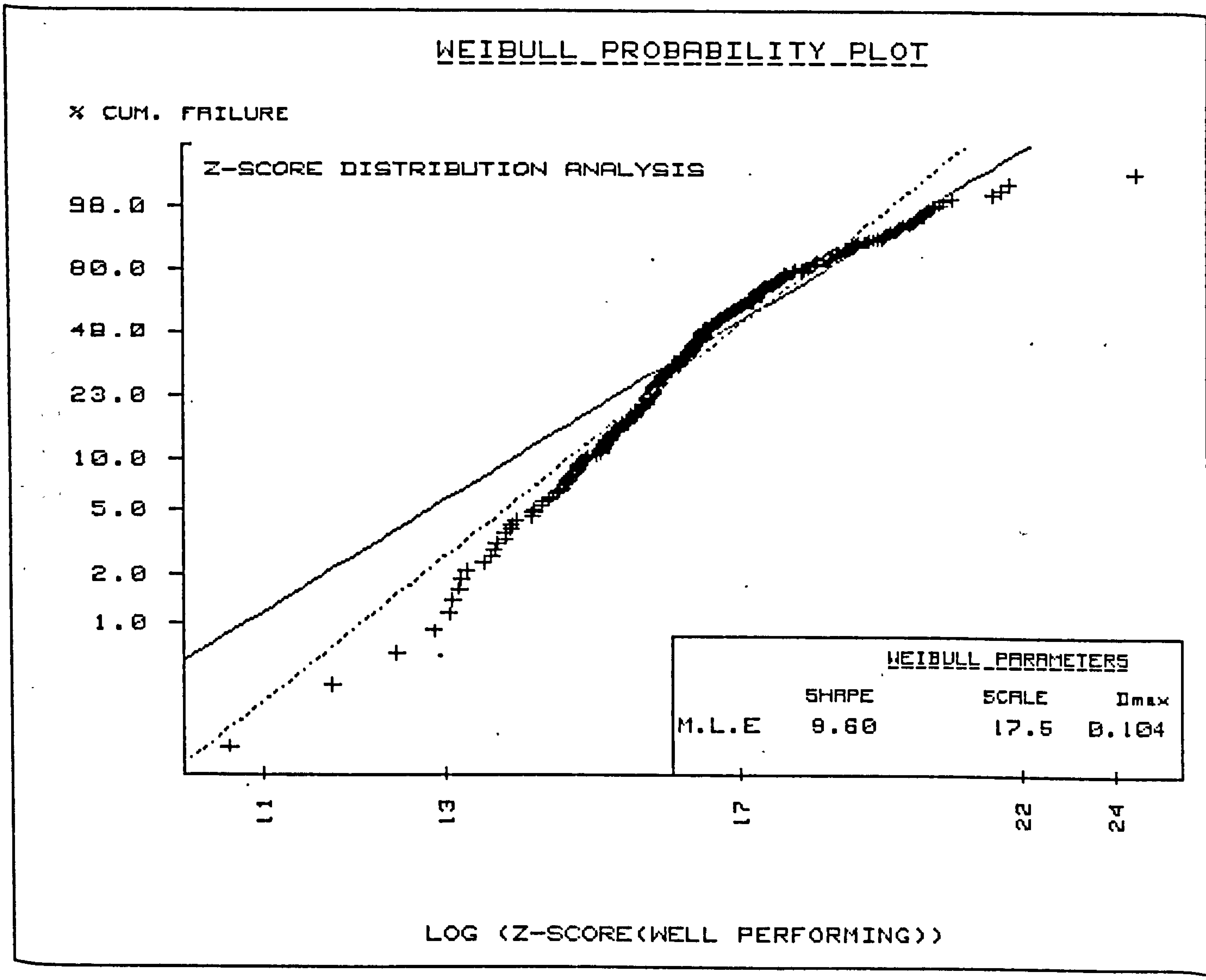


Figure 6.5. Weibull Probability Plot

(Well Performing Companies)

HISTOGRAM

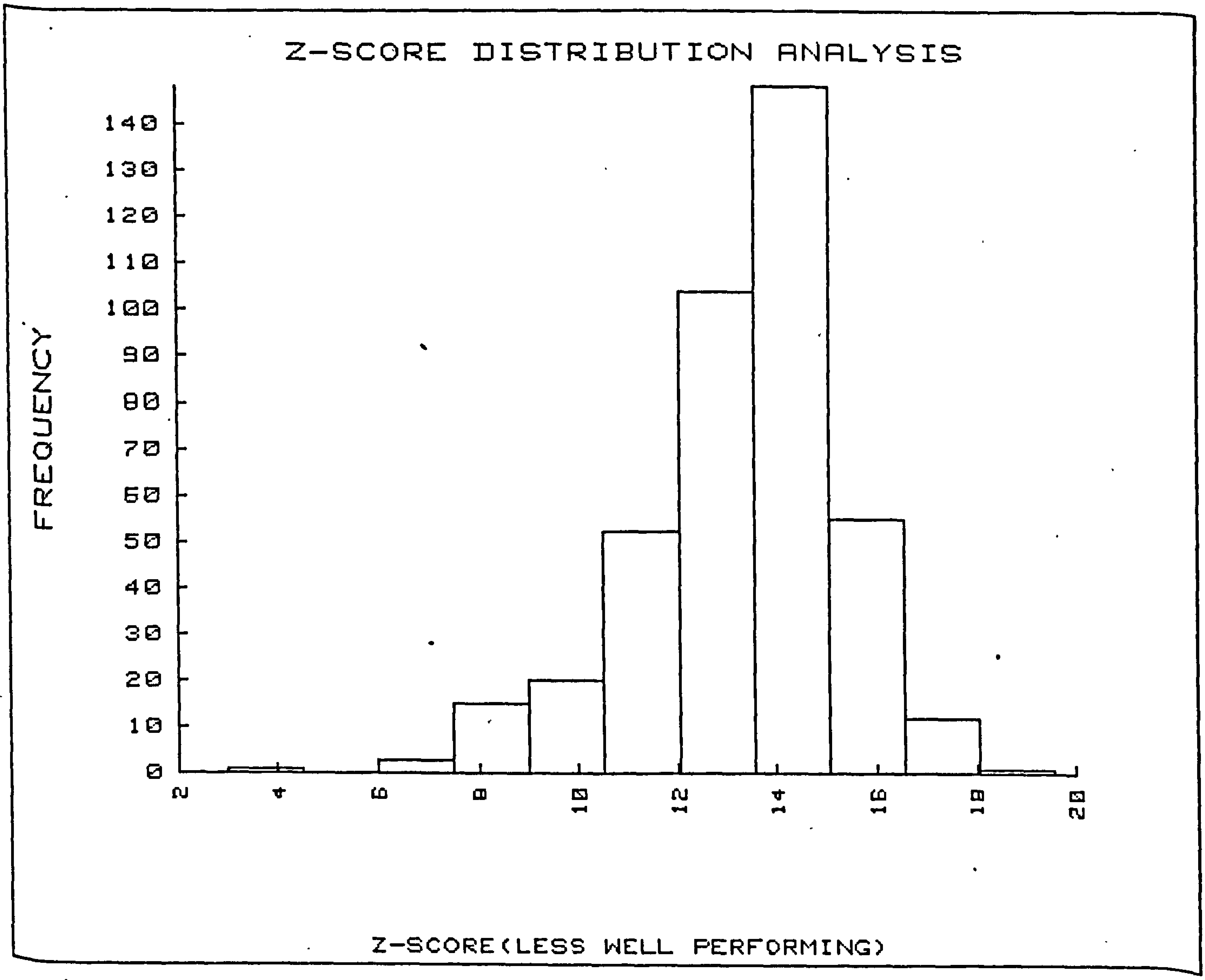


Figure 6.6. Histogram of the Z-Scores of the less Well Performing Companies.

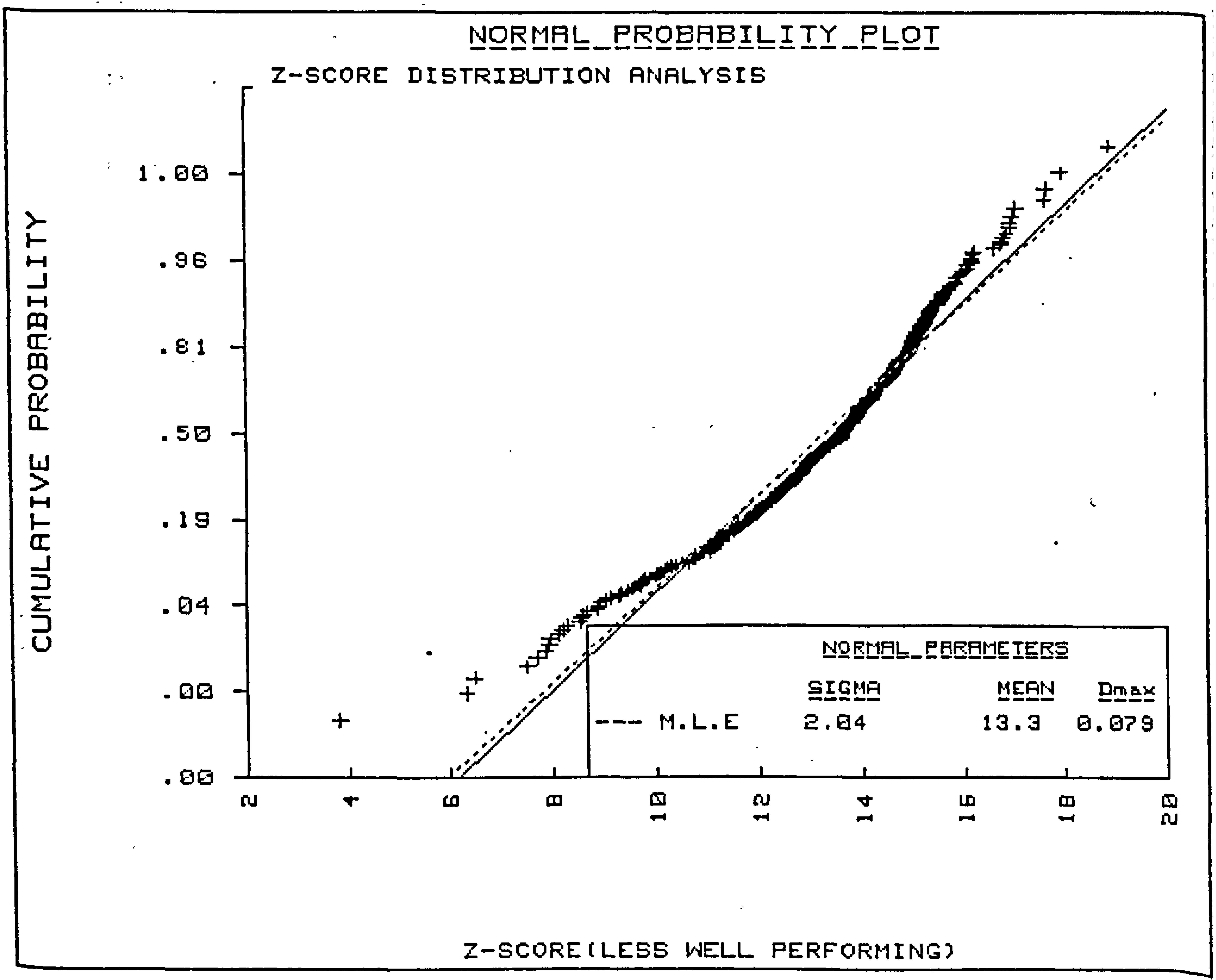


Figure 6.7. Normal Probability Plot (Less Well Performing Companies)

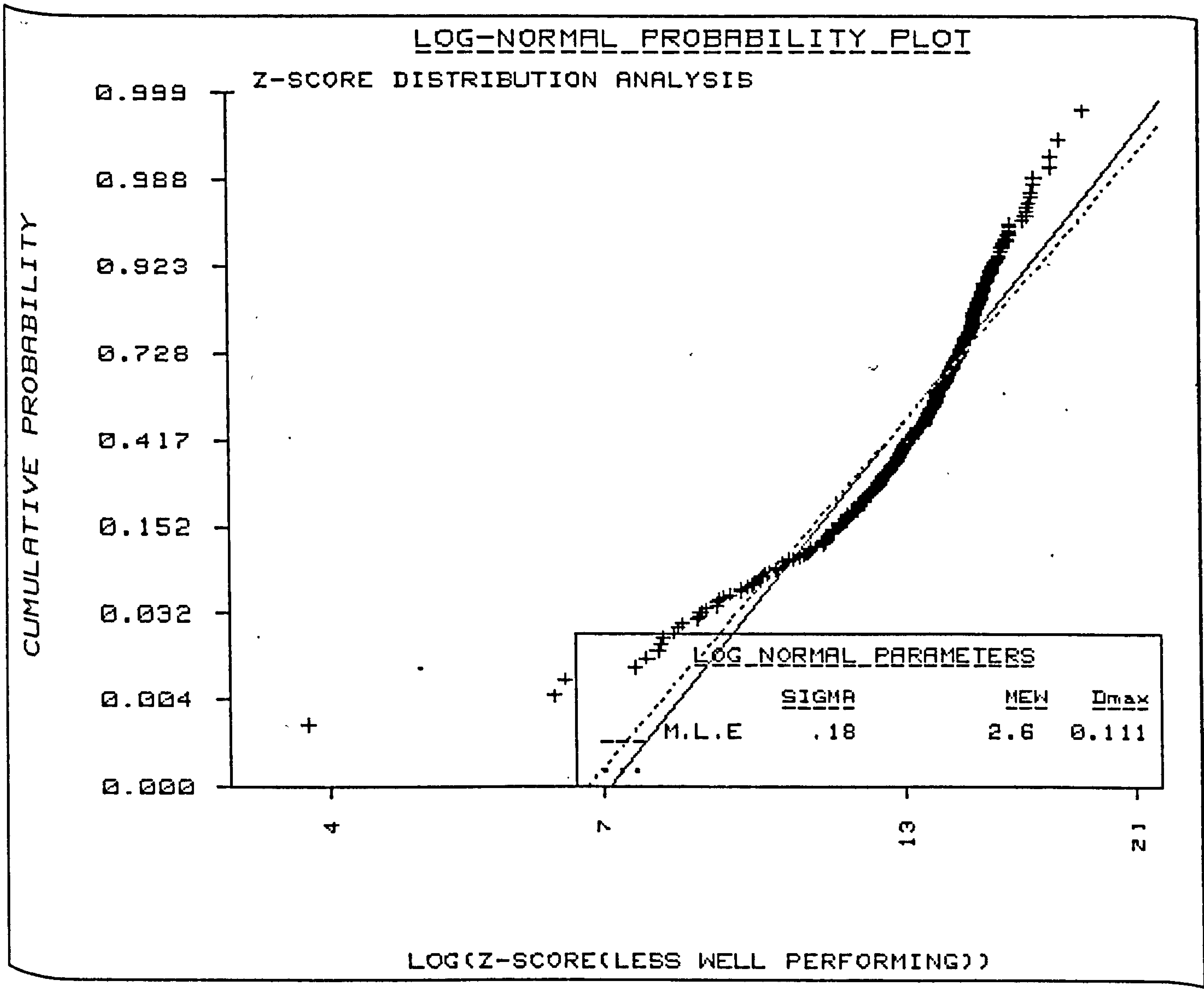


Figure 6.8. Log Normal Probability Plot (Less Well Performing Companies)

