THE PREDICTIVE ABILITY OF DISCRIMINANT ANALYSIS TO IDENTIFY TAKEOVER TARGETS FOR PORTFOLIO SELECTION

by

Mitchell Andrew Fields

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APPROVED:

J. S. Thatcher, Chairman

A. J. Keown

D. J. Johnson

J. M. Pinkerton

F. A. Beams

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Blacksburg, Virginia

To my wife and son,

Sandy and Matthew

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CHAPTER ONE

POTENTIAL GAINS FROM ACQUISITION TARGETS

Introduction

Corporate mergers and acquisitions have continued to be an important area of interest to both academicians and practitioners for many decades. This interest is due in large part to the great number and size of firms engaging in these types of combinations. In addition, the size of these investments whether viewed from the perspective of the involved firms and stockholders, prospective investors, or the general economy, suggests a need to study the relative advantages of such transactions.

In recent years, the number and size of firms being merged and acquired, and the premiums paid for these acquired firms have increased. For example, recent offers have been at least fifty percent higher than the normal trading ranges of the target company stocks (Merjos [1978, p. 167]) and the high level of merger activity during the late 1970's has continued into the early 1980's (Louis [1982, p. 89]). With these types of offers being extended, the economic consequences for the parties involved (firms, stockholders, investors, etc.) can be significant; and as such, it supports the research in the area.

The need for research in the merger and acquisition area also is evident in the financial press. Many authors have presented hypotheses concerning this subject, mostly based upon intuition and conjecture. Unfortunately, many of these hypotheses have yet to be tested scientifically. Of equal importance is the fact that many of the research studies to date have resulted in conflicting findings, thus indicating the need for further and improved research.

There is much study left to be undertaken in the merger and acquisition field. Many conflicts need to be resolved, and many new areas need to be investigated so that additional insights into this phenomenon may be provided. In the next section of this chapter, the specific problem area to be researched will be introduced and developed.

Research Problem Area

As indicated before, many studies of a scholarly nature have been published relating to the merger area. Most of this work has focused on three distinct points of interest. These include: 1) the types of benefits to be achieved by merger, 2) the managerial strategies and options available to both parties in the event of an offer, and 3) the amount of returns to be expected by the stockholders of the acquired and acquiring firms. In each case, the consideration of individual investor portfolio decisions has been secondary or non-existent.

For the investor able to purchase stock in firms that are acquired at a later date, the large potential for gain is a widely recognized and mentioned fact in the financial press. However, little work has actually been done to suggest potential models or an overall framework to aid in this investment selection process. The individual investor has been left to his or her own devices.

The intent of the study is to present and evaluate a model for portfolio selection. In order for a model to have the potential for practical use by a small individual investor, it must be relatively easy to implement, yet powerful enough to work consistently so that the risk involved maintains a manageable level. The information needed as input to the model should be readily available to the potential user.

The analysis of financial ratios has been applied to many problem areas in the field of finance and it appears to be an appropriate application for this study. These ratios and the underlying financial information have proven useful in describing group differences and, in some cases, they have been found to be good predictions of group membership. These ratios are quite available to the individual investor, at least on an annual basis, and, as will be seen, there is a solid foundation upon which to work with ratios in the merger and acquisition area.

A Basic Study Assumption

Even though acquisitions display many similarities, there are many differences among acquired firms when they are considered on a case by case basis. Takeovers occur in different industries and for different reasons. Industry differences can be quite pronounced, just as merger motives can range from intra-industry acquisitions to acquisitions motivated by tax considerations.

This diversity suggests that there may be as many differences between acquisition targets as there are similarities. However, a study of this nature is based on the basic assumption: that there is a large measure of conformity among the features, important to acquiring companies, that make other firms attractive acquisition targets. This conformity must exist if a model based on financial ratios and variables is to identify these attractive features and use them to separate likely takeover targets from firms in the general corporate population.

The financial ratio-variables used in previous studies cover a wide spectrum. It is important that this range be provided so that as many financial dimensions as possible of the involved firms can be considered in a given research effort. These ratios cover the basic relationships within a firm, such as liquidity, leverage, coverage, profitability, and market information, and they also can represent additional characteristics of a firm's situation.

Statement of the Proposed Research

The purpose of this study is to investigate the ability of selected financial ratios and information to aid in predicting the likelihood of a firm receiving a takeover bid. In addition, the study will evaluate the ability of the developed ratio model to perform in an actual portfolio selection setting. Previous studies have indicated some success in using ratios for predictive purposes in such diverse areas as corporate failure (Altman [1968, 1974, and 1977]), capital structure (Martin and Scott [1973]), stock price variability (Klemkosky and Petty [1973]), and rating bonds (Pinches and Mingo [1973]). Previous studies also have extended the use of financial ratios into building models for description and prediction in the area of mergers and acquisitions (Singh [1971] and Stevens [1973]). This study will attempt to expand and improve upon the research conducted in this area.

This research investigates takeover offers through the use of prior financial characteristics in order to identify differences between target firms and those in the general population. The methodology focuses on building a discriminant analysis (DA) model that will indicate the important differences between these groups (acquired versus the general corporate population) and provide a basis for predicting the ex ante attractiveness of a firm to a bid based upon these characteristics. After ex post and intertemporal validation, the model will be subjected to use in an actual market setting through its selection of a portfolio that will be held for a two year period. This portfolio will consist of firms identified as attractive to acquiring companies. The actual portfolio returns then will be used to investigate whether the model is able to select a group of stocks that can outperform the market.

In order to prove useful in a predictive sense, the final DA model that is selected must be small enough to be utilized as a practical portfolio selection device. By investigating the usefulness of a DA model in this manner, it should be possible to determine if further application of DA in the merger and acquisition area will enable the technique to provide a relevant predictive tool for investors or corporate managers. Should the final DA model have little or no predictive ability, the study results will support the efficient markets hypotheses.[1]

This defines the specific problem area to be considered in this research effort. It is an area in which some work has been done, but this

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[1]This is not meant to imply that the presence of a significant predictive capacity provided by a DA model would be inconsistent with the efficient markets hypotheses. It only implies that this is a possibility.

research application concentrates on the small investor, a largely ignored, but interested, segment. The next section of this chapter will consider the relevance of study on this topic in more detail.

Significance of the Research

This study of mergers and acquisitions should be important for several reasons. First, it attempts to improve upon the research methodology used to employ discriminant analysis in much of the previous work. Second, it attempts to determine the usefulness of DA as a predictive tool that can be practically implemented to help indicate likely takeover targets. Third, it may provide insight into the reasons why certain firms are susceptible to takeover bids. Fourth, it should provide additional insight into the theoretical explanations of the acquisition phenomenon.

Recently, several articles have criticized previous applications of discriminant analysis in financial research (Altman and Eisenbeis [1978], Eisenbeis [1978], and others). These articles and their impact on this study are discussed in detail in Chapter Three - Sample Design and Research Methodology.

The financial press contains many case histories concerning the benefits stockholders of acquired firms received from the announcement of an acquisition offer. These gains are usually very large (as indicated before, an average fifty percent premium over the firm's previous stock price). It is small wonder, then, that an equally large number of articles attempt to pinpoint potential targets. However, the use of discriminant analysis to aid in this search has never been adequately assessed.

An examination of the financial press indicates another reason for interest in the common characteristics that target firms share. The managements of many firms are concerned with the possibility of receiving a takeover offer, regardless of whether the offer is of a "friendly" or "hostile" nature. Therefore, much space is devoted to identifying these similar characteristics, as well as, strategies available for coping with and resisting offers. Any additional insight into these characteristics is as welcome here as it is to the academician attempting to establish a theoretical foundation from which to explain merger and acquisition activity.

Beside the possibility of adding to the theoretical body of knowledge concerning mergers and acquisitions, this study has a secondary theoretical implication. As mentioned in the previous section, this study may provide an indirect test of the efficient markets hypotheses. The semi-strong efficient form of market efficiency is a frequently accepted hypothesis that suggests past security price and volume data does not provide information indicative of future price activity, and that all public information is immediately reflected in current stock prices. Should the discriminant analysis model selected be unable to provide a portfolio capable of superior performance, this hypothesis would be supported. However, should the model provide superior performance, the validity of this generally accepted form of the efficient markets hypotheses may be called into question. In either case, the results should be of concern to those with an interest in the field of finance.

A study of this nature has many possible implications, and regardless of the results, they may be of interest to the financial community. Studies in the merger and acquisition area will continue to be of significance because of the importance of the topic. The final section of this chapter provides a summary of the contents of the following four chapters included in this study.

Organization of the Study

This section provides a brief outline of the topics covered in subsequent chapters. Chapter One has already described the scope and direction of the research effort. Chapter Two reviews the existing foundation of research in the merger and acquisition area. Chapter Three provides a description of the data used in the study and presents an explanation of the methodological procedures used to complete the research. Chapter Four presents the study results from all phases of the research and provides an analysis of these results, including the findings of the work done in discriminant analysis. This work concerns the differences between the financial characteristics of firms receiving takeover bids and those in the general population. Also included is a description of the DA model selection process and an evaluation of the model's ability to function in an actual investor portfolio selection setting. Finally, Chapter Five provides a summary of the study's results and conclusions, an explanation of the study's limitations, and a discussion of the implications for further research generated by the conclusions reached in the study.

Chapter Summary

Mergers and acquisitions remain an important area of research interest. To date, much work has been done, but many of the studies conducted have yielded conflicting results, and there are still many avenues of study yet to be explored. Because of the importance of this business phenomenon, it is highly likely that this research will continue to be conducted.

When a takeover is announced, the market price of the acquired company stock is likely to rise to a level higher than its normal trading range. This increase typically occurs around the announcement date. Anyone able to identify these actions in advance will be able to obtain a superior return on stock investments. Therefore, a model able to aid in the identification of takeover targets should be of great interest to many parties, including small investors faced with portfolio choices. Unfortunately, little work has been done to develop such a model.

This study attempts to provide this type of model, recognizing that in order for it to be useful to small investors, the model must be simple enough to manage, and should rely on input data that is readily available. Various financial ratio models have been applied successfully in similar applications, and they have shown promise in this particular area. Of course, this assumes that there is enough similarity among takeover targets to allow ratios to highlight differences between target firms and the general corporate population.

The study combines the use of financial ratios with the discriminant analysis technique. The objective is the development of a model with the capability of identifying takeover targets in advance. The ability of this model is tested in a portfolio selection setting.

The study builds upon and seeks to improve previous work done in the area. It also suggests uses of the discriminant analysis technique for future studies of mergers and acquisitions, and provides information concerning the features that make certain firms attractive to takeover offers. Finally, it provides additional insight into the merger phenomenon, including an indirect test of the semi-strong efficient form of the efficient markets hypotheses.