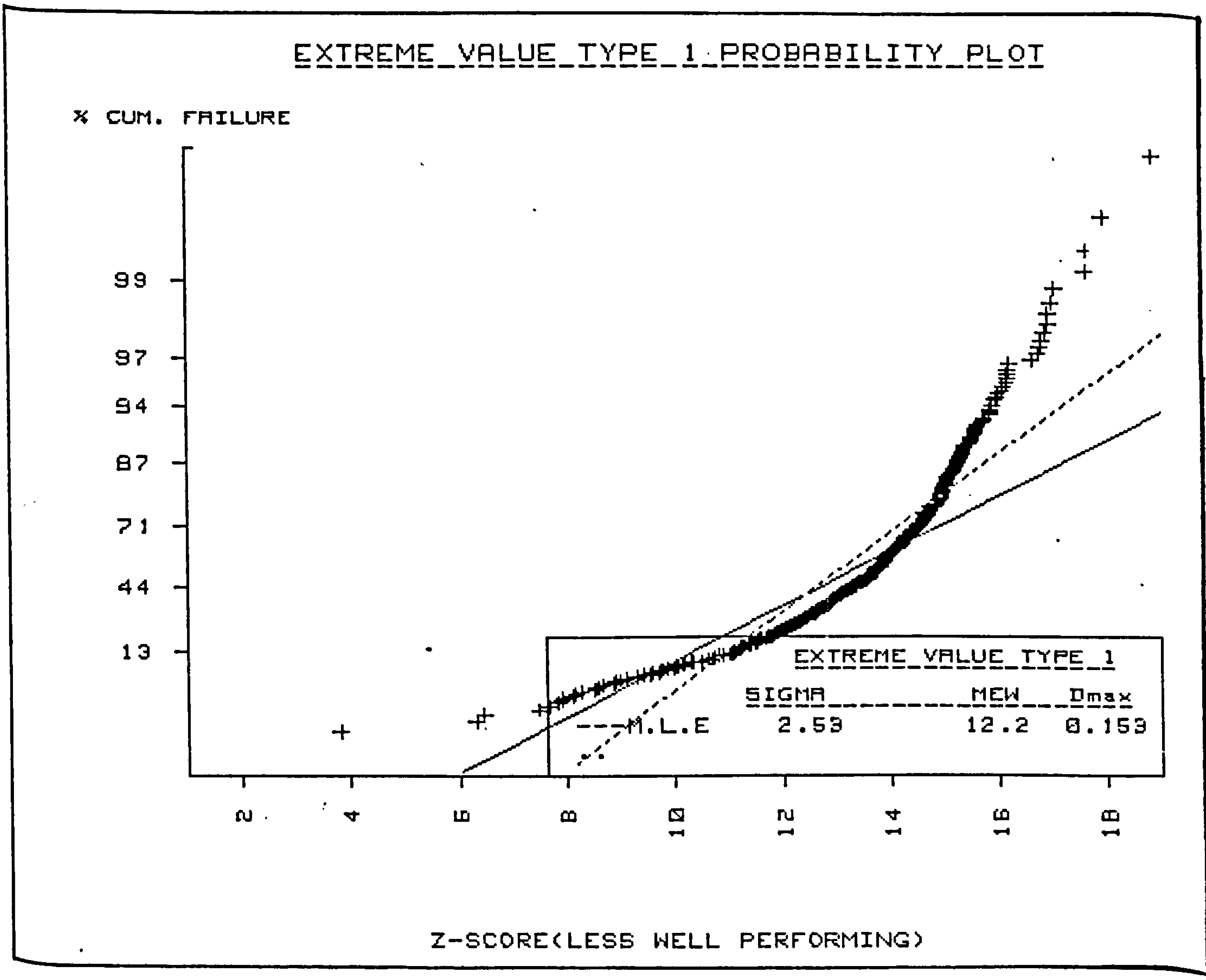


Figure 6.9. Extreme Value Type 1 Probability Plot

(Less Well Performing Companies)

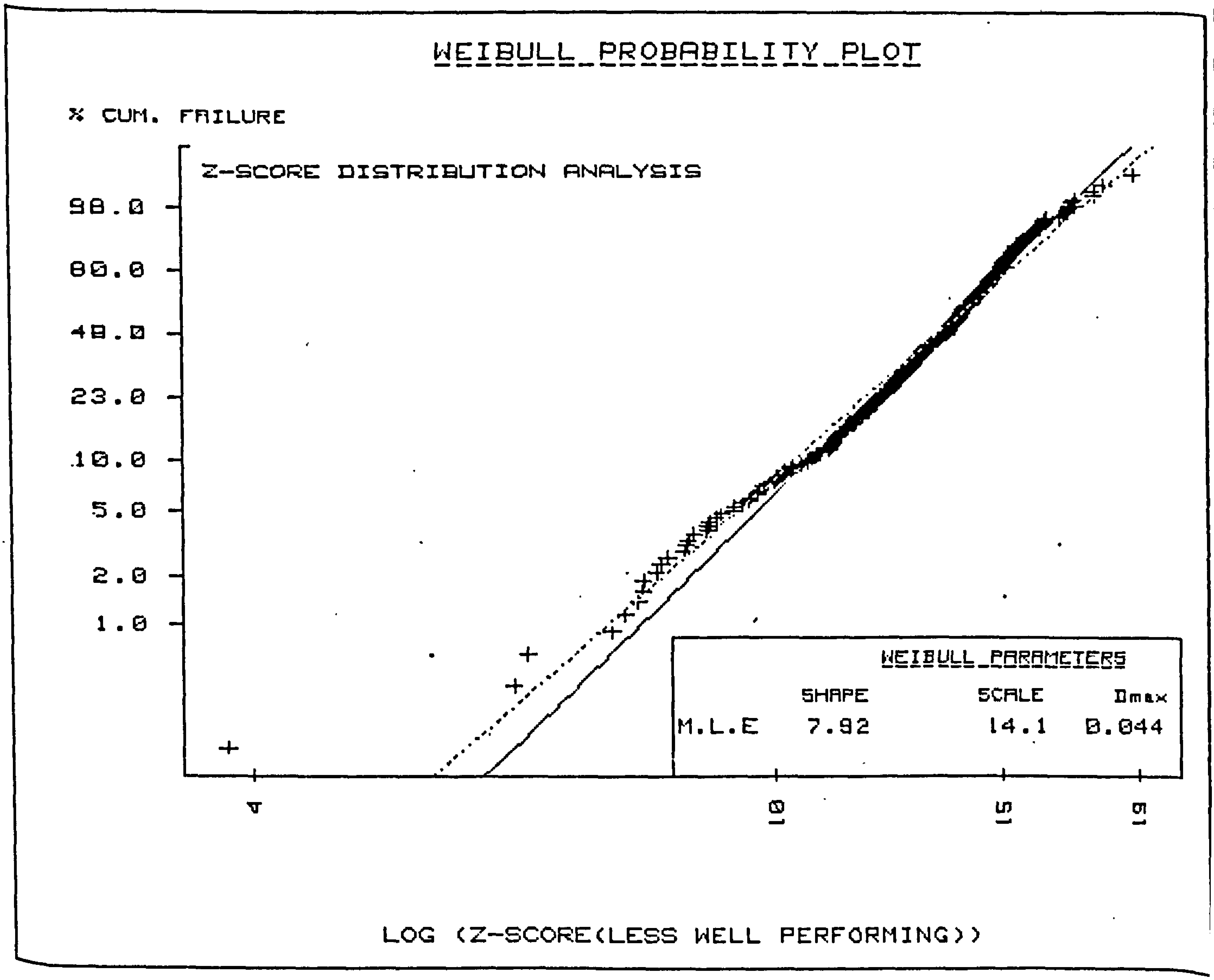


Figure 6.10 Weibull Probability Plot (Less Well Performing Companies)

However, as the normal distribution gives a good fit to the two sets of data, it appears preferable to select it since it would simplify the use of the index. Furthermore, although a certain departure from the assumptions underlying valid application of the discriminant model was noticed, it seems more likely on theoretical grounds, that the z-scores would follow normal distributions even though their dispersion would not be equal.

6.1.9 USE OF THE INDEX

Having selected the normal distribution as the model representing the data, it would then appear preferable to express the z-scores as they were originally, that is without adding any constant. As a result the z-scores of the well performing companies would be distributed as

$$N\ (1.70,\ 1.66)$$

and those of the less well performing group as

$$N\ (-1.70,\ 2.04)$$

A graphical representation is given in figure 6.11

The use of the z-score as an index would therefore simply require a normal distribution table. For example a company with a z-score of, say, 3.85 would mean that there is one chance in ten for any well performing company to have a higher z-score. This value of about .10 is obtained by standardizing the z-score :

$$Z = \frac{3.85 - 1.70}{1.66} = 1.29$$

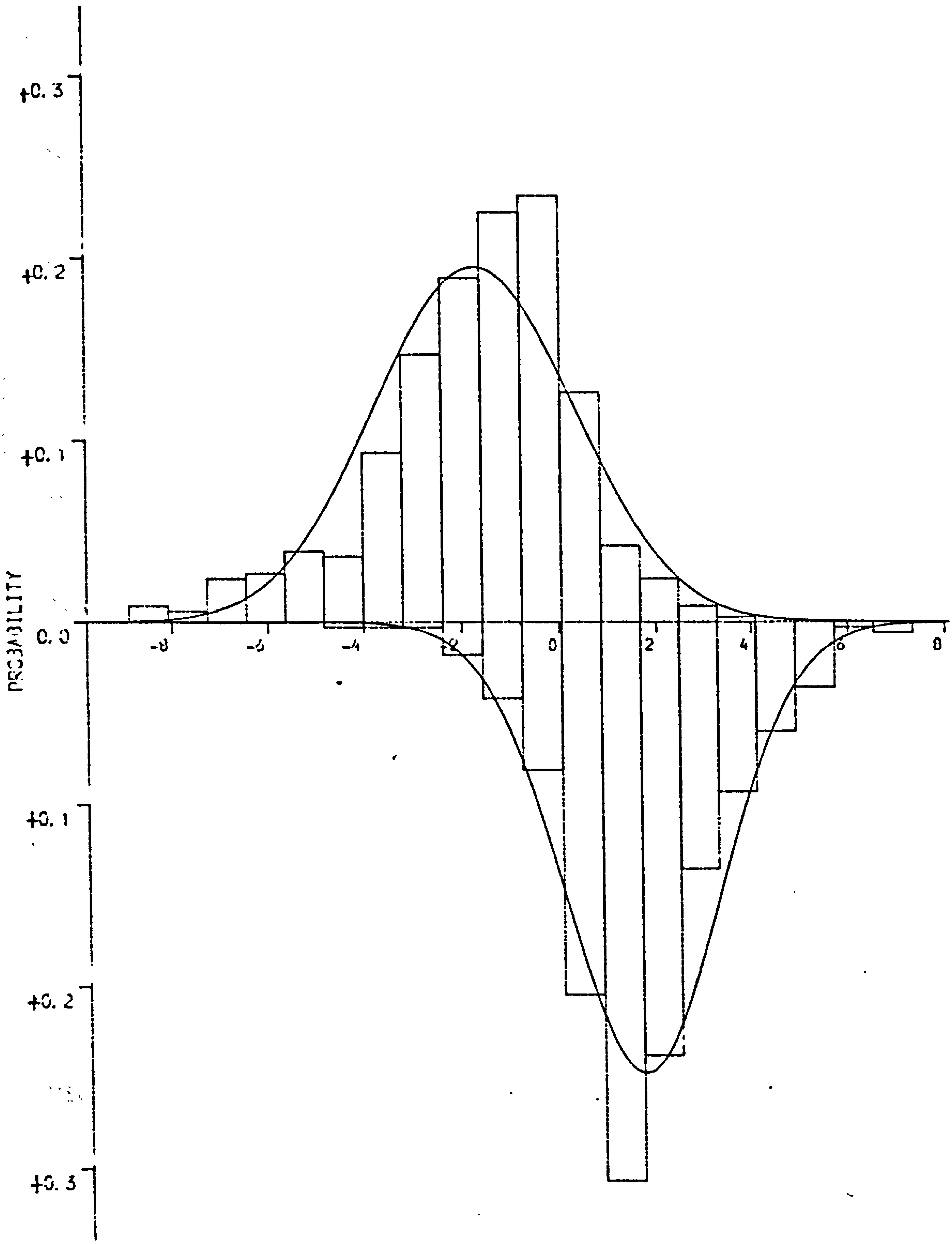


Figure 6.11 Z-Score Distributions with Superimposed Normal distributions.