CHAPTER TWO

AN EXAMINATION OF THE PREVIOUS RESEARCH ON MERGERS AND ACQUISITIONS

Introduction

As an integral force in the corporate sector, mergers and acquisitions have stimulated much discussion. The literature extends from legal questions to the theoretical consequences of these types of business combinations. Additionally, many articles have dealt with the profitability of mergers for the parties involved, the success of the combined firm after merger, the theoretical and practical benefits that mergers offer, and the characteristics that make a firm a likely candidate for combination.

Much of the terminology in this area is confusing. It is the intent here to identify the terms to be used and to adopt the definitions as set forth by Singh [1971, p. XI]:

> Takeover: When a firm A acquires more than 50% of the equity of Firm B, B is deemed to have been taken over by A.
>
> Merger: A merger between two firms A and B is deemed to occur when these two firms amalgamate to form a new legal entity (say) C.

Although the distinction between acquiring and acquired firms may seem arbitrary, it is extremely important to this study that a distinction be made between an acquired firm and some other form of combination, because the returns granted to combining firms by capital markets depend greatly on the respective positions. Many studies indicate that the acquired firms receive the majority of, or the entire amount of, the return generated by the combination (Dodd and Ruback [1978], Elgers and Clark [1980], and others). The likelihood of a firm being the beneficiary of these returns is one focus of this study.

Even with the above definition of takeover, a certain amount of judgement still needs to be employed in the selection of sample firms. According to Singh [1971, p. XII], the general custom is to identify sample firms from any combination where a difference in size exists between the combining firms so that the smaller may be identified as an acquired firm. In the following discussions the terms takeover and acquisition will be used interchangeably.

This study will attempt to provide answers to five general questions. Specifically, the questions to be investigated are: 1) Are there significant differences between likely targets and the general corporate population? 2) If so, what are the differing characteristics between these firms? 3) Is discriminant analysis (DA) able to distinguish between these firms on the basis of these characteristics? 4) If so, is it possible to employ a DA model to make predictions of likely targets so that an investor can capitalize on the market's inefficiency to select a superior portfolio? and 5) What are the theoretical justifiactions for takeovers and how does the empirical findings of this research relate to these theories?

The first three questions stated above provide a foundation necessary for this study to focus upon the predictive ability of DA. Previous research suggests that the findings for questions one through three will be positive (Simkowitz and Monroe [1971] and Stevens [1973]). In additon, other studies (Halpern [1973]; Franks, Broyles, and Hecht [1973]; Mandelker [1974]; Elgers and Clark [1980]; and Keown and Pinkerton [1981]) of respective acquisition gains have shown that after adjustment for risk and market movement, the stockholders of acquired firms are the recipients of large positive abnormal returns in the time period prior to the takeover announcement. This study seeks to answer question four by employing the DA model selected in the first phase of study in a predictive capacity, to demonstrate the ability (or inability) of the model to select takeover targets, allowing an investor to share in the gains that these other studies have shown to exist. The importance of answering question five lies in reconciling the empirical results with the underlying theoretical support through consideration of the differences between acquired and nonacquired firms, and the implication of these differences.

In the next section of this chapter, a brief review and discussion of the theoretical justifications and purposes of takeovers, and hypotheses concerning the existence of stockholder returns from these combinations will be presented. It is not an all inclusive coverage because of the extensive amount of work done in the area. Rather, it is an attempt to describe the nature of the work that has been done. The later sections of this chapter will review the previous empirical research that has been conducted on the subject of acquisitions. Included in this will be studies investigating the existence of stockholder returns, the differential characteristics of acquired firms, and previous applications of discriminant analysis to the field of finance.

Acquisition Justifications and Purposes

There are three theoretical explanations for the takeover phenomenon. First, takeovers can be viewed as an important factor in the efficient allocation of resources performed by capital markets. Second, acquisition activity may reflect the behavioral goals of many firms. And third, acquisitions may occur because of the many types of benefits that acquiring companies perceive as possible. Each of these explanations will be described briefly below.

The basic function of capital markets is to provide for the efficient allocation of resources. The most efficient users of capital will be able to place the highest bid in order to receive these funds. However, as Singh [1971, pp. 2-6] indicates, this does not necessarily mean that firms will continue to use their assets in an efficient manner. In fact, just because an inefficient firm may find its share price adversely affected causing an increase in its cost of capital, does not mean that the market will be able to provide for continued efficient usage of existing assets. Most firms raise funds in the capital markets on an infrequent basis and many firms never use anything other than internally generated funding. Therefore, takeover threats allow the market to insure that existing firm resources are utilized effectively. Inefficient asset utilization will adversely affect the share price of the firm and invite acquisition by a firm better able to use these resources efficiently.

In addition, when firm management is isolated from the owners due to the company size and dispersion of ownership, the role of acquisitions in the functioning of the market becomes even more important. Meade [1968, p. 386] describes this aspect in the following manner,

> A company which sacrifices profit either to an easy life or to unprofitable growth makes itself liable to a take-over bid. Suppose that the management of a large concern has become slack. . . . In such circumstances the replacement of the management by one which is more efficient or profit-minded could increase the market value of the company's shares. It may well be true that the ordinary shareholders dispersed throughout society will not in fact be able to get together to enforce such a change. But a generous bid for the company's shares on the part of some other large company or institution may enable a majority of the shares to be acquired by a single institutional owner which can enforce the change of management, increase thereby the value of the company's shares and thus reap a large benefit. Experience suggests that large companies are in fact threatened with this fate if they fail to be sufficiently profit-minded.

In this approach then, takeovers are an integral part of the market function insuring that resources are efficiently allocated and that firms continue to use existing assets in an effective manner. Singh [1971, p. 13] states:

> In view of the fact that relatively few of the companies with a quotation on the stock market disappear through liquidation or means other than takeovers, the direct expression of the capital-market discipline, particularly for the managerially controlled firms, is embodied very largely if not entirely, in the takeover mechanism.

The second theoretical approach to takeovers deals with the overall theory of the firm. It long has been hypothesized that the goal of the firm in a capitalistic setting is to maximize profit, at least in a purely theoretical setting. Fama and Miller [1972] and others developed this goal further to that of the maximization of the value of the initial shareholders. These hypotheses have been criticized by such authors as Baumol [1962] and Marris [1967, 1968]. The critics contend that the management of many firms seeks to achieve the maximum rate of growth possible, and not profit or value maximization, because manager salaries, power, and prestige are often based upon these criteria. In so far as these goals conflict, management will tend to seek growth.

Marris [1968] extends his theory of the firm to include the function of takeovers. He hypothesizes that management will seek growth as a goal, with a minimum level of profitability as a constraint only when there is a threat of takeover. The concern for profitability will increase only when management's perception of the threat of takeover begins to be a cause for concern. However, as the firm continues to increase in size because of management pursuit of growth maximization, this takeover threat will diminish because it is felt that size and the takeover threat are inversely related.

The third approach to acquisitions is concerned with the varied benefits that an acquiring firm perceives a target firm as offering. Though there are many benefits, no more than one need be available for an offer to be made. These benefits have been summarized by Bain [1950], Weston [1953], and Singh [1971], and are presented below:

(1) Possibility of achieving production economies of scale;

(2) Possibility of achieving distribution and advertising economies;

(3) Financial advantages of large size;

(4) Strategic control of patents;

(5) Acquisition of financial resources;

(6) Response to legal and institutional environment;

(7) Tax advantages;

(8) Gains from sale of securities;

(9) Gains of promoters;

(10) Desire to limit competition; (Singh [1971, pp. 9-10]).

Although there is little argument over the possible existence of these benefits, there is substantial disagreement over their effect on the stockholder returns of the acquired and acquiring firms. Several hypotheses have been advanced concerning the effect of acquisitions on the respective stockholder returns.

Theoretically, in an efficient market a stockholder will not gain from a company's attempt to diversify its assets (through merger or acquisition) because the stockholder will have had that opportunity to diversify and obtain any benefit personally through individual portfolio choices. Therefore, observance of any abnormal returns on an acquisition announcement date indicates that the combining of firms creates another source of value.

Various hypotheses have been advanced concerning the abnormal returns to be received by stockholders of acquiring and acquired firms due to market reaction to an offer. Dodd and Ruback [1977] developed four such competing hypotheses, presented the implied results of each, and empirically tested them. These hypotheses can be divided into two general groupings, the positive impact hypotheses and the zero impact hypothesis.

The zero impact hypothesis provides that no additional value can be derived from a combination of firms, and the market reaction in price will not supply anything other than normal returns to the stockholders involved. This hypothesis contends that unusual returns prior to the announcement of the takeover are due to the prior good performance of the target company and are unrelated to the takeover attempt. The unsuccessful bidder can expect to receive a negative return since the cost of the offer is significant. On the basis of their empirical results, this hypothesis is rejected by Dodd and Ruback for the case of acquired firm stock returns. There is still much empirical conflict over the existence of abnormal returns and the validity of this hypothesis in the case of acquiring firms, however.

The positive impact hypotheses imply that announcement of a takeover offer releases positive information concerning the companies involved and should be reflected in the stock prices of these firms. Three alternative hypotheses fall within this grouping: the monopolistic market power, the synergistic, and the internal efficiency hypotheses.

The monopolistic market power hypothesis assumes that by combining, the two companies involved are able to obtain some form of monopoly rents within their markets. This would imply that a successful bidding firm would share a small part of the positive returns with the acquired firm, and since costs involved in making bids are substantial, unsuccessful firms would receive a negative return.

Under the synergistic hypothesis, the combination of firms provides for some level of synergistic benefits which have a positive value, such as economies of scale, vertical integration, etc. The implications are that the successful firm will share the positive returns and the unsuccessful bidding firm will receive negative returns. This is similar to the previous approach and it is not possible to discriminate between these two hypotheses on the basis of the authors' empirical test.

The last of the positive impact hypotheses, internal efficiency, assumes that prior to the announcement of the offer, the company to be acquired has not been utilizing its assets effectively. The acquiring firm can share in the positive returns here by intervening and removing this inefficiency. As with the previous approaches, the unsuccessful acquiring firm should experience a negative return due to the costs involved in making the offer. However, target companies may still receive positive benefits from the unsuccessful attempt.

In all three cases, firms receiving bids will be the beneficiaries of abnormal positive returns during the event month. When a bid is unsuccessful, the synergistic and monopolistic hypotheses postulate that negative returns will result unless the previously targeted firm is perceived as likely to share these types of benefits with a new suitor in the near future. The internal efficiency hypothesis allows the returns to remain because the firm's management will respond to the market indication that they are internally inefficient by taking corrective action.

Regardless of the debate over merger benefits and the relative stockholder returns, Myers [1976] and others point out that theory fails to explain much of the real merger activity that has occurred. Of particular concern is the fact that merger activity takes place in large groupings or waves rather than in the random pattern that might be expected. Keenan [1978, p. 7] indicates that this may imply the existence of short-run market value disequilibrium. He uses this argument as a possible explanation for these merger waves,

> . . . short-run demand, supply conditions or non-economic 'psychological pressures' may cause the market value of individual firms (or even the market as a whole) to deviate from the full horizon 'expected values.' That is, the market provides real merger opportunities from time to time in addition to the real opportunities always present if there are positive synergistic benefits.

With this brief description of possible theoretical explanations for mergers and acquisitions completed, the remainder of the chapter will consider relevant empirical work that has been conducted. This theoretical work serves as a general foundation upon which to base the empirical research.

Previous Empirical Studies On Acquisition Benefits

Many empirical studies have investigated stockholder benefits from mergers and acquisitions and the reported results conflict. Mandelker [1974] reports that benefits from a merger accrue only to the stockholders of acquired firms and that the stockholders of acquiring firms were found to receive normal returns (no benefit) from the acquisition. A later study by Ellert [1976] indicates that the stockholders of the acquiring firm share in a smaller portion of the positive returns brought about by the acquisition. These two studies are representative of the conflict in the literature.

However, in one respect there is no conflict among those that have completed research in the area. After adjustment for risk and market movement, all studies have reported the existence of very large positive abnormal returns that are received by the stockholders of acquired firms. The only apparent point of disagreement concerns the magnitude of these returns. Halpern [1973] and Mandelker [1974] both reported these returns to be about fifteen percent. In another study, Franks, Broyles, and Hecht [1977] report these returns to average around twenty-six percent.

Two studies have provided consistent results concerning the valuation consequences provided by tender offers, a special case of takeover. Dodd and Ruback [1977] investigated the effect of tender offers on the stockholder returns of firms extending tender offers, both successful and unsuccessful, and also analyzed the return to the stockholders of the acquired firm. The authors found that the acquired companies were the beneficiaries of a significant positive return (twenty-one percent) during the month that the acquisition was announced, and that the stockholders of a target that received an unsuccessful bid had a nineteen percent return during the offer month. Successful bidders were also found to receive a positive benefit during the announcement month, but on a smaller scale (three percent). The results tend to indicate that an unsuccessful bidder neither gains nor loses during the period of the offer.

Kummer and Hoffmeister [1978] studied the effect that resistance to a bid has on the stockholder returns of the company subject to the bid. In a passive situation the target company received large positive gains (sixteen percent) in the month of announcement. In those situations where the target firm resisted, it was found that both successful and unsuccessful attempts provided the target firm with significant gains (twenty percent) as well. In addition, the authors reported that bidding firms received small positive returns during the period of announcement, which is consistent with the results of Dodd and Ruback [1977].

In a recent merger paper, Elgers and Clark [1980], as part of their study, measured the respective stockholder returns. The conclusions from this research were that a portfolio of the sample acquired firms would have outperformed a randomly selected portfolio of similar risk by thirty percent if purchased one year prior to the announcement date. A portfolio consisting of the acquiring firms would have provided a return of six percent over the same period.

The conflict over acquiring firm stockholder returns still remains. In a study that considered only the acquiring firm (Harris [1980]), the author was unable to conclude that positive stockholder benefits exist.

In a research effort that investigated the daily stock returns received by the owners of acquired firms, Keown and Pinkerton [1981] report that significant positive returns begin as early as twenty-five days prior to the announcement of the combination to the public. The cumulative average residual return as of the announcement date was twenty-five percent. The authors not only concluded that the stockholders of the acquired firms were the beneficiaries of this return, but that there is evidence of illegal insider activity in the trading of the shares of stock.

The studies described in this section have considered the respective benefits of acquisition to the stockholders of acquired and acquiring firms. This has demonstrated the potential gains available to investors able to identify firms involved in acquisition activity prior to the announcement date. The next section will review relevant studies that have attempted to determine characteristics of firms that are acquired.

Previous Studies on Acquired Firm Characteristics

While many characteristics have been mentioned by the financial press in connection with the desirability of a firm as a target, few empirical tests have been conducted to identify these characteristics on a multivariate basis. One study which attempted this was a multivariate analysis of the financial characteristics of acquired firms conducted by Singh [1971]. This study attempted to use univariate and multivariate techniques to describe differences between acquired firms and the general population of the United Kingdom. Only ten variables were considered for inclusion in the analysis and all were rejected as significant on a univariate basis. However, using discriminant analysis, the study found size and pre-tax profitability to be somewhat helpful in selecting acquired firms on a multivariate basis. The study used firms of the same size and from the same industry in matched pairs, between which the model attempted to discriminate. This technique is useful in identifying descriptive characteristic differences, but does not necessarily provide a good predictive DA model.

A study by Simkowitz and Monroe [1971] attempted to define important financial characteristics of firms acquired by conglomerates. The sample of firms was taken from acquisitions that occurred during part of 1968 and used to build a discriminant analysis model. The entire sample of forty-six firms consisted of twenty-three firms used to build the DA model, and twenty-three firms to use as a hold-out sample for ex post validation of the model. The profile of financial characteristics of absorbed firms provided a useful guide in identifying likely conglomerate targets. Group differences were shown to be that acquired firms had lower price-earnings ratios, lower dividend payout ratios, lower equity growth rates, and were smaller.

The third and most comprehensive multivariate study to date was undertaken by Stevens [1973]. This study analyzed the financial ratios of acquired firms for the two years prior to the acquisition. A sample of forty firms acquired in 1966 and forty firms from the general population were used to formulate a discriminant analysis model. Financial ratios representing liquidity, profitability, leverage, and activity were used as inputs into the model. However, because of the large number of ratios and multicollinearity, factor analysis was first used to consolidate the variables. The model proved to be significant in rejecting the hypothesis of no difference between the acquired and the general population firms. Acquired firms were found to have, on a multivariate basis, higher liquidity, lower asset turnover, lower profitability, and lower debt levels than the nonacquired population. Ex post validation of the model on a holdout sample of twenty firms resulted in a classification accuracy of 67.5 percent. Intertemporal validation also was attempted using two samples of twenty firms each from two succeeding years. Classification accuracy of seventy percent resulted in each case. A priori probabilities for each group were specified as fifty percent throughout the study.

Other types of studies also have been conducted on the differences between acquired and nonacquired firms. These are described briefly in chronological order below.

A comprehensive compilation of eighty-nine companies receiving tender offers by Austin and Fishman [1969] provided much insight into the characteristics of firms actually acquired by tender offer up to that point in time, the most important of which are described here. The lack of performance compared to the industry average in both sales and operating profit was found to be significant, as was the dividend payout, which tended to be low and inconsistent. The stock performance also was poor. Other factors with less significance included excessive liquidity and various qualitative factors, such as internal conflict within the acquired firm prior to the offer, or the acquisition history of the bidder.

Another tender offer study of interest was done by Yamashita [1970], who investigated contested cash tender offers. The author used discriminant analysis to build a predictive model for success in the offer. The sample included all cash tender offers from 1958 to 1967. The variables used included among others, the premium offered, whether the offer was a surprise, and the means of resistence.

A regression study by Melicher and Nielson [1972] investigated the financial characteristics that explain above market value acquisition prices. A finding of significance was the payment of a higher premium for companies with lower price-earnings ratios and with lower variability in earnings per share growth.

Another study by Hermann [1973] considered the acquisition criteria of conglomerate corporations. A field study collected responses to the important criteria used in selecting targets by groups of conglomerate versus other company executives. A discriminant analysis model was built from these responses and used to test these executive groups for differences in selection criteria. The model was able to classify sixty-one percent of the conglomerate executives correctly and provided significant evidence that there is a difference in the evaluation criteria of the two groups. It appeared from the study results that conglomerate management was interested in acquisitions that could provide diversification and reduction of risk, instead of improved acquisition management and economies of scale.

Shrieves and Stevens [1979] investigated the avoidance of bankruptcy as a motive for merger using discriminant analysis. Using the DA model to predict the likelihood of bankruptcy for the acquired firms, the study found that fifteen percent of the acquired firms were selected. This is significantly higher than the experience in the general population and the authors conclude that bankruptcy avoidance is one of the motivating factors in merger and acquisition activity, although it also might indicate the acquisition of tax advantages.

This completes the summary of research into acquired firm characteristics. However, other articles that deal with the research methodology of this study need to be considered. These will be introduced briefly in the final section of this chapter, and will be discussed at length later when the methodology is presented and explained.

Pertinent Methodological Studies

In a summary article, Chen and Shimerda [1981] report that financial ratios continue to be useful in determining the performance and financial condition of firm entities, and, that the twenty-six studies that they reviewed, had indicated a total of forty-one different significant ratios as a result of the research studies conducted. Using principle components analysis, a technique that groups similar variables together in separate factors, the authors found that the ratios used in bankruptcy prediction could be summarized by a much lower number of factor groupings. They conclude that the diversity of reported ratios is due to the similarity among many of the different ones that have been used in empirical research. They are quick to point out however, that the choice of a ratio from among each of the factor groupings is still a difficult theoretical and practical problem.

The methodology to be used here itself has received considerable attention and discussion in financial literature. Several papers

(Altman and Eisenbeis [1978], Eisenbeis [1978], Joy and Tollefson [1975 and 1978], Scott [1978], and Karson and Martell [1980]) have criticized previous financial applications of discriminant analysis and have suggested improved ways of utilizing this technique. This study will correct and improve upon previous research efforts in four significant areas so that a true test of the predictive ability of DA will be achieved. First, a wider range of variables will be employed in the initial model building. Second, the Lachenbruch procedure will be utilized in the model building stage instead of a hold-out sample, so that all the available data can be included in attempting to identify the best model. Third, a more realistic estimate of the a priori probabilities will be specified rather than the previous fifty-fifty probabilities. And fourth, a complete intertemporal validation will be conducted using both acquired firms and those from the general population, so as to engage the model in an actual predictive setting.

The next chapter will discuss the specific methodology to be used in this study and will incorporate the corrections and improvements of the discriminant analysis technique mentioned above. It is there that these changes will be explained in greater detail.

Chapter Summary

This chapterpresented an overview of the theoretical explanations for merger and acquisition activity. In addition, previous empirical research concerning the acquisition phenomenon was described.

Much work has been conducted in this area, but much more remains to be done. There is still a need for a unified theory of mergers and acquisitions, and this implies the need for more extensive theoretical work and the empirical testing of this.

At least three theoretical explanations for acquisition activity exist. First, acquisitions may be viewed as an important factor in providing for the efficient allocation of resources that is provided by the capital markets. The threat of takeover stimulates the efficient use of funds on a firm specific basis. Second, this activity may simply reflect the behavioral goals of the firms involved. And third, the existence of acquisition benefits to those involved in the takeover of companies may explain the motives behind the activity.

Many studies have indicated the existence of significant positive benefits that are extended to the stockholders of acquired firms. The existence of positive returns to the stockholders of acquiring companies is still not resolved. However, it is clear that an investor able to determine attractive acquisition targets in advance will be able to capitalize on this information for superior portfolio performance.

Many studies also have considered the relevant characteristics that distinguish acquisition targets from those firms that are not acquired. While not entirely consistent in their findings, these studies do indicate the existence of significant group differences and an improving ability to determine these differences. Finally, much work has been done to improve the methodological applications used previously by many of the studies that have utilized discriminant analysis.