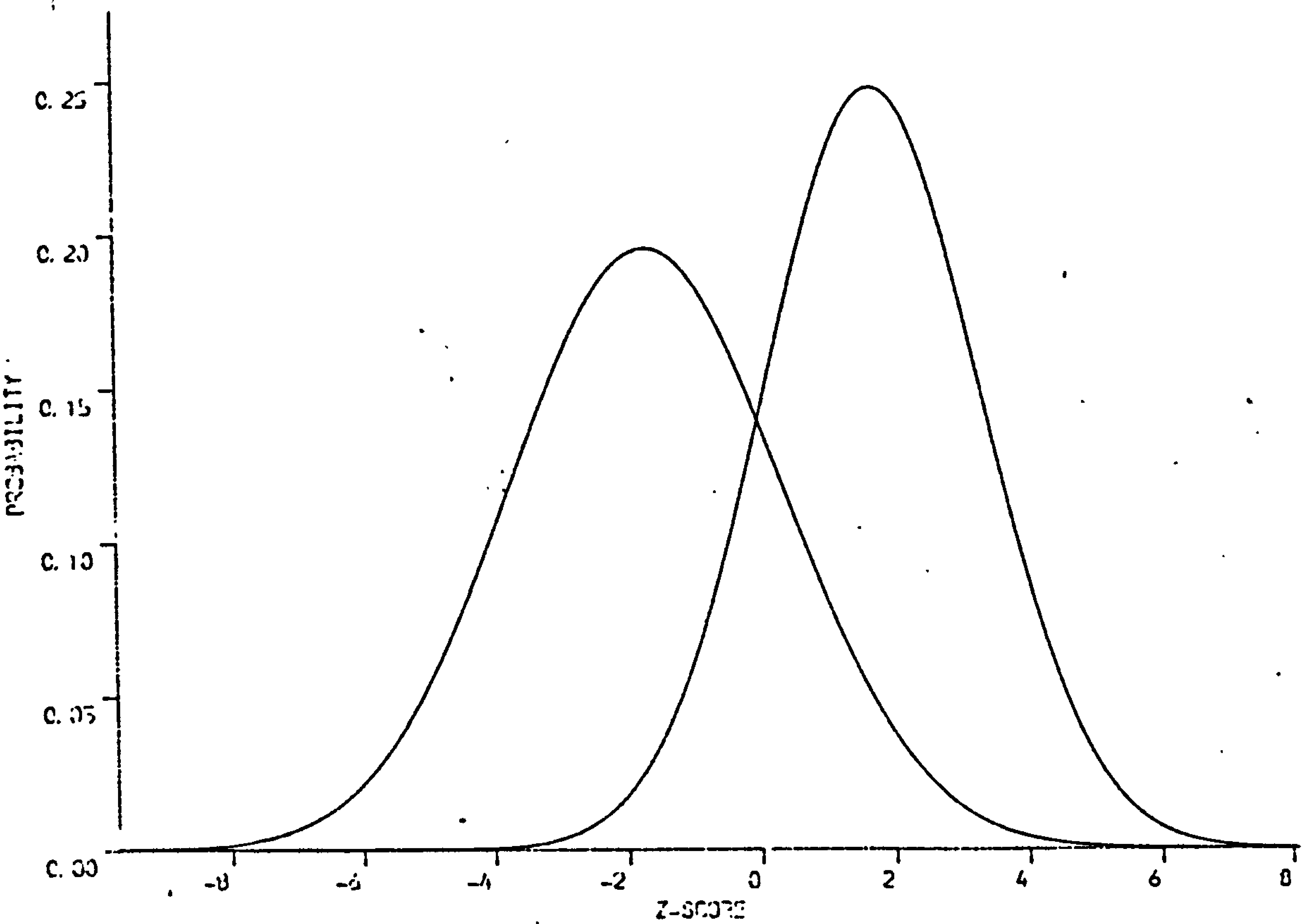


Figure 6.12 Normal Approximations of the Z-Score Distributions

and reading from the normal distribution table the corresponding probability of having a higher z value:

$$P\ (Z > 1.29) = .0985 \simeq .10$$

Taking the whole population of companies, a z-score of 3.85 would mean that this company is among the five percent top performers since the well performing companies represent only one half of the total population of firms.

Similarly a firm with a z-score of -4.35 would be among the worst five percent performers.

However, the application of the model is not as straightforward when the value of the z-score lies in the overlapping area (see figure 6.12).

Take for example, the z-score value of zero. This would imply that 20.33 percent of the less well performing have a z-score value higher than zero. and that 15.39 percent of the well performing companies have a z-score value lower than zero. This in turn means that 47.53 percent of the total population of companies has a z-score value lower than zero.

In order to simplify the utilization of the z-score as an index of overall performance, the probability of having a z-score value higher than a certain level is tabulated in steps of five percent (see table 6.3). The utilization of this new table is now much more simple since the z-score of the company analysed indicates directly the position of the firm. For example a z-score value of 1.0 indicates that the company is among the top forty percent performers while a value of -1.0 indicates that the company is among the bottom thirty five % performers.

TABLE 6.3 TABULATION OF Z-SCORE VALUES

BOTTOM Z-SCORE <	PERCENTAGE	TOP Z-SCORE >
-4.315	5%	3.85
-3.475	10%	3.15
-2.795	15%	2.65
-2.275	20%	2.225
-1.795	25%	1.85
-1.355	30%	1.525
- .75	35%	1.175
- .55	40%	.85
- .185	45%	.515
- .150	50%	.150

6.2 ASSESSING THE STRUCTURAL CHANGE EXPERIENCED BY WELL PERFORMING COMPANIES.

As the results of the discriminant analysis of chapter 5 indicate that an identification of well performers is only possible two years before a high level of performance occurs, the base year will be 1974. Then the values taken by the variables in the successive years to 1978 will be compared to those of year 1974 to evaluate the degree of structural change experienced by the companies included in the high performing and potential high performing samples. The statistical technique used to assess the differences between the variables in successive years is the Student t-test. This was preferred to the F-test used earlier in the study as a modified Student t-test can be used when the dispersion in the two samples are not equal. A description of the Student t-test is given in Appendix V111

Tables 6.4, 6.5 and 6.6 give the variables that are significantly different for the period 1974-1976, 1974-1977 and 1974 - 1978 respectively. The analysis of the period 1974-1975 resulted in no variable showing a significant difference, explaining the somewhat poor performance of the discriminant model in identifying potential well performers two years before they reach a high level of performance.

6.2.1 GENERAL TENDENCIES

From summary table 6.7 two general conclusions can be

TABLE 6.4 STUDENT T-TEST RESULTS (YEARS 1976 AND 1974)

VARIABLES	MEAN		STANDARD DEVIATION		LEVEL OF SIGNIFICANCE *
	YEAR 1976	YEAR 1974	YEAR 1976	YEAR 1974	
RATIOS:					
FINANCIAL LEVERAGE:					
R7:Sales/NW	1.312	1.113	.622	.560	S
WORKING CAPITAL M:					
R11:CA/CL	5.102	5.003	.308	.291	S
R14:WC/TA	23.051	18.621	13.556	13.312	S
R31:CL/ST	0.768	0.668	0.364	6.328	S
R33:WC/NW	54.822	42.408	28.734	29.314	HS
R34:WC/NCE	40.691	29.530	19.320	18.654	HS
RETURN ON INVEST:					
R1 :EBIT/TA	12.123	9.950	2.822	2.762	HS
R2 :EBIT/NCE	20.498	17.214	6.766	7.475	HS
R3 :EBIT/TA	9.752	7.965	3.510	2.805	HS
R4 :EBIT/NW	30.743	24.722	13.016	11.515	HS
BUSINESS TURNOVER:					
R6 :SALES/TA	.394	.237	.360	.382	HS
R26:DAYS DEBTORS	68.033	78.479	25.140	31.318	HS
R27:SALES/DEBTORS	.1864	.2181	.069	.081	HS
DEBT POSITION:					
R9 :SALES/FA	1.640	1.444	.593	.597	S
INTE.COVERAGE:					
R19:EBIT/T.INT.	11.862	6.919	20.046	6.938	S
STABILITY MEASURES:					
INVENTORY M:					
S29:SALES/ST	- 2.350	-1.671	1.020	.914	HS

* S = Significant at $\alpha < .05$
HS = Significant at $\alpha < .01$

TABLE 6.5 STUDENT T-TEST RESULTS (YEARS 1977 AND 1974)

VARIABLES	MEAN		STANDARD DEVIATION		LEVEL OF SIGNIFICANCE *
	YEAR 1977	YEAR 1974	YEAR 1977	YEAR 1974	
RATIOS:					
FINANCIAL LEVERAGE					
R7:SALES/NW	1.330	1.113	.590	.560	HS
WORKING CAPITAL M:					
R11:CA/CL	5.110	5.003	.308	.291	S
R14:WC/TA	24.501	18.631	13.149	13.312	HS
R31:CL/ST	0.791	0.668	0.401	0.328	S
R33:WC/NW	59.477	42.080	30.121	29.314	HS
R34:WC/NCE	37.671	29.530	19.885	18.654	HS
RETURN ON INVEST:					
R1:EBIT/TA	14.070	9.950	2.793	2.762	HS
R2:EBIT/NCE	23.953	17.214	6.214	7.475	HS
R3:EBT/TA	12.039	7.965	3.242	2.805	HS
R4:EBIT/NW	36.023	24.722	12.289	11.515	HS
R5:EBT/SALES	8.465	6.361	3.746	4.068	HS
R22:CF/TL	14.407	11.061	7.862	6.986	HS
R23:CF/CL	22.667	18.019	13.063	13.943	S
R25:CF/TA	7.703	5.793	3.338	2.739	HS
BUSINESS TURNOVER:					
R6:SALES/TA	.412	.237	.364	.382	HS
R10:CA/SALES	.429	.481	.145	.175	S
R26:DAYS DEBTORS	65.360	70.479	23.682	31.312	HS
R27:SALES/DEBTORS	.179	.218	.065	.081	HS
DEBT POSITION:					
R9:SALES/FA	1.726	1.444	.308	.291	HS

TABLE 6.5 (Continued...)

VARIABLES	MEAN		STANDARD DEVIATION		LEVEL OF SIGNIFICANCE *
	YEAR 1977	YEAR 1974	YEAR 1977	YEAR 1974	
CASH POSITION:					
R13:CASH/CL	1.095	.555	1.836	1.704	S
R15:CASH/TA	.098	- .391	1.801	1.795	S
INT. COVERAGE:					
R19:EBIT/T.INT	31.269	6.919	107.011	6.938	S
R29:SALES/ST	2.346	3.211	1.194	2.667	HS
STABILITY MEASURES:					
FINANCIAL LEVERAGE:					
S18:NW/TL	2.069	2.352	.957	1.074	S
INVENTORY MAN:					
S29:SALES/ST	- 2.341	- 1.671	.968	.914	HS
WORKING CAPITAL M:					
BSDM2	4.049	4.479	1.322	1.253	S
STRUCTURAL STAB:					
BSDML:	3.350	3.764	1.354	1.323	S

* S = Significant at $\alpha < .05$
HS = Significant at $\alpha < .01$

TABLE 6.6 STUDENT T-TEST RESULTS (YEARS 1978 AND 1974)

VARIABLES	MEAN		STANDARD DEVIATION		LEVEL OF SIGNIFICANCE *
	YEAR 1978	YEAR 1974	YEAR 1978	YEAR 1974	
RATIOS:					
FINANCIAL LEVERAGE:					
R12:CL/NW	4.312	4.490	.524	.604	HS
R18:NW/TL	4.493	4.312	.492	.592	HS
R20:TA/TL	189.822	177.1956	46.556	56.122	S
R36:NW/TA	47.336	43.565	11.606	13.748	S
WORKING CAPITAL M:					
R8:WC/SALES	19.499	16.095	12.285	13.065	S
R11:CA/CL	5.194	5.003	.304	.291	HS
R14:WC/TA	28.074	18.631	14.378	13.312	HS
R31:CL/ST	.901	.668	.413	.328	HS
R33:WC/NW	60.928	42.408	31.246	29.314	HS
R34:WC/NCE	43.766	29.530	20.896	18.654	HS
RETURN ON INVEST:					
R1:EBIT/TA	15.195	9.950	3.893	2.762	HS
R2:EBIT/NCE	24.030	17.214	6.773	7.475	HS
R3:EBT/TA	13.815	7.965	4.261	2.805	HS
R4:EBIT/NW	33.594	24.722	11.299	11.515	HS
R5:EBT/SALES	9.514	6.361	4.414	4.068	HS
R22:CF/TL	17.337	11.061	8.857	6.986	HS
R23:CF/CL	26.620	18.019	14.652	13.943	HS
R25:CF/TA	8.496	5.793	3.401	2.739	HS
BUSINESS TURNOVER:					
R6:SALES/TA	.424	.237	.348	.382	HS
R10:CA/SALES	.432	.481	.154	.175	HS
R26:DAYS DEBTORS	62.582	70.479	27.543	31.312	HS
R27:SALES/DEBTORS	.172	.218	.075	.081	HS
R28:DAYS CREDITORS	7.305	7.815	1.413	1.741	HS

VARIABLES	MEAN		STANDARD DEVIATION		LEVEL OF SIGNIFICANCE *
	YEAR 1978	YEAR 1974	YEAR 1978	YEAR 1974	
LIQUIDITY:					
R16:QA/CL	9.664	9.213	1.986	1.795	S
R32:ST/CA	47.360	42.080	16.146	15.216	HS
DEBT POSITION:					
R9:SALES/FA	1.694	1.444	.579	.308	S
R35:LTL/WC	2.764	1.981	5.303	2.521	S
CASH POSITION:					
R13:CASH/CL	1.427	.555	1.756	1.704	HS
R15:CASH/TA	.353	- .391	1.718	1.795	HS
INTEREST COVERAGE:					
R19:EBIT/T.INT.	62.395	6.919	206.383	6.938	HS
R29:SHES/ST	2.265	3.211	1.252	2.667	HS
STABILITY MEASURES:					
RETURN ON INVEST:					
S5:EBT/SALES	.033	.271	.962	.983	S
FINANCIAL LEVERAGE:					
S12:CL/NW	2.308	2.645	.895	.910	HS
WORKING CAPITAL M:					
S8:WC/SALES	.746	.996	.841	.822	HS
INVENTORY M:					
S29: SALES/ST	- 2.456	- 1.671	.945	.914	HS
S30:ST/WC	2.809	3.602	1.319	1.590	HS
S31:CL/ST	2.549	2.999	.983	1.118	HS
LIQUIDITY:					
S17:Q4/TA	1.585	1.729	.555	.613	S
S32:ST/CA	.974	1.195	.818	.701	HS

TABLE 6.6 (Continued.)

VARIABLES	MEAN		STANDARD DEVIATION		LEVEL OF SIGNIFICANCE *
	YEAR 1978	YEAR 1974	YEAR 1978	YEAR 1974	
CREDIT M:					
S26:DAYS DEBTORS	1.395	1.814	.922	.963	HS
S28:DAYS CREDITORS	1.505	1.861	.795	.860	HS

* S = Significant at $\alpha < 0.05$
HS= Significant at $\alpha < 0.01$

TABLE 6.6 (Continued.)

TABLE 6.7 STUDENT T-TEST SUMMARY RESULTS
(PERIOD 1974 - 1978)

VARIABLES	1974-1976	1974-1977	1974-1978
RATIOS:			
FINANCIAL LEVERAGE:			
R7:SALES/NW	S	HS	
R12:CL/NW			HS
R18:NW/TL			HS
R20:TA/TL			S
R36:NW/TA			S
WORKING CAPITAL MANG.:			
R8:WC/SALES			S
R11:CA/CL	S	S	HS
R14:WC/TA	S	HS	HS
R31:CL/ST	S	S	HS
R38:WC/NW	HS	HS	HS
R34:WC/NCE	HS	HS	HS
RETURN ON INVESTMENT:			
R1:EBIT/TA	HS	HS	HS
R2:EBIT/NCE	HS	HS	HS
R3:EBT/TA	HS	HS	HS
R4:EBIT/NW	HS	HS	HS
R5:EBT/SALES		HS	HS
R22:CF/TL		HS	HS
R23:CF/CL		HS	HS
R25:CF/TA		HS	HS

VARIABLES	1974-1976	1974-1977	1974-1978
BUSINESS TURNOVER:			
R6:SALES/TA	HS	HS	HS
R10:CA/SALES		S	HS
R26:DAYS DEBTORS	HS	HS	HS
R27:SALES/DEBTORS	HS	HS	HS
R28:DAYS CREDITORS			HS
LIQUIDITY:			
R16:QA/CL			S
R32:ST/CA			HS
DEBT POSITION:			
R9:SALES/FA	S	HS	S
R11: LTL/WC			S
CASH POSITION:			
R13:CASH/CL		S	HS
R15:CASH/TA		S	HS
INTEREST COVERAGE:			
R19:EBIT/T. INTEREST	S	S	HS
R29:SALES/ST		HS	HS
STABILITY MEASURES:			
RETURN ON INVESTMENT:			
S5:EBT/SALES			S

Table 6.7 (Continued.)