CHAPTER THREE

SAMPLE DESIGN AND RESEARCH METHODOLOGY

Introduction

In the two previous chapters, the importance of takeovers and acquisitions was discussed, and the need for an investor oriented model capable of identifying acquired firms was explained. In addition, the relevance of previous applications of the discriminant analysis procedure to this research area was discussed. The purpose of this chapter is to describe the data and sources used and the methodology employed in identifying and testing an investor oriented model.

This research will proceed in three distinct phases. The first phase involves the selection of the most appropriate ratio model from among the many possible ratio-variable combinations obtainable within the initial data. The second phase involves the validation of this model in a later time period, so that the model's predictive ability can be assessed. Finally, the last phase employs the identified model as a portfolio selection device. This phase tests the model's ability to predict likely takeover candidates in an actual investor setting and, in so doing, it assesses the ability of the model to help an investor capitalize on the common stock price premiums that takeover targets can attract from corporate suitors.

In the next section of this chapter the firms and data used in this study are identified. Then, the specific study methodology will be presented.

Data Sample

Data provided for this study were obtained from several sources of secondary information. Four sources were helpful in identifying and selecting the firms included in the sample. These sources include: 1) *Mergers and Acquisitions*; 2) *The Wall Street Journal*; 3) *Standard and Poor's Investment Service*; and 4) *Moody's Investment Service*.

The data needed for use in the calculation of ratios, and portfolio information for each company observation, were obtained from the following sources: 1) *Compustat Annual Industrial File*; 2) *Compustat Research Industrial File*; and 3) *Compustat Price, Dividends, and Earnings File*.

The time period for this study is the four year period between 1976 and 1979. This period was chosen because there were a large number of acquisitions in each of the four years. Also, market and economic conditions were similar enough throughout the period so that major shifts in merger motives would not become an important factor, perhaps as might be the case during longer periods of time. Thus, the time period selected was large enough to provide a good foundation of information, yet not so large that any data similarities between firms would become obscured. The first two years were used to build the model and the second two year period was used to validate the model selection process in phases two and three of the research.

In order to limit the population to a reasonable size, only firms with all data available on the Compustat Files were included. In addition, only those industries appropriate for this type of study were included. Obviously, some industries are so different in their presentation of financial information that a comparison with other industries based on ratio computations would be meaningless.[1] As a result, during 1976 and 1977 there were 2008 firms available from 169 different industries (the industry classifications were based on the Standard Industrial Classifications code). Of these firms, seventy-one were actual acquisition targets during the first two year period. For model building purposes, a random sample of seventy-one firms was selected from the remaining 1937 firms. The financial data of the 142 companies provided the input needed for a two-group discriminant analysis (DA) model. The acquired companies used are listed in Table 3.1, and the random sample from the general corporate population is presented in Table 3.2.

In order for a firm to be included in the population, all relevant financial data had to be available. The methodology employed does not allow for partial specification of variables for any of the firm observations. This meant that all pertinent information for the computation of valid variable metrics had to be available from the sources mentioned previously for a company to be included.

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[1] Industries available from the Compustat Files that were deleted for the purposes of this study included Insurance, Banks, Savings and Loan Associations, Finance, Finance Service, Security and Commodity Brokers, Licensed Small Loan Lenders, Real Estate, Real Estate Investment Trusts, Subdivision Developers, Railroads, Telephone Communication, Electric Utilities, and Natural Gas Transmission.

TABLE 3.1

SEVENTY-ONE FIRMS ACQUIRED
DURING 1976 AND 1977

Company Name	Company Name
Airpax Electronics Inc.	Madison Square Garden
Alcon Laboratories Inc.	Mammoth Mart Inc.
Allied Thermal Corp.	Marquette Co.
Amtel Inc.	Masoneilan International Inc.
Anaconda Co.	McCord Corp.
Avis Inc.	McIntosh Corp.
Aztec Oil & Gas Co.	Menasco Mfg. Co.
Babcock & Wilcox Co.	Microdot Inc.
Beech Aircraft Corp.	Modern Maid Food Products
Brewer (C.) & Co. Ltd.	Molycorp Inc.
Canoga Inds.	Monroe Auto Equipment Co.
Chemetron Corp.	National Industries Inc.
Cook Electric Co.	National Starch & Chemical
Copper Range Co.	Pan Ocean Oil Corp.
Cox Cable Communications Inc.	Pandel-Bradford Inc.
Diamond M Co.	Pickwick International Inc.
Disston Inc.	Pizza Hut Inc.
Dixilyn Corp.	Racon Inc.-Del.
Dynell Electronics Corp.	Raymond Intl. Inc.-Del.
Eason Oil Co.	Riviana Foods Inc.
Eckerd Drugs Inc.-Nc	Rucker Co.
Egan Machinery Co.	Sherwood Medical Inds. Inc.
Emery Industries Inc.	Sky City Stores Inc.
Greyhound Computer Corp.	Stanray Corp.
Her Majesty Inds. Inc.-Cl A	Sycor Inc.
Hoerner Waldorf Corp.	Texstar Corp.
Hoffman Electronics Corp.	Tuftco Corp.
I-T-E Imperial Corp.	Unitek Corp.
Incoterm Corp-Cl A	Veeder Industries Inc.
Inmont Corp.	Vetco Inc.
Intl. Couriers	Wagner Electric Corp.
Intl. Mining Corp.	Weatherhead Co.
Kewanee Industries Inc.	Whiting Corp.
Kingstip Inc.	Widener Place Fund Inc.
Lewis Business Products Inc.	Youngstown Steel Door Co.
Logistics Industries Corp.	

NOTE: Company names are as provided by the Compustat Research File.

TABLE 3.2

SEVENTY-ONE SAMPLED FIRMS FROM THE GENERAL CORPORATE POPULATION: 1976 AND 1977

Company Name	Company Name
Alcan Aluminum Ltd.	Kin-Ark Corp.
American Biltrite Inc.	Lilli Ann Corp.
Analog Devices	Lynch Corp.
Archer-Daniels-Midland Co.	Management Assistance
Armco Inc.	Mansfield Tire & Rubber Co.
Asarco Inc.	Matsushita Electric Indl-Adr.
AVC Corp.	Mays (J. W.) Inc.
Baxter Travenol Laboratories	McDonnell Douglas Corp.
Braun Engineering	Mohasco Corp.
Brown-Foreman Distillers-Cl B	National Mine Service Co.
Cagle's Inc.	National Steel Corp.
Capital Cities Communication	Noel Industries
Castle & Cooke Inc.	Nucor Corp.
Centron Corp.	Owens-Illinois Inc.
Crompton & Knowles Corp.	Pamida Inc.
Crown Central Petroleum-Cp A	Pueblo International Inc.
Curtiss-Wright Corp.	Purex Industries Inc.
Cyclops Corp.	Research-Cottrell
Data General Corp.	Schlumberger Ltd.
Dennison Mfg. Co.	Seaboard Allied Mining
Dutch Boy Inc.	Supron Energy Corp.
DWG Corp.	Systems Engineering Labs
Eastern Gas & Fuel Assoc.	Tab Products
Electronic Research Assoc.	Technitrol Inc.
ETZ Lavud Ltd.	Tracor Inc.
Fed-Mart Corp.	Trans World Corp.
Flexi-Van Corp.	U.N.A. Corp.
Foxboro Co.	Unarco Industries Inc.
General Electric Co.	Vernitron Corp.
Harper & Row, Publishers	West Point-Pepperell
Hercules Inc.	Woolworth (F. W.) Co.
Homestake Mining	Wynn's International Inc.
Honeywell Inc.	Xtra Corp.
Host International Inc.	Zapata Corp.
Inco Ltd.	Zero Corp.
Kay Corp.	

NOTE: Company names are as provided by the Compustat Annual Industrial File.

Data needed for model validation was obtained from the second two-year period. A total population of 1967 firms resulted. Of these, 171 were identified as acquired on an ex post basis. Only the variables included in the final model, selected during the initial phase, were computed at this point. The variables from each of these firm observations were used to validate the model, as explained later in this chapter. The next section describes the initial variables that were selected for study and then explains the methodological procedures.

Financial Variables

Numerous financial variables were considered for inclusion in the final discriminant analysis model. The forty-seven variables used are presented in Table 3.3. These variables include common financial ratios and other measures that have been suggested in the literature on takeover offers and in the application of DA to this area. As Chen and Shimerda [1981] indicate, there are many ratio[2] candidates that could be considered; however, most of these can be classified into general groupings. Even so, one of the problems inherent to this type of research is the inter-relationships that exist between the various ratios chosen due to the "overlapping" of the financial information used in the computation of these metrics. Another complication is the lack of agreement on which ratio within each of the groupings is the best representative of that dimension. Therefore, multiple ratio-variable candidates are included for each of the nine groups listed in Table 3.3 so

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[2]The term ratio is used to describe all variables used even though some are not actually ratios themselves.

TABLE 3.3

VARIABLE GROUPING AND DESCRIPTIONS:
NINE GROUPS AND FORTY-SEVEN VARIABLES

Group	Abbreviation	Variable Description
Liquidity		
	CashTA	Cash/Total Assets
	NWC	Net Working Capital
	CR	Current Ratio
	CRX	Industry Adjusted CR
	CATA	Current Assets/Total Assets
	CATAX	Industry Adjusted CATA
Leverage		
	DR	Debt Ratio
	DRX	Industry Adjusted DR
	BVDMVE	Book Value Debt/Market Value Equity
Coverage		
	TIE	Times Interest Earned
	TIEX	Industry Adjusted TIE
	CFInt	Cash Flow/Interest
	CFIntX	Industry Adjusted CFInt
	CFTD	Cash Flow/Total Debt
	CFTDX	Industry Adjusted CFTD
Profitability		
	NPM	Net Profit Margin
	NPMX	Industry Adjusted NPM
	TAT	Total Asset Turnover
	TATX	Industry Adjusted TAT
	ROA	Return on Assets
	ROAX	Industry Adjusted ROA
	RONW	Return on Net Worth
	RONWX	Industry Adjusted RONW
	EbitTA	Earnings before Interest and Taxes (EBIT)/Interest
	EbitTAX	Industry Adjusted EbitTA
	EbitNW	EBIT/Net Worth
	EbitNWX	Industry Adjusted EbitNW
	CFTA	Cash Flow/Total Assets
	CFTAX	Industry Adjusted CFTA
	CFNW	Cash Flow/Net Worth
	CFNWX	Industry Adjusted CFNW

TABLE 3.3-Continued

Group	Abbreviation	Variable Description
Company Size		
	S	Sales
	TA	Total Assets
Company Growth		
	SGr	Sales Growth
	TAGr	Total Asset Growth
	EPSGr	Earnings per Share (EPS) Growth
Dividend Policy		
	AvgDiv	Average Dividends
	DPSEPS	Dividends per Share/EPS
	DPSEPSX	Industry Adjusted DPSEPS
Variability		
	SVar	Sales Variability
	EPSVar	EPS Variability
Market Factors		
	PE	Price-Earnings Ratio
	PEX	Industry Adjusted PE
	PCF	Market Price/Cash Flow per Share
	MPBV	Market Price/Book Value per Share
	TrOut	Shares Traded/Shares Outstanding
	AccmDp	Accumulated Depreciation/Fixed Assets

NOTE: The variable abbreviations listed above are used extensively in Chapter 4.

that the best possible model can be determined. This problem of interrelatedness is considered in the methodological section later in this chapter.

The nine general categories of variables used include common measures of liquidity, leverage, coverage, and profitability. Also included are measures of company size, growth, dividend policy, and variability. A final category was added to include various market factors that could be important in determining takeovers, such as the ratio of market value to book value per share, and the price-earnings ratio.

For many of these ratios, the industrial classification of the respective companies is an important determinant of the ratio. It is possible for the industry influence to mask any relationship between the basic ratios and attractive acquisition candidates. Therefore, a second variable is included, where appropriate, which will adjust for the possibility of any masking by deriving a measure relative to the industry average. In many practical applications of these types of financial information, a comparison is actually made to an industry average. It is hypothesized here that this adjustment will provide measures with stronger explanative and predictive powers than the unadjusted measures. However, until now, this promising avenue of exploration has been largely ignored. Of the forty-seven ratios included in the study, thirty-one are basic variables and sixteen are basic variables adjusted by industry averages. The remainder of the chapter is devoted to an explanation of the methodology employed in the study.

Methodological Introduction

This study involves three distinct phases of research. The first phase will provide for the elimination of nondiscriminatory and redundant variables as a simple, investor oriented model is developed for later use in the identification of likely takeover targets. The discriminant analysis technique is utilized to develop this model. The second phase validates the model intertemporarily so that the predictive ability of the model may be assessed. If the model cannot perform well in a later time period, its usefulness as a portfolio selection device may be of little value. After the model has been validated, this phase is completed. Assuming adequate intertemporal performance, the model can be tested for its usefulness in an actual market setting.

The third and final phase begins with the selection of a portfolio composed of likely takeover targets identified from the discriminant scores provided by the model. The portfolio returns of this group are compared to general market returns to determine any abnormal positive returns (superior performance) that may be received by an investor utilizing this model in making portfolio selections.

Phase One: Discriminant Analysis

As noted earlier, discriminant analysis has received much attention and numerous financial applications in recent years. The technique is used to investigate significant differences between groups under study, and the discriminant model itself is used to classify each research observation into a priori groups. The technique is best suited to studies where this group membership is based upon nonparametric classified data. Therefore, in developing a predictive model, it is best to apply DA in situations where the groups under study are of a qualitative nature, as the case is here, with group membership based upon the classification of takeover targets versus the general corporate population.

This technique has several other advantages. First, it permits the simultaneous analysis of the set of independently sampled variables associated with each observation, thus testing for multicollinearity. Second, it generally reduces the space dimension from N independent variables to the number of groups minus one. And third, it reduces the problem of differentiating between groups to a univariate analysis (Simkowitz and Monroe [1972, p. 3]).

In many of the financial applications of DA, two of this methodology's underlying assumptions, that all variables are normally distributed and that these variable distributions should have equal dispersion within each of the groups, have often been ignored in the model development. As Joy and Tollefson [1975] and Eisenbeis [1977] have pointed out, the selection of an appropriate DA model must test these assumptions as an initial step.

For this study, the normality of all variable distributions is tested and adjustments are made as needed. Several of the variables selected can be identified as having a highly skewed distribution. These include the net working capital and the total sales variables. Such variables are converted to logarithms in an attempt to correct this problem.

The second assumption is also tested for validity before continuing, and the substitution of a quadratic function is considered. However, this assumption is most often violated in studies that include discrete variables, and since all the variables used here are based upon financial information and are continuous, the validity of this assumption is not as likely to be violated as in several previous studies. In any case, the quadratic specification must offer a significant improvement in the model to be used because the purpose of this research is to determine a simple, investor oriented model and the linear formulation best meets that need. Linear DA model programming routines also are much more readily available.

A second problem must be confronted before the actual model building can begin. This problem is the determination of a priori probabilities to be assigned to the takeover target and general firm populations. As indicated in the data section, the population definition utilized encompasses all companies on the Compustat Annual Industrial File. This population is an important segment of the actual investment population, and as such, it represents a reasonable facsimile of that environment. At the same time, there are enough takeovers within this group to provide an adequate sample. With a total of 2008 firms in the population, seventy-one of which were acquired during the two year model building period, the a priori probability estimates of group membership for the model building phase are .0353 and .9647, respectively, for the takeover target and general firm populations.

Finally, before proceeding into the actual discriminant analysis, it is necessary to determine the usefulness of this technique through a test of the null hypothesis that there is no difference in the variable means between groups.

Ho: $M_{1j} = M_{2j}$ for all j, 1 to 47, where j equals the total range of ratio-variable candidates.

Ha: $M_{1j} \neq M_{2j}$ for some variable j, or some group of variables j.

where: Ho = the null hypothesis (Ha = the alternate),

M_{1j} = the mean for Group 1, the acquired group, on ratio-variable j, and

M_{2j} = the mean for Group 2, the nonacquired group, on ratio-variable j.

Univariate tests for differences in the means of the variables are computed using the standard t-test. Also, the Hotelling T^2 statistic is utilized to determine the acceptance or rejection of this hypothesis since univariate analysis is not likely to establish many strong group differences. This statistic is analogous to the univariate t statistic except that it applies to all the variables simultaneously. If the null hypothesis is rejected, DA is probably an appropriate tool to determine any significant variable combinations which improve prediction, and which might be overlooked by the univariate techniques. The next section will present and discuss the problem of dimension reduction, which is the next step in formulating a final DA model.

Dimension Reduction

The initial model building stage involves dimension reduction because of the large number (forty-seven) of ratio-variable candidates included for consideration. Because of the inter-relatedness of the financial information used to compute the ratios and the similarity of many of the ratios themselves, much multicollinearity is present in the full model. This problem calls for the reduction of the variables to a manageable size, or perhaps a method to combine the variables in an appropriate manner to minimize this intercorrelation between the independent variables.

To achieve the goal of a powerful, but workable model, many available techniques will be employed. One generally recognized and often used approach to dimension reduction is factor analysis. This technique groups variables according to patterns of variation in the date set, while concurrently accounting for as much of the total variation as possible. The variable groups or dimensions that result provide an indication of the type of relationships that exist among variables. This analysis results in groupings, called factors, which provide a measure of the underlying relationships that exist within subgroups of all the variables analyzed. One difficult problem to confront with factor analysis is the interpretation of each of the factors. Every factor includes several of the variables, but these variable groups may not have a logical explanation for their being included together in a factor. For example, a factor that included the current ratio and net working capital, as well as other measures of liquidity, would be relatively easy to explain. However, the inclusion of net working capital and the net profit margin together in a factor would be much more difficult to interpret and explain.

If the factors identified prove to be conceptually meaningful, they are considered for possible inclusion in the model. However, inclusion of factors instead of the variables themselves increases the complexity of the model, and this may defeat the purpose of building a simple, investor oriented model. In any case, previous experience indicates that there will be some difficulty in interpreting the factors, and generally, the factors are used to provide information, but are not directly input into the DA phase.

Even when the factors themselves prove to be of little assistance, this technique still provides insight into the relationships between the variables and into the relative importance of a variable in the makeup of its factors. Factor loadings, a numerical weight which indicates the amount of involvement a variable has in a particular factor pattern, are available from the analysis and they provide a relative ranking of the importance that each variable holds within its dimensional group. Pinches and Mingo [1973, p. 4] utilized factor loadings as the sole criterion in selecting one variable from each of the factor groups (liquidity, debt, etc.) for inclusion in the final discriminant model, thus attempting to limit the correlation in the model. Attempting to limit multicollinearity is of concern, but the Pinches and Mingo approach has been criticized for being the sole approach to variable selection. DA relies upon the multivariate interaction of variables to provide its discriminatory power and this method disavows many of the possible interactions, some of which may prove to be quite strong. The highest factor loading does not guarantee that a particular variable will provide the best combination with other variables in forming a model. However, the factor loadings do provide useful information to the researcher in gaining insight into the relative importance of the variables.

Even though it does not provide the specific method for selection from within groups of correlated variables, factor analysis still remains a powerful tool in this type of problem, in that it highlights the relatedness between variables and allows the researcher to avoid inclusion of highly correlated variables in the final model. By carefully studying the variables included in final model candidates, it is possible to eliminate models that appear to have a high degree of discriminatory power that arises partially from the existence of multicollinearity. Principal components analysis is the simplest of available factor techniques and the one generally accepted for this type of application. It is presented in its basic form in the next section. Afterward, the discussion of dimension reduction will resume.

Principal Components Analysis

Principal components analysis, one form of factor analysis, is the method generally used as an initial step in the reduction of financial variables in previous studies. Chen and Shimerda [1981, p. 53] explain the reason for this by stating,

> One of the functions performed by principal components analysis is to group variables into a few factors that retain a maximum of information contained in the original variable set. This tool is a useful first step for subsequent analyses. The use of principal components analysis, along with other statistical methods, produces a more powerful and basic analysis.

Because this technique is one of several factor analysis techniques available, the development that follows will apply to general factor analysis and then the difference between principal components and classical factor analysis will be described.

As a basic statistical tool, factor analysis has four distinct advantages in business research (Wells and Sheth [1971, p. 212-213]). First, it can highlight latent dimensions that determine the realtionships among a set of observed values. Second, it can be quite helpful in bringing attention to existing relationships within the set of observed values that were not easily determined beforehand. Third, it is useful for the grouping of observed data that it provides. And fourth, it is useful for the empirical clustering of observed data.

Factor analysis begins with a matrix of correlations between all variables as its input. Correlation coefficients are standardized scores where the averages of the variables have been set to equal zero and the variances have been set to equal one. These coefficients do not necessarily have to be the input matrix, but because of their nature, correlation coefficients are relatively easy to interpret. Even more important however, is the need to standardize the matrix when the initial variables are denoted in vastly different units, as is the case here among the forty-seven variables to be used.

One way to consider the technique of factor analysis is through the definition of a factor. Each factor is a linear combination of the variables, described in the following manner:

$$F_{ij} = a_{1k}x_{i1} + a_{2k}x_{i2} + a_{3k}x_{i3} + \ldots.. + a_{nk}x_{in}, \; j=1,n \qquad (3.1)$$

where:

F_{ik} = the factor score for factor k, for company i,

a_{jk} = the factor loading, or representative of the correlation between factor k and variable j, and

x_{ij} = the observed value of variable j for company i.

In the present case, the number of companies i equals 142 (seventy one acquired and seventy-one drawn randomly from the general corporate population). The number of variables j equals forty-seven and the number of factors k equals m, the value of m being discussed later in this section of the chapter.