VARIABLES	1974-1976	1974-1977	1974-1978
FINANCIAL LEVERAGE:			
S12:CL/NW			HS
S18:NW/TL		S	
WORKING CAPITAL MANG.:			
S8:WC/SALES			HS
BSMD2		S	
INVENTORY MANAGEMENT:			
S29:SALES/ST	HS	HS	HS
S30:ST/WC			HS
S31:CL/ST			HS
STRUCTURAL STABILITY:			
BSMD1		S	
LIQUIDITY:			
S17:QA/TA			S
S32:ST/CA			HS
CREDIT MANAGEMENT:			
S26:DAYS DEBTORS			HS
S29:DAYS CREDITORS			HS

S = Significant at the 0.05 level
HS= Significant at the 0.01 level

TABLE 6.7 (Continued.)

drawn about the behaviour of the variables as the year analysed is further and further away from the base year (1974):

A) A tendency for more and more variables to become significantly different. The comparison between year 1974 and year 1976 revealed only sixteen variables with significant differences. This number increases to twenty seven and forty one for the comparisons of years 1974-1977 and years 1974-1978 respectively. This is particularly noticeable regarding the stability measures.

B) A tendency for the variables that showed some degree of significance in the three periods analysed to indicate a greater and greater significance in their differences.

6.2.2 YEAR BY YEAR ANALYSIS

The comparison of years 1974 and 1976 indicates that the financial dimensions showing the larger significant differences are Return on Investment, Working Capital Management and Business Turnover where most of the financial variables loading on them are significantly different. Then three other financial ratios related to the Financial Leverage, Debt Position and Interest Coverage dimensions are also significant together with a stability measure associated with the Inventory Management Stability dimension.

The comparison of years 1974 and 1977 rather than revealing more financial dimensions becoming significantly different since the cash position dimension is the only one added to the previous financial dimensions showing some degree of difference, tends to emphasise the differences already noticed. Concerning the stability measures, one can observe three more stability measures becoming significant, related to the Financial Leverage Stability, the Working Capital Management Stability and the Structural Stability dimensions respectively.

The same conclusions can be reached regarding the comparisons of the years 1974 and 1978 with more and more stability measures becoming significantly different. Three more stability dimensions present variables with significant difference:

- Return on Investment Stability
- Liquidity Stability
- Credit Management Stability

Concerning the financial ratios, only one more financial dimension appears to be significant; the liquidity dimension. However, one may notice an increase in the difference between years of the financial ratios already found significant.

To summarize the findings of this section, one may conclude that as a company improves its performance, the areas of its financial structure most affected are Working Capital

Management, Business Turnover, Return on Investment and at the same time a general increase in the performance stability is noticeable. Although the observed differences might be due to external factors that could have affected the variables analysed, it was felt that the period investigated 1974 to 1978 was not characterised by exceptional economic events and that these results are in agreement with the cross sectional analysis of Chapter 5.

CHAPTER 7

CONCLUSION

CHAPTER 7.

The present study aimed to establish whether:

i) companies that utilise more efficiently their resources present specific characteristics in their financial profile.

ii) on the basis of these characteristics a global model of performance could be constructed that would include, along side variables associated with resource utilisation, other financial variables measuring the financial strengths of companies in areas such as financial leverage, liquidity, credit management, stability of performance...etc.

iii) potential high performers could be identified some time before they reach a high level of performance.

7.1 MAIN CONCLUSIONS OF THE STUDY

On both a single variable and multivariate level differences in the financial profile of well performing and less well performing companies were found to be statistically significant on almost every aspect. That is financial variables associated with financial strengths projected a better image of the companies which utilised their resources more efficiently. This was particularly noticeable on a single variable level in areas such as

- long term solvency
- short term liquidity

- cash position
- interest coverage
- working capital position

and - stability of past performance

On the basis of these first findings, it was expected that variables other than those measuring asset utilisation would prove to be significant on a multivariate level and enter the global model of performance. The ensuing discriminant model was found to be highly significant and correctly classified 85 per cent of the samples. The inclusion of variables associated with dimensions such as:

- financial leverage
- working capital management
- cash position
- capital turnover stability
- inventory management stability

indicated that to be considered as well performing a company should not only efficiently use its resources but have a well balanced structure, a sufficient level of working capital, sufficient liquidity and anticipate change in its environment (stability of past performance). This explained why some of the companies were misclassified by the discriminant model and proved that classification obtained from the discriminant model is more reliable since it is based on a combination of variables that are generally recognised to be of importance in assessing the level of performance of a firm.

Regarding the identification of potential high performers even though statistically significant differences were found in the financial profile of potential high performers up to five years back, their identification was possible with a level of accuracy high enough for management or investment purpose only for the year before they reached a high level of performance. The model had an accuracy of 80 per cent and indicates that every basic financial characteristic (profitability, managerial performance and solvency) should be "looked after" if a firm is to become a high performer.

7.2 RECOMMENDATIONS FOR FURTHER WORK

The points discussed below are areas where further research could be carried out:

i) Criterion of resource utilisation.

Although the criterion chosen (EBIT/TA) is widely accepted in management circles as an index of resources utilisation, it is the author's view that measures of growth and other measures of return on investment should be combined to form a more comprehensive index of resource utilisation. Techniques such as principal component analysis could be used to estimate the weights of the variables. Unlike Burch (1972)'s method, not only the first component should be considered but all the components found significant. The weighting of the components could be deducted from the corresponding eigenvalues.

ii) Measures of ratio stability.

These measures were estimated from the standard deviation of each ratio over a moving three year period. In doing so an amelioration in the value of a ratio would lead to an increase in its corresponding stability measure and as such project a bad image of the firm when its situation is in fact improving in this particular area. In order to overcome this problem semi-variance type measures could be substituted whereby only worsening of the value of the ratio would be taken into account. Two possible methods could be used to calculate such semi-variance measures. The first would be to calculate the mean of the ratio over the three year period and to consider only the deviation from the mean that indicate a worsening of the ratio value. The second would be to use regression analysis and to take only the differences between the points and the regression line that indicate a worsening of the ratio score.

iii) Financial ratios.

Financial ratios covering other aspects should be included, particularly value added ratios.

iv) Variables selection.

Rather than selecting the variables on a purely statistical basis, there should be some financial theory to support the selection process. The findings of this study and other related studies could be amalgamated to propose a framework within which similar investigation could be carried out.

v) Identification of potential high performers.

The poor results of the discriminant model based on purely financial variables indicates that other variables should be considered. In the second chapter the review of studies on company performance revealed that management attributes and other purely environmental, strategic and organisational factors were important in explaining performance. Such variables could complement purely financial indicators and possibly lead to an improved discriminant model for the identification of potential high performers. However, owing to the reluctance of companies to disclose inside information, this kind of analysis would certainly reduce considerably the number of companies considered.

APPENDICES

APPENDIX I

Matrix Algebra

1. Definitions

Matrix. A matrix is a rectangular arrangement of number or of symbols that represent number.

Transpose. The transpose of a matrix is a new matrix formed by writing the rows of the original matrix as the columns of the new matrix. The transpose of matrix A is denoted as A'

Order. The order of a matrix is the number of rows and columns it has.

Column vector. A column vector is a matrix of order $n \times 1$, a matrix having only one column.

Row vector. A row vector is a matrix of order $1 \times n$, a matrix having only one row.

Determinant. If a matrix is square, that is the same number of row and column, it has a determinant. The determinant of matrix A is denoted as $|A|$.

2. Operations with Matrices.

Addition and subtraction. Matrix of the same order may be added (subtracted) by summing (subtracting) corresponding elements to produce a new matrix.

Multiplication. The product of two matrices may be obtained only if the number of columns of the first matrix equals the number of rows of the second matrix. Then the i,j^{th} elements of the product matrix is the sum of the products of the corresponding elements in the ith row of the first matrix and the jth column of the second matrix. The order of the product matrix corresponds to the number of rows of the first matrix and the number of columns of the second matrix.

Note that matrix multiplication is not commutative. (that is AB is not necessarily equal to BA), but it is associative and distributive.

A special case of matrix multiplication is the scalar multiplication where all the elements of the matrix are multiplied by the same constant.

Division. The division in matrice algebra, is performed by firstly calculating the inverse of the divising matrix and then by multiplying this inverse matrix by the matrix to be divided. The inverse of A is denoted as A^{-1}. However, it should be noted the inverse of A exists only if A is a square and non singular ($|A| \neq 0$).

3. Differentiation

The formula to obtain the derivative with respect to A of $A' B A$ where A is a vector and B a matrice can be illustrated as follows:

Let $A' = [a_1, a_2]$, $B = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$ and $A = \begin{bmatrix} a_1 \\ a_2 \end{bmatrix}$

$$A'BA = [a_1b_{11} + a_2 b_{21},\ a_1 b_{12} + a_2 b_{22}] \begin{bmatrix} a_1 \\ a_2 \end{bmatrix}$$

$$= b_{11} a_1^2 + (b_{21} + b_{12}) a_1a_2 + b_{22} a_2^2$$

If we take the partial derivatives of $A'BA$ with respect to a_1 and a_2 we obtain the following results:

$$\frac{\partial(A'\ B\ A)}{\partial a_1} = 2b_{11}a_1 + (b_{21} + b_{12})\ a_2$$

and $$\frac{\partial(A'\ B\ A)}{\partial a_2} = (b_{21} + b_{12})\ a_1 + 2b_{22}a_2$$

Re-arranging them in the form of a column vector we have

$$\frac{\partial(A'\ B\ A)}{\partial A} = \begin{bmatrix} 2b_{11}a_1 + (b_{21} + b_{12})\ a_2 \\ (b_{21} + b_{12})\ a_1 + 2b_{22}a_2 \end{bmatrix}$$

$$= \left\{ \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{21} \\ b_{12} & b_{22} \end{bmatrix} \right\} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix}$$

$$= (B + B')\ A$$

This result can be generalized to vector of order pxl and matrices of order pxp.

The following rules are worth mentioning for obtaining partial derivatives of $A'BA$ with respect to A, B, A'

-1 $$\frac{\partial(A'BA)}{\partial A} = (B + B')\,A$$

-2 $$\frac{\partial(A'BA)}{\partial A'} = A(B + B')$$

-3 $$\frac{\partial(A'BC)}{\partial A} = \frac{\partial(C'BA)}{\partial A} = BC$$

-4 $$\frac{\partial(A'BC)}{\partial A'} = \frac{\partial(C'BA)}{\partial A'} = C'B$$

-5 $$\frac{\partial(A'BA)}{\partial B} = AA'$$

If B is symetric then

-6 $$\frac{\partial(A'BA)}{\partial A} = 2B\,A$$

-7 $$\frac{\partial(A'BA)}{\partial A'} = 2A'B$$

-8 $$\frac{\partial(A'BA)}{\partial B} = A\,A' - D$$

in which the diagonal matrix

$$D = \begin{bmatrix} a_1^2 & 0 & 0 & \cdots & 0 \\ 0 & a_2^2 & 0 & \cdots & 0 \\ 0 & 0 & a_3^2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \\ 0 & 0 & 0 & & a_p^2 \end{bmatrix}$$

4. Evaluating the Determinant of a Matrix

If we define the minor(m_{ij}) of the ijth element of the determinant of a matrix A as the remaining determinant obtained by eliminating the ith row and the jth column of the original determinant, and the cofactor as

$$e_{ij} = (-1)^{i+j} m_{ij}$$

the determinant of A can be computed from

$$|A| = \sum_{i=1}^{n} a_{ij} e_{ij} = \sum_{j=1}^{n} a_{ij} e_{ij}$$

5. Evaluating the Inverse of a Matrix

The inverse of a matrix A may be evaluated as follows:

1. Construct the matrix of cofactors E
2. Obtain the transpose of E, E' called the adjoint of A, (adj(A)).
3. Divide each element of adj(A) by $|A|$.
   The resulting matrix is A^{-1} the inverse of A.

6. Obtaining the Solution of a Matrix Equation of the form $(A - \gamma_i I) V_i = 0$.

The solution of an equation of the form

$$(A - \gamma I) V = 0$$

involves finding the eigenvalues γ_i of A and their corresponding eigenvectors V_i. The solution for γ_i and V_i can be obtained using the following procedure:

1) Solve the characteristic equation of A.

$$| A - \gamma I | = 0$$

for the γ_is

2) Compute the adj(A - γI)

3) Each j^{th} column of the adj(A - γI) is an eigenvector corresponding to j^{th} eigenvalue. The eigenvector are then normalised by dividing each of its elements by their sum of squares.

APPENDIX II

Minimising Total Probability of Misclassification

Welch (1939) proposed the following solution to the problem of minimising the total probability of misclassifications. Let $f_1(X)$ be the density function of X if it belongs to population I (Π_1) and $f_2(X)$ be the density function of X if it belongs to population II (Π_2). Let P_1 be the proportion of Π_1 in the total population and p_2 $(1 - p_1)$ be the proportion of Π_2 in the total population.

Define a region R_1 such that if (X) is in that region it will be assigned to Π_1 and a region R_2 such that if X is in that region it will be assigned to Π_2.