Each factor is a linear combination of the variables weighted by the factor loadings. Based upon the factor loadings, a factor score for a given factor can be computed for each company observation. Each company will have a factor score for each of the factors computed. Each factor loading, a_{jk}, represents the correlation between variable j and factor k. Or stated differently, the factor loading represents the importance of factor k in measuring variable j. The result is a matrix of factor loadings with dimensions of m by forty-seven, where m represents the number of factors and forty-seven the number of variables. Thus, the loadings can be viewed columnwise, as well as rowwise.

Just as the factors are linear combinations of the variables, the variables can be represented as linear combinations of the factors. Each of the original company variables can be expressed in terms of the factors and an error term as follows:

$$x_{ij} = a_{j1}F_{i1} + a_{j2}F_{i2} + \ldots\ldots + a_{jm}F_{im} + e_{ij},\ k=1,m \qquad (3.2)$$

where the terms remain the same as before in equation 3.1.

Eigenvalues, which measure the amount of total variance explained by each of the factors, can be computed by squaring all the loadings for a particular factor and summing them. Eigenvalues are the regression equivalent of the sum of squares, and by dividing each factor eigenvalue by the total variance (forty-seven in this case since the standardized variance of each of the variables equals one) it is possible to measure the percentage of the total variance explained by the factor. Adding the contribution that each factor makes toward the explanation of variance yields an estimate of the part of the variance explained by the factors as a group. This measure is equivalent to the regression R^2 statistic.

Another important measure in this technique is commonality or h^2, which is an estimate of the percentage of a variable's total variance explained by "common" factors. Wells and Sheth [1971, p. 215] explain this as follows,

> Common factors are those which are shared by at least two variables. All other factors are called unique factors. The total variance of a variable then can be considered to be divided into two types of factors: common and unique.

Now that the essentials of this technique have been presented, it is possible to explain the difference between classical factor analysis and principal components analysis. There are two basic differences here (Aaker [1971, pp. 209-211]). First, the error term in equation 3.2 does not exist in principal components. In the classical approach, a variable's variation is explained by the common factors and a unique factor that contains the residual variation left by the common factors. Since in the factor analysis approach it is hoped that the underlying variables will be combined into a smaller set of factors, it is the common factors that are of interest to the researcher. In principal components, the common factors are assumed to contain the total variance of one for each variable. In the classical factor technique, the estimated commonalities are substituted in for the variable variation.

The second difference arises from the use of rotational methods. With principal components, the factors may prove to have moderate correlation with variables that do not form a logical set. This makes interpretation difficult. In the classical approach, one of several rotational methods is selected and the factors are rotated to a new orthogonal or nonorthogonal axis. The rotation is an attempt to find the factors that will provide the best interpretability. In practice this difference does not usually exist, as rotational methods are commonly used in principal components, as well as classical factor analysis, in order to achieve the interpretability that often does not exist in "pure" principal components. In financial applications such as this, the varimax rotation is generally combined with principal components because it attempts to rotate the factors in order to simplify the columns of the factor matrix. The result is a clearer interpretation of the variables that identify with each of the factors. This rotational method will be used here.

Theoretically, then, these differences mean that the basic approach to modeling is quite the opposite. Kendall [1961, p. 162] explains:

> In component analysis, we begin with the observations and look for components in the hope that we may be able to reduce the dimensions of variation and also that our components may, in some cases, be given a physical meaning. We work from the data toward a hypothetical model. In factor analysis, we work the other way around; that is to say, we begin with a model and require to see whether it agrees with the data and, if so, to estimate its parameters.

It is for this reason that principal components analysis is the generally accepted form of factor analysis used in this type of financial research. In the present study, the financial variables are analyzed in the hope that underlying relationships within the data will exist, that they will be logical and relatively simple to explain, and that they will provide information useful in the formulation of a hypothetical model concerning the attractive characteristics of acquired firms.

A final problem to confront in the use of this technique is in deciding when to stop factoring. At some point the contribution of additional factors becomes unimportant. There are two statistical approaches to aid in this decision. The first is to determine an appropriate amount of variance to be explained and to retain only those factors that have contributed a significant amount to this, say at least five percent. The second approach excludes any factor that has an eigenvalue less than one. The second approach is much more objective because it uses a predetermined range for including factors and avoids any judgemental bias present in the other approach; therefore, it will be used here.

The use of factor analysis does have its limitations (Wells and Sheth [1971, pp. 226-227]). The reliability of the results may be overstated by the researcher. The technique is influenced by the choice of original variables that are included. The data provided is itself "imperfect", in that measurement error may impair validity and the relationships may be unstable over time. Another problem is that much judgement must be exercised in applying the technique and these decisions will affect the outcome. It is quite possible for differing conclusions to be reached from the same data set.[3]

It can be seen from the preceding discussion that factor analysis can provide much insight into the problem of dimension reduction. The next section will continue the discussion of dimension reduction and will suggest additional approaches that are available for dealing with the problem.

Final Model Selection

In the search for the best combination of variables to include in the final model, no one method is generally accepted as the "correct" approach - there are many. Beside principal components analysis, other methods are available for use. It is important to note that these methods do not have to be applied exclusively of all the others. The best approach is one that gathers the information that several acceptable methods provide and utilizes it all in the search for this final model.

One such approach is a general selection procedure suggested by Altman [1968, p. 594]. This procedure calls for: (1) observation of the statistical significance of various alternative functions - including determination of the relative contributions of each independent variable (this includes F-tests on each variable to indicate its univariate basis as an independent distinguishing feature); (2) evaluation of the inter-correlation between the relevant variables; and

[3]Much of the discussion in this section was adapted from Aaker [1971] and Wells and Sheth [1971]. For a more rigorous development of the technique see Harman [1976].

(3) observation of the predictive accuracy of the various profiles, based at this point on the original data set. Validation of the predictive ability of the chosen model occurs at a later stage.

Since the univariate F-test treats each variable independently of the others, Eisenbeis, Gilbert, and Avery [1973] have suggested three alternatives to replace this procedure. These alternatives include: (1) stepwise forward methods based on the variable's contribution to the multivariate F-statistic, (2) stepwise backward methods similar to the forward methods above, and (3) a conditional deletion method which removes each variable from the full model then replaces it to determine the effect on the overall ability of the model to discriminate among groups, as measured by the n-1 variable F-test. A commonly used variation of this conditional method is to begin by removing the variable with the lowest contribution to the F-statistic, as long as it is below a certain level. After each additional variable is removed, all previously removed variables are reconsidered for entry back into the model. The final model is achieved when no further eliminations can take place and none of the removed variables can return. These authors recommended use of the conditional method because each variable is evaluated conditionally on its inclusion with all others, allowing important relationships to be discerned. However, Altman and Eisenbis [1978] point out in a later article that there is no absolute test to determine variable importance.

Regardless of the method employed, to reduce the dimensionality of the final model, it is important that each variable of the group selected as appropriate for analysis, and variable combination, be given a chance to enter the model. As stated by Eisenbeis [1977, pp. 886-887]:

> The available evidence suggests . . . that it may be unwise to drop dimensions or variables without first exploring in more detail what the possible effects may be. If classification accuracy is a primary goal, then the criteria for keeping or deleting variables and dimensions should be related to the overall efficiency of the classification results. Therefore, the results using all variables should be compared with those based upon various subsets of variables . . . The implication is that concern for dimension reduction should 'follow' and not precede the development and validation of alternative classification schemes as has been the case in most of the applied literature.

With proper attention given to conceptual formation, a solid foundation for an empirically tested predictive model can be established. The selection of variables provided by the preceding techniques should enable the discriminant analysis input variables to be small in number, and yet provide a powerful tool for prediction. This is most crucial for an investor oriented model. The basic DA technique will be presented and developed in the next section, after which the discussion will turn to the problem of model validation.

Discriminant Analysis Technique

The basic function of the discriminant analysis technique is to predict the group membership of each individual observation based upon the sets of group means for each of the included variables, as well as the sample variances of and the covariances between each of these variables. The purpose is to place the observation into the one group, from a mutually exclusive set, which has the characteristics most like its own. This is done statistically by maximizing the ratio of among-group to within-group variance-covariances developed from the set of variables.

Based upon the observed values for each variable, the technique will predict the probability of membership in each group for each of the company observations. In the discussion that follows, only the basic two-group model will be utilized. Using the two-group model and Bayes' Theorem, the relation of membership between groups can be expressed as such:

$$\frac{P(I/X_i)}{P(II/X_i)} = \left(\frac{l(X_i/I)}{l(X_i/II)}\right)\left(\frac{P(I)}{P(II)}\right) \qquad (3.3)$$

where:

X_i = the observed company i, with the vector of variable values X_{ij},

$P(I)$ = the unconditional (prior) probability that a company belongs to Group I,

$P(I/X_i)$ = the conditional (posterior) probability that a company belongs to Group I, given the observed values for that company, and

$l(X_i/I)$ = the likelihood that a company has this vector of variable values, X_{ij}, given that X_i belongs to Group I, (Morrison [1969, pp. 159-160]).

The definitions above apply to Group II as well. Equation 3.3 can be stated verbally in the following manner:

$$\text{Posterior Odds} = \text{Likelihood Ratio X Prior Odds} \qquad (3.4)$$

The resultant ratio of posterior odds establishes group membership for an observation in that group which has the more favorable probability.

A ratio of four would indicate an eighty percent probability that the observation belongs in Group I, versus a twenty percent probability of membership in Group II. A ratio of .25 would indicate just the opposite.

The discriminant function is derived by taking the logarithms of the components in equation 3.4. Then, the logarithm of the likelihood ratio for each company observation is a linear combination of the variables included in the study, the form of which is shown below:

$$\log\ (\text{likelihood ratio}) = b_o + b_1x_{i1} + \ldots + b_nx_{in},\ j=1,n \qquad (3.5)$$

where:

x_{ij} = the observed value of variable j for company i, and

b_j = the discriminant coefficients.

When the result of this linear combination is added to the logarithm of the prior odds, the standard discriminant score has been obtained. In the case of the prior odds being equally weighted, the logarithm of the prior odds ratio will be zero. When the prior odds are different from .5, a constant value unaffected by the observed variable values will result. This constant will cause a shift in the discriminant score toward the range of the group with the higher a priori probability of occurence.

The standard form of the linear discriminant function is shown below:

$$Z_i = b_0' + b_1x_{i1} + b_2x_{i2} + \ldots + b_nx_{in} \qquad (3.6)$$

where:

Z_i = the discriminant score for firm i.

b_j = the discriminant coefficient for the jth variable,

b_0' = the constant b_0 from equation 3.5 plus the logarithm of the prior odds ratio, and

x_{ij} = the jth independent variable for firm i.

For reclassifying and predictive purposes using a two group model, there is only one Z critical value derived to divide the groups. In two group discriminant space, the technique will derive a line to divide observations into the two groups. This translates into one point on the Z scale, and this point represents the critical classification point between groups. If the discriminant function derives a Z value above this point, the firm being observed is classified in one group and a lower value places it in the other. The critical Z value is computed by substituting the grand mean of all observations for each variable into equation 3.6.