Assuming that R_1 and R_2 are virtually exclusive and that their union includes the entire space R, the total probability of misclassification would be

$$\begin{aligned} TM &= p_1 \int_{R_2} f_2(X)\, dX + p_2 \int_{R_1} f_2(X)\, dX \\ &= p_1 \left[1 - \int_{R_1} f_1(X)\, dX\right] - p_2 \int_{R_1} f_2(X)\, dX \\ &= p_1 + \int \left[p_2\, f_2(X) - p_1\, f_1(X)\right] dX \end{aligned}$$

This quantity is minimised if R_1 is chosen so that

$$(p_2 f_2(X) - p_1 f_1(X) < 0)$$

for all points in R_1

The classification rule is then assign X to:

Π_1 if $f_1(X) / f_2(X) > p_2 / p_2$

Π_2 otherwise

Including the possibility of unequal costs of misclassification, the rule would be modified as follows. Assuming the cost of misclassifying a member of Π_1 is C_1 and C_2 the cost of misclassifying a member of Π_2. The region R_1 and R_2 would be defined such as to minimise:

$$\begin{aligned} TM &= C_1\, p_1 \int_{R_2} f_1(X)\, dX + C_2 p_2 \int f_2(X)\, dX \\ &= C_1\, p_1 \left[1 - \int_{R_2} f_1(X)\, dX\right] + C_2 p_2 \int_{R_1} f_2(X)\, dX \\ &= C_1\, p_1 + \int_{R_1} \left[C_2 p_2\, f(X) - C_1 p_1 f_1(X)\right] dX \end{aligned}$$

TM is minimised if R_1 is chosen so that

$$(C_2\, p_2\, f_2\, (X) - C_1\, p_1\, f_1\, (X) < 0)$$

in R_1 which is equivalent to assigning X to:

Π_1 if $f_1(X) / f_2(X) > C_2 p_2 / C_1 p_1$

Π_2 otherwise

APPENDIX III

The Multivariate Normal Distribution

As the univariate normal distribution is defined as

$$k\,e^{-\frac{1}{2}\,a(x\,-\,b)^2} \;=\; k\,e^{-\frac{1}{2}\,(n\,-\,b)\;a(x\,-\,b)}$$

the density function of a multivariate normal distribution can be written in an analogous form where

- the variable x is replaced by a vector

$$X \quad = \quad \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_p \end{bmatrix}$$

- the constant b is replaced by a vector

$$B \quad = \quad \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_p \end{bmatrix}$$

- the positive constant is replaced by a symmetric positive definite matrix

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1p} \\ a_{21} & a_{22} & \cdots & a_{2p} \\ \vdots & \vdots & & \vdots \\ a_{p1} & a_{p2} & & a_{pp} \end{bmatrix}$$

Therefore the density function of a p variate normal distribution is:

$$f(x_1, x_2, \ldots, x_p) = k\, e^{-\frac{1}{2}(X - B)' A (X - B)}$$

where

$$(X - B)'A(X - B) = \sum_{i,j=1}^{p} a_{ij}(x_i - b_i)(x_j - b_j)$$

$f(x_1, x_2, \ldots, x_p)$ being symetric and since A is positive definite

$$(X - B)' A (X - B) \geq 0$$

the density is bounded; that is

$$f\,(x_1,\, x_2,\, ----,\, x_p) \leqslant k$$

k is determined so that the integral multivariate normal distribution as defined above over the dimensional space is equal to one. Anderson (1958) showed that

$$k = \sqrt{|A|}\,(2\Pi)^{-\frac{1}{2}p}$$

Finding the first and second moments of X leads to:

$$E(X) = B = \mu$$

$$E\left[(X-\mu)\,(X-\mu)'\right] = A^{-1} = \Sigma$$

Thus the multivariate normal density function is defined:

$$\underline{N}(x/\mu,\, \Sigma) = (2\Pi)^{-\frac{1}{2}p}\left|\Sigma\right|^{-\frac{1}{2}}\, 1^{-\frac{1}{2}(X-\mu)'\Sigma^{-1}(X-\mu)}$$

where

μ is the vector mean

Σ the variable covariance matrix.

APPENDIX IV

Multivariate Analysis of Variance

The multivariate analysis of variance starts by defining Wilks' criterion as follows:

$$\Lambda = \frac{|W|}{|T|}$$

in which:

W is the within group sum of squares and cross products matrix.

T is the total sum of squares and cross products matrix.

Then the null hypothesis that

$$\mu_1 = \mu_2 = \text{-----} \; \mu_g$$

can be tested using an F - distribution in the following cases assuming that the g population are multinormal.

Value of g	Value of p	Statistic distributed as F	Degrees of freedom of
Any Value	2	$\frac{1-\sqrt{\Lambda}}{\sqrt{\Lambda}}\left(\frac{N-g-1}{g-1}\right)$	2(G - 1), 2(N - g - 1)
2	Any Value	$\frac{1-\Lambda}{\Lambda}\left(\frac{N-p-1}{p}\right)$	p , N - p - 1
3	Any Value	$\frac{1-\sqrt{\Lambda}}{\sqrt{\Lambda}}\left(\frac{N-p-2}{p}\right)$	2p, 2(N - p - 2)

where

g = the number of groups

p = the number of variables.

However, when $p \geqslant 3$ and $G \geqslant 4$, the exact sampling distribution of Λ does not conform to any well known model such as F or χ^2 distributions and approximations are used. These are:

1 - Bartlett's V. Bartlett (1947) defined the following statistic,

$$V = \left[N - 1 - (p + g)/2\right] \ln \frac{1}{\Lambda}$$

where

N = total number of observations.

p, g = defined as above.

Then he showed that V is approximately distributed as a χ^2 distribution with $p(g - 1)$ degree of freedom for large value of N

2 - Rao's R. A slightly better approximation is based on a statistic due to Rao (1952):

$$R = \frac{1 - \Lambda^{1/s}}{\Lambda^{1/s}} \left(\frac{ms - p(g-1)/2 + 1}{p(g-1)} \right)$$

where

$$m = N - 1 - (p + g)/2$$

$$s = \left[\frac{p^2(g-1)^2 - 4}{p^2 + (g-1)^2 - 5} \right]^{1/2}$$

R is distributed approximately as $F(n_1, n_2)$ with $n_1 = p(g - 1)$ and $n_2 = ms - p(g - 1)/^2 + 1$ when the null hypothesis is true. If n is not an integer extrapolationtothe closest integer value should be used.

Exact probabilities significance can be obtained when p is an even number or g is an odd number. Scheetzoff (1966) prepared tables for use in such cases based on Bartlett'V.

Although other statistics have suggested for testing the hypothesis that

$$U_1 = U_2 = \ldots\ldots = U_g$$

those based on Wilks' Lambda were described because they are the most widely used and available in canned computer package.

APPENDIX V

KOLMOGOROV-SMIRNOV TEST

Critical values, $d_\alpha(N)$, of the Maximum Absolute Difference between Sample and Population Cumulative Distributions.

Values of $d_\alpha(N)$ such that $Pr[\max|S_N(x) - F_0(x)| > d_\alpha(N)] = \alpha$, where $F_0(x)$ is the theoretical cumulative distribution and $S_N(x)$ is an observed cumulative distribution for a sample of N.

Sample size (N)	Level of significance (α)				
	0.20	0.15	0.10	0.05	0.01
1	0.900	0.925	0.950	0.975	0.995
2	0.684	0.726	0.776	0.842	0.929
3	0.565	0.597	0.642	0.708	0.828
4	0.494	0.525	0.564	0.624	0.733
5	0.446	0.474	0.510	0.565	0.669
6	0.410	0.436	0.470	0.521	0.618
7	0.381	0.405	0.438	0.486	0.577
8	0.358	0.381	0.411	0.457	0.543
9	0.339	0.360	0.388	0.432	0.514
10	0.322	0.342	0.368	0.410	0.490
11	0.307	0.326	0.352	0.391	0.468
12	0.295	0.313	0.338	0.375	0.450
13	0.284	0.302	0.325	0.361	0.433
14	0.274	0.292	0.314	0.349	0.418
15	0.266	0.283	0.304	0.338	0.404
16	0.258	0.274	0.295	0.328	0.392
17	0.250	0.266	0.286	0.318	0.381
18	0.244	0.259	0.278	0.309	0.371
19	0.237	0.252	0.272	0.301	0.363
20	0.231	0.246	0.264	0.294	0.356
25	0.21	0.22	0.24	0.27	0.32
30	0.19	0.20	0.22	0.24	0.29
35	0.18	0.19	0.21	0.23	0.27
over 35	$\frac{1.07}{\sqrt{N}}$	$\frac{1.14}{\sqrt{N}}$	$\frac{1.22}{\sqrt{N}}$	$\frac{1.36}{\sqrt{N}}$	$\frac{1.63}{\sqrt{N}}$

APPENDIX Vl

The Exponential Distribution

The exponential probability density function of the continuous random variable x is given by:

$$f(x) = \frac{1}{\beta} e^{-x/\beta} \qquad x>o,\ \beta>o$$

$$= o \qquad \text{otherwise}$$

Its mean and variance are evaluated as follows:

$$E(x) = \beta$$

and

$$\mathrm{Var}(x) = \beta^2$$

respectively.

The exponential distribution is characterised by an inverse J shaped curve, β behaving as a scale parameter.

APPENDIX V11

Matching Moment Estimation of Parameters

The method of matching moments consists in equating the first moments of a distribution with the corresponding moments of a sample.

The k^{th} moment of sample about the origin of a set of observation $x_1, x_2, - -, x_n$ is defined as,

$$\mu' k = E(x^k) = \frac{\sum_{i=1}^{n} x_i^k}{\mu}$$

The first moment being the expected value of $x_i (i = 1,...,n)$

$$\mu'_1 = E(x) = \frac{\sum_{i=1}^{n} n_i}{\mu} = \bar{x}$$

However, in estimating parameters, moments about the mean or central moments are mostly used. The k^{th} central moment is defined as,

$$\mu' k = E(x - \mu'_1)^k$$

The number of equations needed should be equal to the number of unknown parameters.

In the case of the Gamma distribution, that is the distribution parameters for which this method was used, two equations are needed.

$$\mu'_1 = \bar{x} = \frac{\alpha}{\beta}$$

$$\mu'_2 = s^2 = \frac{\alpha}{\beta^2}$$

leading to

$$\beta = \frac{\bar{x}}{s^2} = \frac{\bar{x}\,(n - 1)}{\sum (x_i - x)^2}$$

$$\alpha = \frac{\bar{x}^2}{s^2} = \frac{\bar{x}^2\,(n - 1)}{\sum (n_i - \bar{x})^2} = \beta\bar{x}$$

APPENDIX VIII

Difference of Mean Test

1. Student t - test:

One of the most useful difference of mean test is the t - test. t is computed as follows:

$$t = \frac{(\bar{X}_1 - \bar{X}_2) - (\mu_1 - u_2)}{\hat{\sigma}\,(\bar{X}_1 - \bar{X}_2)}$$

where

$\bar{X}_1$ = estimate of sample 1 mean

$\bar{X}_2$ = estimate of sample 2 mean

μ_1 and μ_2 = mean of population 1 and 2 respectively

$\hat{\sigma}\,(\bar{X}_1 - X_2)$ = estimate of the standard error of the difference between sample means

Since under the null hypothesis

$$H_o: \mu_1 = \mu_2 ,$$

the expression of t reduces to

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\hat{\sigma}\,(X_1 - X_2)}$$

and follows a t - distribution.

Assuming that the sample variances are equal $\hat{\sigma}(\bar{X}_1 - X_2)$ is evaluated as follows:

$$\hat{\sigma}(\bar{X}_1 - \bar{X}_2) = \sqrt{\frac{N_1 s_1 + N_2 s_2}{N_1 - N_2 - 2}}$$

where

s_1 and s_2 = the variance of sample 1 and 2 respectively

N_1 and N_2 = the number of observations in sample 1 and 2 respectively

degrees of freedom = $(N_1 + N_2 - 2)$

However, when the sample variance are not equal, instead of taking the pooled variance of the two samples, their variance is estimated separately and

$$\hat{\sigma}(\bar{X}_1 - \bar{X}_2) = \sqrt{\frac{s_1^2}{N_1 - 1} + \frac{s^2}{N_2 - 1}}$$

Therefore

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{s_1}{N_1 - 1} + \frac{s_2}{N_2 - 1}}}$$

Difficulties arise in estimating the correct degrees of freedom and the following formula has been suggested to approximate them:

$$df = \frac{\left(\frac{s^2_1}{N_1 - 1} \cdot \frac{s_2^2}{N_2 - 1}\right)^2}{\left(\frac{s_1^2}{N_1 - 1}\right)^2\left(\frac{1}{N + 1}\right) + \left(\frac{s_2^2}{N_2 - 1}\right)^2\left(\frac{1}{N_2 + 1}\right)} - 2$$

It should be noticed that this second procedure for evaluating $\hat{\sigma}(\bar{X}_1 - \bar{X}_2)$ does not require the sample variances to be unequal. If they happen to be equal the ensuing t - test would be less efficient. However, when the samples are large, the two procedures will give very similar results.

A prerequisite of the t - test for mean difference is that the sample underlying distributions are normal.

2. Analysis of Variance

One way analysis of variance can be used to test whether the means of several populations are equal. Therefore, the null hypothesis is

$$H_o: \mu_1 = \mu_2 = \ldots\ldots = \mu_n$$

Each of the population means can be arbitrarily divided into two parts: the overall mean and the difference between the mean of each population and the overall mean.

$$\mu_i = \mu + \alpha_i$$

where

μ_i = mean of sample i

μ = overall mean

α_i = difference between μ_i and μ.

Then each observation can be expressed as:

$$Y_{ij} = \mu + \alpha_i + E_{ij} \quad i = 1,\ldots\ldots, a\ ; j = 1, \ldots\ldots, n$$

where

a is the number of populations

n the number of observations in each population.

Assuming that

1. The populations are normally distributed
2. The variances of the populations are equal.
3. The observations are independent.

E_{ij} is distributed as a normal distribution whose mean is 0 and variance is 6^2. It should also be noted that:

$$\sum_{i=1}^{a} \alpha_i = 0$$

When the population parameters are not known, they are estimated as follows:

$$\hat{\mu}_i = \bar{Y}_i = \frac{Y_{i1} + \ldots + Y_{in}}{n}$$

$$\hat{\mu} = \bar{Y}\ldots = \frac{(Y_{11} + \ldots + Y_{1n}) + \ldots + (Y_{a1} + \ldots + Y_{an})}{an}$$

giving

$$Y_{ij} = \bar{Y}.. + (\bar{Y}_i - \bar{Y}..) + (\bar{Y}_{ij} - \bar{Y}_i)$$

which can be re-written as:

$$Y_{ij} - \bar{Y}.. = (\bar{Y}_i - \bar{Y}..) + (Y_{ij} - \bar{Y}_i)$$

When this expression is squared over all the observations, we obtain:

$$\sum_{i=1}^{a} \sum_{j=1}^{n} (Y_{ij} - \bar{Y}..)^2 = \sum_{i=1}^{a} \sum_{j=1}^{n} (\bar{Y}_i - \bar{Y}..)^2 + \sum_{a=1}^{a} \sum_{j=1}^{n} (Y_{ij} - \bar{Y}_i)^2$$

Thus the sum of the squared deviation of observation Y_{ij} from the overall mean equals the sum of squared deviations of the sample means from the overall mean plus the sum of the squared deviations of the observations from the sample means. It is, therefore, broken down into two parts: the first is said to be "between or among groups", the second is said to be "within group".

The summary of the sum of squared deviations is given in the table below:

Source of Variation (1)	Sum of Squares (2)	Degrees of Freedom (3)	Mean Square (4)	Expected Mean Square (5)	Computed F (6)
Between groups	$ss_b = n\sum_{i=1}^{a}(\bar{Y}-Y..)^2$	$a-1$	$Ms_b = ss_b/(a-1)$	$\sigma^2+n\gamma^2$	$\frac{MSb}{s^2}$
Within groups	$ss_w = \sum_{i=1}^{a}\sum_{j=1}^{n}(Yij-Yi)^2$	$a(n-1)$	$s^2 = ss_w/a(n-1)$	σ^2	
Total	$ss_t = \sum_{i=1}^{a}\sum_{j-1}^{n}(Y_{ij}-\bar{Y}..)^2$	$an-1$			

where $\gamma^2 = \sum_{i=1}^{a}\sigma^2/(a-1)$

When the population means are equal, it can be shown that MS_b provides an unbiased estimate of the variance σ^2. If the population means differ widely, the sample mean will greatly vary around the overal mean $\bar{Y}..$, MS_b will tend to be large. On the other hand s^2 will not show a tendency to be large because of large differences among the samples means.

To test the equality of sample means, an F statistic is computed:

$$F = Msb / 6^2$$

which follows an F distribution with a - 1 and a (n - 1) degrees of freedom under the null hypothesis.

It should be noted, however, that in the two group situation, this test is equivalent to the t - test described above.

As a last point, the following remarks by Dunn and Clark (1974) regarding the robustness of the analysis of variance test to departures from the assumptions should be noted:

> " ... non normality of the data is not very troublesome in testing equality of means. Inequality of variances is seldom serious if there are equal sample sizes".

APPENDIX IX

Terminology and Definition of the Variables Utilised.

Cash	Cash and equivalent.
CA (Current Assets)	Cash plus other items that can easily be turned into cash or sold/ consumed during the normal operating cycle (Cash + receivables + quoted investment + debtors + inventories).
CF (Cash Flow)	Change in cash from recurring operations (retained earning - exceptional items + depreciation).
CL (Current Liabilities)	Includes all liabilities due within a year from debt statement (Bank loans and overdrafts + short term borrowings + Creditors + payables + current taxation (duties and taxes + proposed dividend).
CR (Creditors)	
Days Debtors	Is the average collection period. This measure indicates the average duration from inception to collect-

ion of the accounts receivable. The formula is

$$\frac{\text{debtors} \times 365}{\text{Sales}}$$

Days Creditors	Represents the length of time taken by a company to pay its suppliers. The formula used is: $$\frac{\text{creditors} \times 365}{\text{Sales}}$$
EBIT (Earning before interest and taxes)	This item is defined in chapter 3. It represents the benefit of a firm before taxes and interest paid are deducted.
FA (Fixed Assets)	These are the assets of a permanent nature held for use in the operation of a company. They include total net property and net other fixed assets.
Inventory	Stocks (see below)
LTL (Long term liabilities)	These are the debts contracted by a company which would take more than a year to mature. (Total assets - shareholders fund-current liabilities

NCE (Net capital Employed)	Total assets minus current liabilities. These are the long term resources of a firm.
NI (Net Income)	Profit after deduction of taxes, and interests.
NW (Net worth)	Same as shareholders fund or equity. (Preferred capital + ordinary capital + share premium account + reserves + government grants).
QA (Quick assets)	These are the most liquid items of the current assets (current assets - inventory).
QL (Quick liabilities)	As the current assets can be classified in order of liquidity the current liabilities can be ordered according to their exigibility. The quick liabilities represent that part of the current liabilities, that is the most exigible.
SA (Sales)	The volume of business transacted during the year evaluated in

	pounds (£).
SA (Stocks)	This is the sum of stocks of raw materials, finished goods and work in progress..
TA (Total assets)	Include fixed assets, intangible assets, associated companies, trade investments, current assets.
T. Int. (Total interest)	This comprises of all the interests. paid (short-term interest + long term interest + interest capitalised).
TL (Total liabilities)	They include all the debt of a firm : short-term and long term (Total assets minus shareholders fund).
VA (Value added)	This item is described in chapter 3.
WC (Working Capital)	Current assets minus current liabilities.

Including all the items composing certain of the elements described above would have been too long, for more precision, the reader is referred to the Exstat User Manual. (1979)