Effectively, each observation is placed on the Z scale according to its discriminant score. As mentioned above, the influence of a priori probabilities other than .5 is not to shift the relative positions of the firm observations, but to move the classification point so as to enlarge the territory of the group with the higher probability. The position of a firm's Z score allows the interpretation of the probability that this observation belongs to a particular group. This indicates that the firm on one end of the Z range is the one most likely to belong to Group I, while the firm on the other end is the least likely member. All the observations in between retain their relative rankings on this scale.

In order to aid in the classification of individual observations, classification functions can be developed. These are derived from the within-groups covariance matrix and the centroids for the discriminating variables. There is one function for each group and its form is similar to that of equation 3.6. A firm is classified into the group whose function provides the highest score. These functions provide a basis for determining the probability of a firm belonging to a particular group.

One of the advantages of a linear classification procedure is that it allows for a clear interpretation of the effect that each of the individual variables has upon the group classification. The sign of the discriminant coefficients indicates their effect on the Z value, and thus, value judgements concerning the differences between the groups can be made. For example, if a high Z score was indicative of acquisition targets, a positive sign on the current ratio variable would indicate that acquisitions generally had more liquidity than firms in the general corporate population, given the conditions set by all the other variables in the model. A quadratic specification of the discriminant function does not offer as clear an interpretation.

Although it is possible to determine group differences based on the discriminant coefficients for each variable, determination of the relative importance of each of the variables to the discriminant function is not as clear. In most cases, the variables themselves will be expressed in widely disparate units of measure. By dividing each of the variables by its standard deviation, standardization between units will be present. This normalization of data, of course, will affect the discriminant coefficients, but it will not affect the basic analysis. These normalized coefficients have been used as an indication of a variable's importance to the discriminant function; the more the Z score is affected by the variable coefficient, the more its importance. However, this approach is not necessarily valid. Eisenbeis, Gilbert, and Avery [1973] examine five different methods that approach this problem, but are unable to conclude that any of these is completely satisfactory. Pinches [1980, p. 436] states that,

> The only acceptable procedure presently available is to examine the contribution of variables by a number of different methods and hope they all provide a similar indication of variable importance.

The relative importance of the variables is not a key question to this study. However, the characteristics that differentiate acquisition targets from other firms is of great interest. Therefore, the variables that remain in the final model, as well as their importance to that model, will be evaluated.

A final comment concerning the effect of group size is in order. As shown before, the a priori probabilities affect only the constant in the discriminant function and not any of the possible variables that are being studied. However, the classification of observations into groups is affected. If the size of one group dominates the other, then it is possible that the logarithm of the a priori odds will dominate the logarithm of the likelihood ratio. This means that most of the observations to be classified will be placed in the larger group. Often, more are classified in the larger group than belong in it.

It is usually the smaller of the two groups that is of most interest, as in the study of acquisition targets. This has three important implications. First, it may be difficult to interpret the classification table. Second, the sample drawn from the smaller group, and not the total sample, is the key to determining the ability of the model to discriminate between groups. And third, the ability of the independent variables to discriminate becomes cloudy (Morrison [1969, pp. 160-161]).

Since the discriminant model will classify observations using the a priori group probabilities specified, care must be taken in assessing the model performance. With a priori probabilities of .95 and .05, ninety-five percent accuracy could be achieved by placing all companies in the larger group. This clearly would be of little use to the researcher. Concentration on the performance with the smaller group is in order; however, as mentioned above, the model may classify a smaller proportion of observations into the small group than it actually contains. One solution to this problem is to rank the observations according to their group classification probabilities and to place the appropriate number from this scale in the small group. This will be discussed further in the section concerning intertemporal validation.

Sample size will not pose a problem here. Both samples of acquisition targets from each two-year period under study contain an adequate number of observations for use.

The discriminatory ability of the variables in a model is best analyzed when the two groups have classification probabilities of .5 each. In the model building phase, a random sample of seventy-one firms from the general corporate population was drawn to match the number available in the acquisition group. A larger number was not used so that the best variable model selection could proceed. A larger group would have brought the logarithm of the prior odds into a discriminant function. However, in the validation phase, a realistic sample of firms from both groups will be used in order to judge the final model's ability in an actual setting.

The problem of measuring model performance, as well as the related subject of misclassification costs, will be discussed in the section on phase two of the study-intertemporal validation. However, before this can proceed, model validation on an ex post basis must occur. Ex post validation is the subject of the next section.

Ex Post Model Validation

When a final model has been identified, it will be possible to enter the validation stage. Validation, particularly for a predictive model, should take place in two phases - on an ex post and intertemporal basis. Ex post validation involves classifying observations from the same time period as those used to build the model. Intertemporal validation is obtained by measuring model performance in a later time period.

Of course, the validation procedure will depend upon the type of classification scheme that has been selected for use in the ex post validation of the model. Eisenbeis [1977] summarizes ten of these methods that were previously evaluated by Lachenbruch and Mickey [1968] and Cochran [1968]. The alternatives fall into three categories: 1) those that employ holdout samples as a means to estimate error rates, 2) those that employ the assumption of normality to make these estimates, and 3) those that employ the Lachenbruch U procedure.

The Lachenbruch U approach, which until recently had received little attention in financial applications, requires that each company be held out individually so that all the other companies in the model building sample can be used to provide information toward that classification. Eisenbeis [1977] concludes that this approach is superior, as did Lachenbruch and Mickey [1968], particularly when it is applied in a situation of either large dimensionality or small samples, the former being the case in this study. Pinches [1980, p. 440] states:

> Studies indicate the U method yields almost unbiased estimates of the appropriate error rates, performs better than the resubstitution method, and is reasonably robust to extreme values of m (the number of variables) and N (the number of observations).

The advantage of this approach, which does not assume normality, is that it uses all possible information in building a model instead of segmenting the observations into an original and a holdout sample. Of course, when using this method, the model building and ex post validation stages occur at the same time. The main disadvantage of the Lachenbruch U method is that it requires sophisticated computer programming that is not as readily available as other computer routines. However, it is the method to be applied here.

This phase of research will conclude with the reclassification of the companies used to build the model. As described previously, the companies to be used in this phase come from the 1976-77 time period and are in two equal groups of seventy-one firms from both the acquisition and general corporate groups. With a priori probabilities of .5 each, a random chance reclassification success rate of fifty percent is the appropriate benchmark to use in measuring the model's performance. If the model fails to improve prediction significantly over this random chance classification, then the model will have little value in a predictive capacity. Excellent reclassification results also are not necessarily significant because these are to be expected when the model is used to make predictions on the same data from which it was built. Intertemporal validation, the process to be conducted in phase two of this research, is needed so that the predictive ability of the final model can be assessed more carefully.

Phase Two: Intertemporal Validation

The final stage of validation requires an intertemporal test. Here the model will be used to classify a total of 1967 companies that represent a realistic population of investment choices.[4] The firms were drawn from the subsequent two year period, 1978-79, and include a total of 171 acquisitions.

Poor model performance at this stage may result from two sources of bias. The first results from the model building. An obvious problem is that important variables will not even be considered for inclusion in the study. However, of those that are, it is not uncommon for some of the variables included to be randomly correlated to the dependent variable. This randomness does not become apparent until the model is applied to data other than the original. The second source of bias is sampling bias and results from the imperfections inherent in the measurement of variables and in the sample selection process itself.

[4] This includes corporate failures.

The result of the model's group classification versus the actual group membership will be compared to an appropriate random chance performance measure and this will provide the basis for a conclusion as to the predictive ability of the final model. However, the model's performance must be carefully measured. The a priori probabilities for the two groups in the second period are 8.7 percent versus 91.3 percent. In the case of equal probabilities, the model's ability to produce results better than 50 percent is the measure of performance. However, when the groups are of disproportionate size, this is not true.

A maximum chance criterion would use the higher of the two groups' a priori probabilities as a performance measure. In this case 91.3 percent would be used. This is what could be achieved by classifying all observations into the larger group. If the sole objective of model performance is to maximize the percentage classification of both groups, then this is the appropriate measure. If the objective of model performance is in its ability to correctly identify the members of both groups because of research interest in one of these groups, then another criterion is needed.

The appropriate criterion for use in this case is a proportional chance criterion that is based on the a priori probabilities and the number actually classified into each of the groups. This is computed as follows:

$$P_{cor} = pq + (1-p)(1-q) \tag{3.7}$$

where:

p = the true proportion of Group I.

1-p = the true proportion of Group II.

q = proportion classified as Group I, and

1-q = proportion classified as Group II.

If the model actually selects p firms to be placed into Group I (p=q), then the criterion of proportional chance for the observations correctly classified (P_{cor}) would be 84.1 percent for this phase of research.

A final note on model performance measurement is in order. It is possible that the model will improve performance only slightly over the criterion. With the group of interest representing only a small proportion of the population, this can be misleading. Most of this improvement may occur in the smaller group, but this would be heavily outweighed by the performance with the larger group. For example, most of the firms placed in the acquisition group may indeed belong to this group, but this may be masked by a large number of acquisitions being classified incorrectly. This would represent acceptable performance for this type of study since it is the model's ability to classify acquisition targets, not its ability to classify the general corporate population, that is important. As long as the model can select an adequate number of acquisitions for portfolio selection, it will be performing well. Therefore, the most important criterion for performance measurement will be the model's conditional classification ability with the acquisition group.

Misclassification costs also are an important consideration in assessing model performance. The cost of reducing portfolio performance by including firms from the general population must be carefully weighed against the opportunity cost of overlooking additional acquisition targets. Over-looking additional targets is not crucial as long as the model is able to identify enough for inclusion in a portfolio. However, the cost of including firms from the general population is a key issue here, but there is little basis available for making a comparison of this type. Previous applications of discriminant analysis to this area have ignored this problem. This problem will not be dealt with directly here; however, the evaluation of the model's portfolio selection ability will indirectly incorporate the issue of misclassification costs into the analysis.

This stage is crucial to the proposed study because this is the time period in which a portfolio will be selected (during the next phase of research) from the general population using the critical Z value provided by the model. If the model does not prove to be valid intertemporally, then its use in the next phase is of little value. However, should the model prove to be valid, then this study will conclude its work with discriminant analysis and proceed into the next methodological phase. The results to this point will be utilized for portfolio selection in an attempt to operationalize the discriminant model in an investor setting.

Phase Three: Portfolio Selection

In this, the final phase of research, the discriminant model will be used to select individual stocks for investment purposes. The model will be allowed to perform in a realistic setting in order to assess its predictive ability. The population of 1967 stocks represents the most well known stocks, and, as a group, represents a highly probable investment population for an individual investor. Firms that failed subsequent to the portfolio selection date were also included as a valid portion of this population.

The discriminant model can provide the investor with a ranking of the stocks involved. Based upon the classification function, the list will range from the most likely acquisition target to the least likely target. The model provides the order of the stocks to be included in a portfolio. However, the model will not provide much insight into the optimal size of the portfolio to be selected.