APPENDIX X

COMPUTER PROGRAMMES

```
C
C
C   THIS PROGRAM CALCULATES FINANCIAL RATIOS,
C   STABILITY MEASURES AND TRENDS FOR THE WHOLE
C   SET OF COMPANIES AVAILABLE ON THE EXSTAT TAPE
C
C
      PROGRAM DJUM
      INTEGER FCLASS(2),OCLASS(2),COUNT(4,2),NOUT1(2),NOUT2(2)
      REAL INC(5,10)
      DIMENSION H(36,10),SCA(0:10),SH(36,10),BS(3,10),C(10,10)
     C,E(20,0:10),FF(8,0:10),IY(10),IM(10),ID(10),TR(5,10)
     C,BSD(4,10),TAD(4,10),TLD(4,10)
     C,BS3(3,10),E3(10),AM(2,2)
      CHARACTER*35 A
      COMMON /AT/ E,FF,H,N,IY,IM,ID,INC,SCA,BS,BSD,TAD,TLD
     C,ABON,BS3,E3
      PRINT*,'N. OF CASES ?'
      READ*,NCASES
      PRINT*,'N. OF YEARS STABILITY TO BE CALCULATED ON ?'
      READ*,NYT
      AM(1,1)=14.995
      AM(2,1)=15.216
      AM(1,2)=11.315
      AM(2,2)=11.383
C
C   INITIALISATION
C
      ION=0
      DO 91 K1=1,4
      DO 91 K2=1,2
      COUNT(K1,K2)=0
   91 CONTINUE
      DO 10 I=1,NCASES
      DO 197 I1=0,10
      SCA(I1)=0.0
      DO 197 I2=1,20
      E(I2,I1)=0.0
  197 CONTINUE
      DO 198 I1=1,8
      DO 198 I2=0,10
      FF(I1,I2)=0.0
  198 CONTINUE
      CALL READ(A,K,N)
      IF(N.EQ.0)  GO TO 10
      CALL COMP1(E,N,IY,IM,ID)
C
C   CHECK FOR MISSING VALUES
C
      IF(K.LT.9.OR.K.GT.76) GO TO 10
      IF(N.NE.7)  GO TO 10
      IF(IY(N).LT.1977) GO TO 10
      IF(IY(N).EQ.1977.AND.IM(N).LT.5.OR.IY(N).EQ.1978
     C.AND.IM(N).GT.6) GO TO 10
      NERTAI=0
      DO 50 IJ=2,20
      IF(E(IJ,N).GE.99999999999.0) NERTAI=1
```

```
   50 CONTINUE
      IF(NERTAI.NE.0) GO TO 10
      DO 60 IJ=1,N
      C(1,IJ)=E(2,IJ)
      C(2,IJ)=E(7,IJ)
      C(3,IJ)=E(9,IJ)
      C(4,IJ)=E(11,IJ)
      C(5,IJ)=E(12,IJ)
      C(6,IJ)=E(14,IJ)
      C(7,IJ)=E(15,IJ)
      C(8,IJ)=E(16,IJ)
      C(9,IJ)=E(19,IJ)
      C(10,IJ)=E(20,IJ)
   60 CONTINUE
      CHECK=0.0
      DO 70 IJ=1,N
      IF(E(3,IJ).EQ.0.0) CHECK=1.0
      IF(E(8,IJ).EQ.0.0) CHECK=1.0
      AB123=E(15,IJ)-E(16,IJ)-E(20,IJ)
      IF(AB123.EQ.0.0) CHECK=1.0
      IF(E(13,IJ).EQ.0.0) CHECK=1.0
      DO 70 IQ=1,10
      IF(C(IQ,IJ).LE.0.0) CHECK=1.0
   70 CONTINUE
      IF(CHECK.NE.0.0) GO TO 10
      CALL COMP2
      IF(ABON.EQ.1.0) GO TO 10
      CALL STABI(H,SH,N,NYT)
      CALL SELECT(H,FCLASS,OCLASS,AM,NOUT1,NOUT2,COUNT)
C
C   TREND IN TOTAL ASSETS
C
      CALL TREND(E,TR,N,15,1,NYT,20,SCA)
C
C   TREND IN SALE
C
      CALL TREND(E,TR,N,2,2,NYT,20,SCA)
C
C   TREND IN INVENTORIES
C
C     CALL TREND(E,TR,N,11,3,NYT,20,SCA)
C
C   TREND IN DEBTORS
C
      CALL TREND(E,TR,N,12,4,NYT,20,SCA)
C
C   TREND IN CREDITORS
C
      CALL TREND(E,TR,N,19,5,NYT,20,SCA)
      ION=ION+1
C     WRITE(7,250) ION,A,IY(N),N,OCLASS(1),OCLASS(2)
C 250 FORMAT(1H ,I4,1X,A35,'LAST',I5,2X,'HELD',I2,2(2X,I2))
C     INCR=1
      NOUT=INCR
      JK=N
      WRITE(NOUT,260) ION,IY(JK),IM(JK),ID(JK),(H(J,JK),J=1,36)
     C,(SH(J,JK),J=1,36),(BS(J,JK),J=1,3),(BS3(J,JK),J=1,3)
```

```
     C,(TR(J,JK),J=1,5),(INC(J,JK),J=1,5),E(15,JK)*E3(JK),E(2,JK)
     C*E3(JK),FCLASS(1),FCLASS(2)
      DO 175 JK=N-1,NYT,-1
      INCR=INCR+1
      NOUT=INCR
      WRITE(NOUT,260) ION,IY(JK),IM(JK),ID(JK),(H(J,JK),J=1,36)
     C,(SH(J,JK),J=1,36),(BS(J,JK),J=1,3),(BS3(J,JK),J=1,3)
     C,(TR(J,JK),J=1,5),(INC(J,JK),J=1,5),E(15,JK)*E3(JK),E(2,JK)
     C*E3(JK),OCLASS(1),OCLASS(2)
  260 FORMAT(1H ,2(I4,1X),2I2,6(1X,F9.3)/10(8(1X,F9.3)/),2(1X,F9.3)
     C,2(F12.0),2(1X,I2))
  175 CONTINUE
      JL=NYT-1
      INCR=INCR+1
      NOUT=INCR
      WRITE(NOUT,261) ION,IY(JL),IM(JL),ID(JL),(H(J,JL),J=1,36)
     C,(BS(J,JL),J=1,3),(INC(J,JL),J=1,5),E(13,JL)*E3(JL)
     C,E(2,JL)*E3(JL),OCLASS(1),OCLASS(2)
  180 CONTINUE
  261 FORMAT(1H ,2(I4,1X),2I2,6(1X,F9.3)/4(8(1X,F9.3)/),6(1X,F9.3)
     C/2(1X,F12.0),2(1X,I2))
      JM=JL-1
      INCR=INCR+1
      NOUT=INCR
      WRITE(NOUT,262) ION,IY(JM),IM(JM),ID(JM),(H(J,JM),J=1,36)
     C,E(13,JM)*E3(JM),E(2,JM)*E3(JM),OCLASS(1),OCLASS(2)
  262 FORMAT(1H ,2(I4,1X),2I2,6(1X,F9.3)/3(8(1X,F9.3)/),6(1X,F9.3)
     C/2(1X,F12.0),2(1X,I2))
   10 CONTINUE
      WRITE(7,'(1H ,"NUMBER OF COMPANIES ANALYSED",I10)') ION
      WRITE(7,'(1H ,///)')
      WRITE(7,500)
  500 FORMAT(1H ,T15,'PERFORM',T25,'MEDIUM')
      DO 11 IE=1,4
      WRITE(7,400) IE,(COUNT(IE,IR),IR=1,2)
   11 CONTINUE
  400 FORMAT(1H ,'GROUP',I3,T18,I3,T28,I3)
      STOP
      END
      SUBROUTINE READ(A,K,N)
C
C   THIS SUBROUTINE READS COMAPNY NAME
C   AND NUMBER OF YEARS OF DATA AVAILABLE
C
      CHARACTER*11 A*35,IND,TA
      READ(8,100) A,K,N
  100 FORMAT(A35,2I2)
      RETURN
      END
      SUBROUTINE COMP1(E,N,IY,IM,ID)
C
C   THIS SUBROUTINE READS AT A TIME A YEAR OF DATA
C
      DIMENSION E(20,0:N),IY(N),IM(N),ID(N)
      READ(8,100) (IY(J),IM(J),ID(J),(E(I,J),I=1,20),J=1,N)
  100 FORMAT(I4,2I2,F1.0,11X,F14.0,12X,2F12.0/4F12.0,12X
     C,F11.0/22X,5F11.0/F13.0,F12.0,22X,2F11.0/2F11.0)
```

```
C      RETURN
C      END
C      SUBROUTINE COMP2
C
C    THIS SUBROUTINE CALCULATES THE FINANCIAL
C    RATIOS AND MEASURES OF DECOMPOSITION
C
       COMMON /AT/ E,FF,H,N,IY,IM,ID,INC,SCA,BS,BSD,TAD,TLD
      C,ABON,BS3,E3
C      REAL INC(5,10)
C      DIMENSION E(20,0:10),FF(8,0:10),H(36,10),BS(3,10),E3(10)
      C,IY(10),ID(10),IM(10),SCA(0:10),BS3(3,10)
C     C,BSD(4,10),TAD(4,10),TLD(4,10)
C      ABON=0.0
C      DO 222 I=1,N
C
C    SCALING FACTOR
C
C      SCA(I)=10**E(1,I)
       E3(I)=10**(E(1,I)-3.0)
C
C    EBIT : EARNINGS BEFORE TAX + INTEREST
C
C      FF(1,I)=E(3,I)+E(8,I)
C
C    QUICK ASSETS : CURRENT ASSETS - INVENTORIES
C
       FF(2,I)=E(14,I)-E(11,I)
C
C    TOTAL LIABILITIES : TOTAL ASSETS - NET WORTH
C
C      FF(3,I)=E(15,I)-E(16,I)
C
C    AVERAGE STOCK
C
       FF(4,I)=(E(11,I-1)*SCA(I-1)+E(11,I)*SCA(I))/2
C
C    WORKING CAPITAL : CURRENT ASSETS - CURRENT LIABILITIES
C
       FF(5,I)=E(14,I)-E(20,I)
C
C    CAPITAL EMPLOYED : TOTAL ASSETS - CURRENT LIABILITIES
C
C      FF(6,I)=E(15,I)-E(20,I)
C
C    LONG TERM LIABILITIES : TOTAL LIABILITIES - CURRENT LIABILITIES
C
       FF(7,I)=FF(3,I)-E(20,I)
C
C    CASH FLOW
C
       FF(8,I)=E(4,I)-E(5,I)-E(6,I)+E(7,I)
C
C                                 PROFITABILITY
C
C    RETURN ON CAPITAL
C
```

```
C
C    EBIT / TOTAL ASSETS
C
C      H(1,I)=FF(1,I)/E(15,I)*100
C      IF(H(1,I).GT.100.0.OR.ABON.EQ.1.0) THEN
C         ABON=1.0
          GO TO 222
C      END IF
C
C    EBIT / NCE
C
C      H(2,I)=FF(1,I)/FF(6,I)*100
C
C    EBT / TOTAL ASSETS
C
C      H(3,I)=E(3,I)/E(15,I)*100
C
C    E B I T / N W
C
C      H(4,I)=FF(1,I)/E(16,I)*100
C
C    PROFIT MARGIN
C
C
C    E B T / SALES
C
       H(5,I)=E(3,I)/E(2,I)*100
C
C    CAPITAL TURNOVER
C
C
C    SALES / T A
C
       H(6,I)=E(2,I)/E(15,I)
C
C    SALES / N W
C
       H(7,I)=E(2,I)/E(16,I)
C
C    W C / SALES
C
       H(8,I)=FF(5,I)/E(2,I)*100
C
C    SALES / C A
C
       H(9,I)=E(2,I)/E(14,I)
C
C    SALES / F A
C
C      H(10,I)=E(2,I)/E(9,I)
C
C                                   SOLVENCY
C
C
C    SHORT-TERM LIQUIDITY
C
C
```

```
C   C A / C L
C
C     H(11,I)=E(14,I)/E(20,I)*100
C
C   C L / N W
C
C     H(12,I)=E(20,I)/E(16,I)*100
C
C   CASH / C L
C
C     H(13,I)=E(13,I)/E(20,I)*100
C
C   W C / T A
C
C     H(14,I)=FF(5,I)/E(15,I)*100
C
C   CASH / T A
C
C     H(15,I)=E(13,I)/E(15,I)*100
C
C   Q A / C L
C
C     H(16,I)=FF(2,I)/E(20,I)*100
C
C   Q A / T A
C
C     H(17,I)=FF(2,I)/E(15,I)*100
C
C   LONG TERM SOLVENCY
C
C
C   N W / T L
C
C     H(18,I)=E(16,I)/FF(3,I)*100.0
C
C   E B I T / T INT.
C
C     H(19,I)=FF(1,I)/E(8,I)
C
C   T L / T A
C
C     H(20,I)=FF(3,I)/E(15,I)*100.0
C
C   N W / L T L
C
C     H(21,I)=E(15,I)/FF(7,I)*100.0
C
C   CASH FLOW
C
C
C   C F / T L
C
C     H(22,I)=FF(8,I)/FF(3,I)*100
C
C   C F / C L
C
C     H(23,I)=FF(8,I)/E(20,I)*100
```

```
C
C   W C / C F
C
C     H(24,I)=FF(5,I)/FF(8,I)*100
C
C   C F / T A
C
      H(25,I)=FF(8,I)/E(15,I)*100.0
C
C                                  MANEGERIAL PERFORMANCE
C
C
C   CREDIT POLICY
C
C
C   DAYS DEBTORS
C
      H(26,I)=E(12,I)*365.0/E(2,I)
C
C   SALES / DEBTORS
C
C     H(27,I)=E(2,I)/E(12,I)
C
C   DAYS / CREDITORS
C
C     H(28,I)=E(19,I)*365.0/E(2,I)
C
C   INVENTORIES
C
C
C   SALES / STOCKS
C
      H(29,I)=E(3,I)*SCA(I)/FF(4,I)
C
C   STOCKS / W C
C
C     H(30,I)=E(11,I)/FF(5,I)*100.0
C
C   C L / STOCKS
C
C     H(31,I)=E(20,I)/E(11,I)*100.0
C
C   STOCKS / C A
C
      H(32,I)=E(11,I)/E(14,I)*100.0
C
C   ASSET-EQUITY STRUCTURE
C
C
C   W C / N W
C
C     H(33,I)=FF(5,I)/E(16,I)*100.0
C
C   W C / N C E
C
C     H(34,I)=FF(5,I)/FF(6,I)*100.0
C
```

```
C   L T L / W C
C
C     H(35,I)=FF(7,I)/FF(5,I)*100.0
C
C   N W / T A
C
C     H(36,I)=E(16,I)/E(15,I)*100.0
  222 CONTINUE
C     IF(ABON.EQ.1.0) GO TO 444
C
C                             COMPUTATION OF CHANGE OVER PREVIOUS YEAR (%)
C
C     I=1
C        INC(1,I)=1.0
C        INC(2,I)=1.0
C        INC(3,I)=1.0
C        INC(4,I)=1.0
C        INC(5,I)=1.0
      DO 777 I=2,N
C
C   CHANGE IN TOTAL ASSETS
C
         INC(1,I)=(E(15,I)*SCA(I)-E(15,I-1)*SCA(I-1))/
C    C            (E(15,I-1)*SCA(I-1))*100
C
C   CHANGE IN SALE
C
C        INC(2,I)=(E(3,I)*SCA(I)-E(3,I-1)*SCA(I-1))/
C    C           (E(3,I-1)*SCA(I-1))*100
C
C   CHANGE IN STOCKS
C
C        INC(3,I)=(E(11,I)*SCA(I)-E(11,I-1)*SCA(I-1))/
C    C           (E(11,I-1)*SCA(I-1))*100.0
C
C   CHANGE IN DEBTORS
C
         INC(4,I)=(E(12,I)*SCA(I)-E(12,I-1)*SCA(I-1))/
C    C           (E(12,I-1)*SCA(I-1))*100.0
C
C   CHANGE IN CREDITORS
C
C        INC(5,I)=(E(19,I)*SCA(I)-E(19,I-1)*SCA(I-1))/
C    C           (E(19,I-1)*SCA(I-1))*100.0
C 777 CONTINUE
      IF(ABON.EQ.1.0) GO TO 444
C       I=1
C
C                             COMPUTATION OF PROPORTIONS
C
C
C   BALANCE SHEET
C
C
C   CURRENT ASSETS
C
C        BSD(1,I)=(E(14,I)/E(15,I))/2.0
```

```
C
C     FIXED ASSETS
C
           BSD(2,I)=0.5-BSD(1,I)
C
C     CURRENT LIABILITIES
C
           BSD(3,I)=(E(20,I)/E(15,I))/2.0
C
C     NET WORTH AND LONG-TERM LIABILITIES
C
           BSD(4,I)=0.5-BSD(3,I)
C
C     TOTAL ASSETS
C
C
C     FIXED ASSETS
C
           TAD(1,I)=E(9,I)/E(15,I)
C
C     INVENTORIES
C
           TAD(2,I)=E(11,I)/E(15,I)
C
C     DEBTORS
C
           TAD(3,I)=E(12,I)/E(15,I)
C
C     OTHER ASSETS
C
           TAD(4,I)=(E(15,I)-E(9,I)-E(12,I)-E(11,I))/E(15,I)
C
C     TOTAL LIABILITIES
C
C
C     EQUITY
C
           TLD(1,I)=E(16,I)/E(15,I)
C
C     LONG-TERM LIABILITIES
C
           TLD(2,I)=(E(15,I)-E(16,I)-E(20,I))/E(15,I)
C
C     CREDITORS
C
           TLD(3,I)=E(19,I)/E(15,I)
C
C     BANK OVERDRAFTS, SHORT-TERM LOANS AND OTHER CURRENT LIABILITIES
C
           TLD(4,I)=(E(20,I)-E(19,I))/E(15,I)
           BS(1,I)=1.0
           BS(2,I)=1.0
           BS(3,I)=1.0
        DO 666 I=2,N
C
C     COMPUTATION OF BALANCE SHEET PROPORTIONS
C
```

```
C
C   CURRENT ASSETS
C
          BSD(1,I)=(E(14,I)/E(15,I))/2.0
C
C   FIXED ASSETS
C
C         BSD(2,I)=0.5-BSD(1,I)
C
C   CURRENT LIABILITIES
C
          BSD(3,I)=(E(20,I)/E(15,I))/2.0
C
C   NET WORTH AND LONG-TERM LIABILITIES
C
C         BSD(4,I)=0.5-BSD(3,I)
C
C   COMPUTATION OF TOTAL ASSETS PROPORTION
C
C
C   FIXED ASSETS
C
          TAD(1,I)=E(9,I)/E(15,I)
C
C   INVENTORIES
C
          TAD(2,I)=E(11,I)/E(15,I)
C
C   DEBTORS
C
C         TAD(3,I)=E(12,I)/E(15,I)
C
C   CASH AND OTHER CURRENT ASSETS
C
          TAD(4,I)=(E(15,I)-E(9,I)-E(12,I)-E(11,I))/E(15,I)
C
C   COMPUTATION OF LIABILITIES PROPORTIONS
C
C
C   EQUITY
C
          TLD(1,I)=E(16,I)/E(15,I)
C
C   LONG-TERM LIABILITIES
C
C         TLD(2,I)=(E(15,I)-E(16,I)-E(20,I))/E(15,I)
C
C   CREDITORS
C
          TLD(3,I)=E(19,I)/E(15,I)
C
C   BANK OVERDRAFTS, SHORT-TERM LOANS AND OTHER CURRENT LIABILITIES
C
          TLD(4,I)=(E(20,I)-E(19,I))/E(15,I)
C
C   BALANCE SHEET DECOMPOSITION MEASURE
C
```

```
      BS(1,I)=0.0
      DO 112 I1=1,4
      BS(1,I)=BS(1,I)+BSD(I1,I)*LOG(BSD(I1,I)/BSD(I1,I-1))
  112 CONTINUE
      BS(1,I)=BS(1,I)*10**4
C
C   TOTAL ASSET DECOMPOSITION
C
      BS(2,I)=0.0
      DO 113 I2=1,4
      BS(2,I)=BS(2,I)+TAD(I2,I)*LOG(TAD(I2,I)/TAD(I2,I-1))
  113 CONTINUE
      BS(2,I)=BS(2,I)*10**4
C
C   TOTAL LIABILITIES DECOMPOSITION
C
      BS(3,I)=0.0
      DO 114 I3=1,4
      BS(3,I)=BS(3,I)+TLD(I3,I)*LOG(TLD(I3,I)/TLD(I3,I-1))
  114 CONTINUE
      BS(3,I)=BS(3,I)*10**4
  666 CONTINUE
    DO 555 I=1,2
      BS3(1,I)=1.0
      BS3(2,I)=1.0
      BS3(3,I)=1.0
  555 CONTINUE
    DO 333 I=3,N
C
C   BALANCE SHEET DECOMPOSITION MEASURE
C
      BS3(1,I)=0.0
      DO 122 I1=1,4
      BS3(1,I)=BS3(1,I)+BSD(I1,I)*LOG(BSD(I1,I)/BSD(I1,I-2))
  122 CONTINUE
      BS3(1,I)=BS3(1,I)*10**4
C
C   TOTAL ASSET DECOMPOSITION
C
      BS3(2,I)=0.0
      DO 123 I2=1,4
      BS3(2,I)=BS3(2,I)+TAD(I2,I)*LOG(TAD(I2,I)/TAD(I2,I-2))
  123 CONTINUE
      BS3(2,I)=BS(2,I)*10*4
C
C   TOTAL LIABILITIES DECOMPOSITION
C
      BS3(3,I)=0.0
      DO 124 I3=1,4
      BS3(3,I)=BS3(3,I)+TLD(I3,I)*LOG(TLD(I3,I)/TLD(I3,I-2))
  124 CONTINUE
      BS3(3,I)=BS3(3,I)*10**4
  333 CONTINUE
  444 CONTINUE
    RETURN
    END
    SUBROUTINE STABI(H,SH,N,NYT)
```

```
C
C   THIS SUBROUTINE CALCULATES THE STABILITY MEASURES
C
      DIMENSION H(36,10),SH(36,10)
      DO 10 K=N,NYT,-1
      N1=K-NYT+1
      N2=K
      DO 10 I=1,36
      SUMH=0.0
      SUMSH=0.0
      DO 20 J=N1,N2
      SUMH=SUMH+H(I,J)
      SUMSH=SUMSH+H(I,J)**2
   20 CONTINUE
      AMEAN=SUMH/NYT
      SH(I,K)=SQRT((SUMSH-NYT*AMEAN**2)/(NYT-1))
   10 CONTINUE
      RETURN
      END
      SUBROUTINE TREND(R,TR,N,NP,NL,NYT,IL,SCA)
C
C   THIS SUBROUTINE CALCULATES THE TREND MEASURES
C
      DIMENSION R(IL,0:10),TR(5,10),SCA(0:10)
      DO 10 K=N,NYT,-1
      N1=K-NYT+1
      N2=K
      IT=0
      SUMXY=0.0
      SUMX=0.0
      SUMSX=0.0
      SUMY=0.0
      DO 20 J=N1,N2
      IT=IT+1
      SUMXY=SUMXY+IT*LOG(R(NP,J)*SCA(J))
      SUMX=SUMX+IT
      SUMSX=SUMSX+IT**2
      SUMY=SUMY+LOG(R(NP,J)*SCA(J))
   20 CONTINUE
      TR(NL,K)=(EXP((NYT*SUMXY-SUMX*SUMY)/(NYT*SUMSX-SUMX**2))-1)*100
   10 CONTINUE
      RETURN
      END
      SUBROUTINE SELECT(X,FCLASS,OCLASS,AM,NOUT1,NOUT2,COUNT)
C
C   THIS SUBROUTINE CLASSIFIES COMPANIES ACCORDING TO
C   THE CRITERION OF PERFORMANCE DISCRIBED IN CHAPTER 3
C
      INTEGER FCLASS(2),OCLASS(2),COUNT(4,2),NOUT1(2),NOUT2(2)
      DIMENSION X(36,10),AM(2,2)
      C1=(X(1,7)+X(1,6)+X(1,5))/3.0
      C2=(X(1,1)+X(1,2)+X(1,3)+X(1,4))/4.0
      DO 90 K=1,2
      IF(C1.GT.AM(1,K)) THEN
         FCLASS(K)=1
         NOUT1(K)=1
         IF(C2.LT.AM(2,K)) THEN
```

```
              OCLASS(K)=1
              NOUT2(K)=1
              COUNT(1,K)=COUNT(1,K)+1
            ELSE
              OCLASS(K)=3
              NOUT2(K)=3
              COUNT(3,K)=COUNT(3,K)+1
           END IF
         ELSE
           FCLASS(K)=2
           NOUT1(K)=2
           IF(C2.LT.AM(2,K)) THEN
              OCLASS(K)=2
              NOUT2(K)=2
              COUNT(2,K)=COUNT(2,K)+1
            ELSE
              OCLASS(K)=4
              NOUT2(K)=4
              COUNT(4,K)=COUNT(4,K)+1
           END IF
         END IF
   90 CONTINUE
      RETURN
      END
```

```
      PROGRAM UP
C
C
C   KOLMOGOROV-SMIRNOV GOODNESS-OF-FIT TEST
C          NORMAL DISTRIBUTION
C
C
      EXTERNAL FN
      COMMON/T/S,XA
      DIMENSION X(800),Y(800),B(50),XL(800),XS(800),XIN(800)
     1,H(50),XST(800),DM(4),X10(200),X11(200),X12(200),X13(200),
     1CF(0:20),XTH(20),XTH2(20),SMIR(800),X1(200),X2(200),X3(200)
     1,X4(200),X5(200),X6(200),X7(200),X8(200),X9(200),XW(800)
     1,X14(200),X15(200),X16(200),X17(200),X18(200),X19(200)
      CHARACTER*4 A(12)
      A(1)='   ('
      A(4)='15X,'
      A(8)='  F1'
      A(9)='0.3 '
      A(10)='   ,'
      A(12)='(/))'
      IVAR=0
  400 FORMAT(1H ,2I4)
  401 FORMAT(1X,2A4)
  500 FORMAT(1H ,I4)
  501 FORMAT(1X,A4)
      PRINT*, ' N. OF CASES ?'
      READ*, NCASES
      AT=170
      SKOL1=1.36/SQRT(AT)
      SKOL2=1.22/SQRT(AT)
      WRITE(2,'(1H ,T49,"KOL-SMIR TEST 99%",F5.3,"   91%",F5.3)')
     C SKOL1,SKOL2
      WRITE(2,'(T65,"TRANSFORM")')
      WRITE(2,'(1X,"VAR. NO.",T20,"MEAN",T30,"S.D.",T50,
     C "NONE",T60,"LOG",T70,"SQR",T80,"INV.")')
C
C   THIS SECTION OF THE PROGRAM ALTERS THE FORMAT
C   IN ORDER TO READ A VARIABLE AT A TIME
C
      DO 10 I=1,12
C     WRITE(4,400) I-1,12-I
C     REWIND 4
C     IF(I.EQ.1) THEN
C        READ(4,401) A(2),A(11)
C        REWIND 4
         IN=6
         A(3)='    '
         A(2)='    '
       ELSE IF(I.EQ.12) THEN
         READ(4,401) A(2),A(11)
         REWIND 4
         IN=2
         A(3)='(/),'
        A(4)='    '
         A(10)='    '
         A(11)='    '
```

```
         A(12)='   )'
       ELSE
         READ(4,401) A(2),A(11)
         REWIND 4
         IN=8
         A(3)='(/),'
         A(4)='    '
         A(10)='   ,'
      END IF
      DO 10 J=1,IN
      ACHEK=0.0
      IVAR=IVAR+1
      REWIND 1
      WRITE(5,500) J-1
      REWIND 5
      IF(J.EQ.1) THEN
         A(5)='    '
         A(6)='    '
         A(7)='    '
       ELSE
         READ(5,501) A(5)
       REWIND 5
         A(6)='(10X'
         A(7)='  ),'
      END IF
      WRITE(*,444) (A(JI),JI=1,12)
  444 FORMAT(1H ,12A4)
      NW=0
      DO 100 IT=1,NCASES
      READ(1,A,END=238) XW(IT)
      IF(XW(IT).EQ.0) THEN
         NW=NW+1
         GO TO 100
      END IF
      X(IT-NW)=XW(IT)
 1111 FORMAT(59X,F10.3,11(/))
C     PRINT*,X(IT)
  100 CONTINUE
  238 CONTINUE
      PRINT*,IT
      N=IT-(NW+1)
C
C   ESTMATION OF STANDARD DEVIATION IN ORDER TO
C   SPLIT THE SET OF OBSERVATIONS TO INCREASED
C   THE EFFICIENCY OF THE SORTING SUBROUTINE
C
      CALL REGRES(X,Y,E1,E2,XA,YA,S,N,XST,1)
      AMEAN=XA
      ASD=SQRT(S)
      N1=0
      N2=0
      N3=0
      N4=0
      N5=0
      N6=0
      IL1=1
      IL2=2
```

```
      IL3=3
      IL4=4
      IL5=5
      IL6=0
      AT1=AMEAN-1.25*ASD
      AT2=AMEAN-.3*ASD
      AT3=AMEAN+.3*ASD
      AT4=AMEAN+1.25*ASD
      DO 1020 I1=1,N
      IF(X(I1).LT.AT1) THEN
         N1=N1+1
         X1(N1)=X(I1)
       ELSE IF(X(I1).LT.AT2) THEN
           N2=N2+1
           X2(N2)=X(I1)
       ELSE IF(X(I1).LT.AT3) THEN
         N3=N3+1
         X3(N3)=X(I1)
       ELSE IF(X(I1).LT.AT4) THEN
         N4=N4+1
         X4(N4)=X(I1)
       ELSE
         N5=N5+1
         X5(N5)=X(I1)
      END IF
 1020 CONTINUE
      WRITE(*,'(1H ,"N",I1," = ",I4,5X,"N",I1," = ",I4)')
     C IL1,N1,IL2,N2,IL3,N3,IL4,N4,IL5,N5,IL6,N6
      CALL SORTA(X1,N1)
      CALL SORTA(X2,N2)
      CALL SORTA(X3,N3)
      CALL SORTA(X4,N4)
      CALL SORTA(X5,N5)
      DO 1021 I1=1,N1
      X(I1)=X1(I1)
 1021 CONTINUE
      DO 1022 I2=1,N2
      X(I2+N1)=X2(I2)
 1022 CONTINUE
      P3=N2+N1
      DO 1023 I3=1,N3
      X(I3+P3)=X3(I3)
 1023 CONTINUE
      P4=P3+N3
      DO 1024 I4=1,N4
      X(I4+P4)=X4(I4)
 1024 CONTINUE
      P5=P4+N4
      DO 1025 I5=1,N5
      X(I5+P5)=X5(I5)
 1025 CONTINUE
      SD=SQRT(S)
      II=0
      IF(X(1).LE.0.0.AND.X(N).GT.0.0) THEN
 1060 II=II+1
      IF(X(II).EQ.0.0) THEN
         ACHEK=1.0
```

```
         IZER=II
         GO TO 1050
       ELSE IF(X(II).GT.0.0) THEN
         ACHEK=2.0
         IZER=II
         GO TO 1050
      END IF
      GO TO 1060
      END IF
 1050 CONTINUE
         DO 102 I22=1,N
         XST(I22)=(X(I22)-XA)/SD
  102    CONTINUE
C
C   TEST OF THE DATA
C
      CALL TEST(CM,XA,S,NP,B,XST,N,JI,CF,XTH,XTH2,SMIR,DMAX,M,CELL,T)
      DM(1)=DMAX
      IF(X(1).LT.0.0) GO TO 452
      IF(ACHEK.EQ.1.0) GO TO 453
C
C   LOG TRANSFORM
C
          DO 103 I22=1,N
          XL(I22)=ALOG(X(I22))
  103     CONTINUE
          CALL REGRES(XL,Y,A1,A2,XA,YA,S,N,XST,0)
      CALL TEST(CM,XA,S,NP,B,XST,N,JI,CF,XTH,XTH2,SMIR,DMAX,M,CELL,T)
      DM(2)=DMAX
  453 CONTINUE
C
C   SQUARE ROOT TRANSFORM
C
          DO 104 I22=1,N
          XS(I22)=SQRT(X(I22))
  104     CONTINUE
          CALL REGRES(XS,Y,A1,A2,XA,YA,S,N,XST,0)
      CALL TEST(CM,XA,S,NP,B,XST,N,JI,CF,XTH,XTH2,SMIR,DMAX,M,CELL,T)
      DM(3)=DMAX
  452 CONTINUE
C
C   INVERSE TRANSFORM
C
      IF(ACHEK.EQ.1.0) GO TO 455
      IF(X(1).LT.0.0.AND.X(N).LT.0.0) THEN
         NA=N+1
         ACHEK=2.0
         DO 1007 I33=1,N
         XIN(I33)=1/X(NA-I)
 1007    CONTINUE
       ELSE IF(X(1).LT.0.0) THEN
         DO 107 I22=1,IZER-1
         XIN(I22)=1.0/X(IZER-I22)
  107    CONTINUE
         IC1=N+1
         DO 108 I22=IZER,N
         IC1=IC1-1
```

```
          XIN(I22)=1.0/X(IC1)
  108     CONTINUE
         ELSE
           DO 105 I22=1,N
           XIN(I22)=1.0/X(N+1-I22)
  105      CONTINUE
        END IF
           CALL REGRES(XIN,Y,A1,A2,XA,YA,S,N,XST,0)
        CALL TEST(CM,XA,S,NP,B,XST,N,JI,CF,XTH,XTH2,SMIR,DMAX,M,CELL,T)
        DM(4)=DMAX
  455 CONTINUE
C
C   PRINTING OF THE RESULTS
C
        IF(X(1).GT.0.0) THEN
          WRITE(2,'(1H ,T8,I2,T15,F9.3,T25,F9.3,T45,F9.3,
       C T54,F9.3,T64,F9.3,T74,F9.3)') IVAR,AMEAN,ASD,(DM(IJ),IJ=1,4)
        ELSE IF(X(1).GE.0.0) THEN
          WRITE(2,'(1H ,T8,I2,T15,F9.3,T25,F9.3,T45,F9.3,
       C T64,F9.3)') IVAR,AMEAN,ASD,DM(1),DM(3)
        ELSE IF(ACHEK.EQ.2.0.AND.X(1).LT.0.0) THEN
          WRITE(2,'(1H ,T8,I2,T15,F9.3,T25,F9.3,T45,F9.3,
       C T74,F9.3)') IVAR,AMEAN,ASD,DM(1),DM(4)
        ELSE IF(ACHEK.EQ.1.0.AND.X(1).LT.0.0) THEN
          WRITE(2,'(1H ,T8,I2,T15,F9.3,T25,F9.3,T45,F9.3,
       C )') IVAR,AMEAN,ASD,DM(1)
        END IF
   10 CONTINUE
        STOP
        END
        SUBROUTINE SORTA(X,N)
C
C   THIS SUBROUTINE SORT THE VALUE OF AN ARRAY X
C   OF DIMENSION N IN ASCENDING ORDER
C
        DIMENSION X(N)
        M=N-1
   20 K=0
        DO 10 I=1,M
        IF (X(I).LE.X(I+1)) GO TO 10
        CALL SWAP(X(I),X(I+1),K)
   10 CONTINUE
        IF(K.GT.0) GO TO 20
        RETURN
        END
        SUBROUTINE SWAP(X,Y,K)
        K=1
        Z=X
        X=Y
        Y=Z
        RETURN
        END
        SUBROUTINE REGRES(X,Y,A1,A2,XA,YA,S,N,XST,IC)
C
C   THIS SUBROUTINE ESTIMATES THE STANDARD DEVIATION
C   OF VARIABLE X
C
```

```
      DIMENSION X(N),Y(N),XST(N)
      B=0
      E=0
      DO 10 I=1,N
      B=B+X(I)
      E=E+X(I)**2
   10 CONTINUE
      XA=B/N
      S=(E-N*XA**2)/(N-1)
      SD=SQRT(S)
      IF(IC.EQ.1) GO TO 1322
      DO 1321 I=1,N
 1321 XST(I)=(X(I)-XA)/SD
 1322 CONTINUE
      RETURN
      END
      FUNCTION FN(X)
C
C   THIS FUNCTION ESTIMATES THE CUMULATIVE STANDARD
C   NORMAL DISTRIBUTION USING PAGE'S METHOD
C
      Y1=0.7988*X*(1+0.04417*X**2)
      EX=EXP(2*Y1)
      FN=EX/(1+EX)
      RETURN
      END
      SUBROUTINE TEST(CM,XA,S,NP,B,XST,N,JI,CF,XTH,XTH2,SMIR,DMAX,M
C
C   THIS SUBROUTINE ESTIMATE THE DMAX VALUES
C
     C ,CELL,T)
      EXTERNAL FN
      DIMENSION CF(0:NP),CM(3,N),XTH(N),B(NP),XTH2(JI),SMIR(N),XST(N)
      D2=0.0
      A=0.0
      B1=0.0
      D=0.0
      T1=N
      GO TO 1002
      CF(0)=-4.5+T*CELL
      DO 1212 I=1,NP
      CF(I)=-4.5+(I+T)*CELL
 1212 CONTINUE
      DO 1313 I=1,NP-1
      XTH(I)=N*(FN(CF(I))-FN(CF(I-1)))
 1313 CONTINUE
      XTH(NP)=N*(1-FN(CF(NP-1)))
      DO 1414 I=1,NP
      D=D+(B(I)-XTH(I))**2/XTH(I)
      WRITE(2,'(1H ,"XTH(",I2,")= ",F6.2,"  D = ",F6.2,"  DIFF. = ",F6.2
     C "  CUM. DIFF. = ",F6.2)')I,XTH(I),B(I),D-A,D
      A=D
 1414 CONTINUE
      DO 1515 I=2,JI-1
      XTH2(I)=N*(FN(XST(M*I))-FN(XST(M*(I-1))))
 1515 CONTINUE
      XTH2(1)=N*(FN(XST(M)-FN(XST(1))))
```

```
      XTH2(JI)=N*(1-FN(XST(M*(JI-1))))
      DO 1717 I5=1,JI
      D2=D2+(M-XTH2(I5))**2/XTH2(I5)
      WRITE(2,'(1H ,"XTH2(",I2,")=",F6.2,"  DIFF. = ",F6.2,
     C "  CUM. DIFF. = ",F6.2)') I5,XTH2(I5),D2-B1,D2
      B1=D2
 1717 CONTINUE
 1002 CONTINUE
      FMAX=0.0
      CMAX=0.0
      DO 1616 I=1,N
      B1=I/T1
      B2=(I-1)/T1
      SMIR1=B1-FN(XST(I))
      SMIR2=B2-FN(XST(I))
      IF(ABS(SMIR1).GT.FMAX) THEN
         FMAX=ABS(SMIR1)
         IMAX1=I
      END IF
      IF(ABS(SMIR2).GT.CMAX) THEN
         CMAX=ABS(SMIR2)
         IMAX2=I
      END IF
 1616 CONTINUE
      JDF1=NP-1
      JDF2=JI-1
      AT=N
      SKOL1=1.22/SQRT(AT)
      SKOL2=1.36/SQRT(AT)
      DMAX=AMAX1(FMAX,CMAX)
 1001 FORMAT(1H ,'CHI SQUARE',10X,'D F'/2(2X,F8.3,11X,I3/))
 1003 FORMAT(1H ,//'KOLMOGOROV-SMIRNOV TEST',2X,'99%',4X,'91%'/
     17X,F8.3,6X,F4.3,2X,F4.3)
      RETURN
      END
```

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