The investor will be aware of the a priori probabilities of the two groups from the model building stage, but will not be cognizant of these probabilities for the period under investigation. As can be seen from the two consecutive two-year periods used here the probabilities might be very different. Whatever the probabilities, there is no one portfolio that can be selected as being the appropriate choice. Rather, a range of portfolios will be considered. Starting with a small core of stocks, additional groups from the stock rankings will be added until the portfolio becomes quite large. Thus, a wide range of portfolio choices will be analyzed to determine the feasibility of this selection device.

One method available for determining the size of each of the subsequent portfolios is to alter the input of a priori probabilities into the discriminant function. The investor will be unaware of the exact value and by increasing this figure, additional stocks will be added to the portfolio. Starting with a specification of .03 for the acquisition group (this is close to the actual figure in the model building phase), increments of .01 will be added to the a priori specification until the size of the portfolio becomes unmanageable.[5] It is important to note that this method of determining portfolio size is not a preferred method, but just one that is suggested so that the portfolio selection technique might be evaluated. What results is nothing more than arbitrary points on the ranked list of stocks that place the stocks on the acquisition side of the points into the ever-increasing portfolio. Another method that would achieve the same result would be merely to set an arbitrary number of stocks to draw off the list for inclusion in a portfolio.

With the composition of each of the portfolios determined, the stockholder's return for each may be identified and evaluated. A simple buy and hold investment strategy will be incorporated for each of the portfolios. The investment in each portfolio will be assumed to begin at the end of December, 1977, and it will be held for a 24 month period until the end of 1979.

The portfolio return for this period will be based upon the opening and closing prices for each stock, and any dividends paid during this period. For any stock that is acquired during this period, the cash inflow from the acquisition will be assumed to be reinvested in treasury securities for the time period that remains before the end of 1979. Individual security returns will be equally weighted in computing the portfolio return.

The return generated from each of the selected portfolios will be compared to the return indicated by the Standard and Poor 500 Stock

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[5]Eventually, the size of the portfolio will become so large that it would be infeasible for an individual investor to purchase that many securities given the investment strategy implied by this research.

Composite Index with adjustments for dividends. A simple measure of risk will also be computed. Beta estimates for each security in the total portfolio will be taken from the Compustat Price, Dividend, and Earnings File for the five year period up to and including the year 1978.[6] This will provide the basis for an average measure of risk for each of the portfolios, and in conjunction with the portfolio return, will provide the basis for a preliminary comparison of risk-adjusted returns between the portfolios and the market in general. Treynor's [1967] measure of portfolio performance will be used to consider the risk adjusted portfolio performance.[7] This simple measure will provide an indication of the usefulness of this approach in the selection of acquisition targets for inclusion in a portfolio, and it will indicate whether further research into this application of the predictive ability of discriminant analysis is warranted. The results obtained from the implementation of this study as outlined are presented in Chapter 4.

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[6]This computation of individual betas will be an acceptable measure of security risk and will be combined to provide estimates of average portfolio riskiness. The calculation was carried into the middle of the holding period because it is necessary to assess the risk faced by an investor utilizing this technique. It is highly likely that a shift in the beta parameter results through acquisition activity, and, because of this, one year of the holding period was included so that a conservative measure of portfolio performance may be obtained, i.e., the beta estimates may be higher here than would be the case with a five year period ending at the start of the investment holding period. The subject of beta nonstationarity is beyond the scope of this study, but it does offer the possibility of further study as it applies to this area.

[7]This measure, and others, have been criticized by Roll [1978] because it measures the efficiency of the market proxy and not necessarily portfolio performance. However, it will be used here because it is the best alternative available given the type of comparison being conducted. Conclusions drawn from its application will be tentative, but it will provide a preliminary consideration of the DA model's ability to provide superior portfolio performance.

Chapter Summary

This research will proceed in three distinct phases. The first will involve the selection of a discriminant analysis model consisting of financial ratios selected from among many possible ratio candidates. The second phase will be an intertemporal test of the validity of the model. And, the third phase will apply the selected model to the problem of identifying stocks as likely takeover candidates for inclusion in a portfolio.

A total of forty-seven variables from nine different ratio groups were included and an initial sample of seventy-one acquired firms were identified for use. A control group of seventy-one firms was selected randomly from the general corporate population during the two years of 1976 and 1977. A total of 1967 firms comprise the identified corporate population during the following two-year period, in which phases two and three of the study occur.

The underlying methodology of this research involves the application of discriminant analysis to the problem of identifying likely takeover targets. This technique will be applied in a proper sequence of steps so that a valid model development can occur. These steps include a test of the underlying DA assumptions and the reduction of variables through the various dimension reduction approaches that are available. One such approach is in the use of principal components analysis for gaining insight into the dimension reduction problem.

A final ratio model will be selected from among the many possible candidates and this model will provide a critical Z score that is used to separate the firm discriminant scores into two separate groups. The validity of the model in making this group prediction will be tested by classifying the original firms using the Lachenbruch U method. Also, the variables that remain in the model will indicate the important differences that exist between likely takeover candidates and those firms in the general corporate population.

Using firms from the following two-year period, the model will be validated on an intertemporal basis. Care must be taken in assessing the predictive capacity of the model since the group of interest (acquisitions) comprises such a small percentage of the population.

The final phase of analysis involves the use of the model in the selection of portfolios. Using the discriminant scores, a ranking of the firms can be obtained that indicates the likelihood of a firm becoming a takeover target. Using this ranking, firms that are likely targets will be included in the portfolio. A small portfolio will be evaluated first and then additional firms will be added until the portfolio size becomes unmanageable. Each of these portfolios will be evaluated to determine whether the predictive ability of the discriminant analysis model improves an investor's portfolio selection ability enough to capitalize on the premiums paid to the stockholders of acquired firms. The average betas for each of these portfolios will provide an indication of the risk relative to the general market that this investment strategy will imply, and these will be used in conjunction with the portfolio return to indicate the usefulness of the model as a portfolio selection device.

CHAPTER FOUR

DISCRIMINANT ANALYSIS AND THE PREDICTION OF ACQUISITION TARGETS

Introduction

The previous chapter outlined the methodology to be used and described the firms and variables included in the study. The purpose of this chapter is to present the results of the research following the sequence of steps already explained. Each of the three phases of study will be considered and the conclusions and implications from the results will be provided.

The first phase involves the selection of a ratio model through use of the discriminant analysis (DA) technique. The model selection phase is presented in the following sections of the chapter. Afterward, phase two, intertemporal model validation, is discussed. The chapter concludes with the presentation of phase three, which involves the utilization of the model as a portfolio selection device.

This study has concentrated on a multivariate technique because of its previous successful application to this problem area. Univariate analysis generally has been poor in providing a basis for assigning group membership between takeover targets and the general corporate population. However, before proceeding into the multivariate analysis, it is useful to consider the results from a univariate approach. The next section will consider the ability of individual variables to specify group differences statistically.

Univariate Analysis

As mentioned previously, univariate analysis is useful in considering differences between groups that are under study, but generally it is unable to perform satisfactorily in identifying acquisition targets. However, the results from this type of analysis are helpful in highlighting variables that are important statistically in distinguishing between groups. This is useful in the dimension reduction phase of a multivariate analysis even though it should not limit the use of variables that do not appear statistically significant. A t-test for equality between the group means for all forty-seven variables is presented in Table 4.1.[1] Included in the table for each variable are the means for both groups, the t score, and the probability of obtaining a t score higher than that computed for the variable.

A total of five variables are significant at the level of .01. Another seven variables are significant at the .05 level. In the liquidity group, only the net working capital (NWC) variable is significant. It appears that acquired firms generally have less net working capital than those firms in the general group. This is due either to lower liquidity or the smaller size of acquired companies.

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[1]The variable abbreviations in this and later tables in this chapter are based upon the notation in Table 3.3.

TABLE 4.1

T-TEST OF EQUALITY
BETWEEN GROUP MEANS FOR FORTY-SEVEN VARIABLES

Variable	Mean		T Score	Prob>|T| [c]
	Group I	Group II		
Liquidity				
CashTA	0.08997	0.08125	0.6341	0.5270
NWC	1.24780	1.60261	-2.9460	0.0038[a]
CR	2.68837	2.38681	1.2856	0.2007
CRX	0.06209	-0.27957	1.5660	0.1196
CATA	0.56362	0.56785	-0.1235	0.9019
CATAX	0.00460	-0.00364	0.3582	0.7208
Leverage				
DR	0.41191	0.49530	-3.4148	0.0008[a]
DRX	-0.04749	0.04136	-3.6495	0.0004[a]
BVDMVE	0.01316	0.02012	-2.1770	0.0312[b]
Coverage				
TIE	16.78902	11.51226	0.9357	0.3510
TIEX	-6.42851	-9.30915	-0.8807	0.3800
CFInt	12.88970	9.20489	0.7561	0.4508
CFIntX	-4.05525	-7.32408	-0.8752	0.3830
CFTD	0.32265	0.22430	2.1142	0.0363[b]
CFTDX	0.01759	-0.06885	1.9219	0.0567
Profitability				
NPM	0.06123	0.04322	1.6242	0.1066
NPMX	0.00672	-0.00173	0.8607	0.3909
TAT	1.36554	1.52881	-1.0248	0.3072
TATX	-0.04764	-0.09156	0.4546	0.6501
ROA	0.06806	0.04245	2.5986	0.0104[b]
ROAX	0.00645	-0.01184	1.9786	0.0498[b]
RONW	0.12403	0.08875	1.7376	0.0845
RONWX	-0.00050	-0.01551	0.6591	0.5109
EbitTA	0.14291	0.10832	2.4529	0.0154[b]
EbitTAX	0.00856	-0.01505	1.6268	0.1060
EbitNW	0.26920	0.25656	0.3765	0.7071
EbitNWX	-0.02455	-0.00755	-0.4664	0.6417
CFTA	0.11010	0.08382	2.4371	0.0161[b]
CFTAX	0.00904	-0.00964	1.7011	0.0911
CFNW	0.20877	0.21003	-0.0362	0.9712
CFNWX	-0.01133	0.01129	-0.6582	0.5115

TABLE 4.1-Continued

Variable	Mean		T Score	Prob>|T| [c]
	Group I	Group II		
		Company Size		
S	1.97148	2.33616	-3.3604	0.0010 [a]
TA	1.89411	2.21396	-2.8679	0.0048 [a]
		Company Growth		
SGr	0.21454	0.20973	0.1468	0.8835
TAGr	0.18830	0.19313	-0.1601	0.8730
EPSGr	0.18860	0.06670	1.1322	0.2595
		Dividend Policy		
AvgDiv	1.41812	11.29757	-2.3534	0.0200 [b]
DPSEPS	0.16713	0.17265	-0.0790	0.9371
DPSEPSX	-0.08448	-0.06911	-0.2190	0.8270
		Variability		
SVar	0.40417	0.41128	-0.2267	0.8210
EPSVar	0.80723	0.97801	-1.3996	0.1638
		Market Factors		
PE	9.66161	7.28233	0.6922	0.4906
PEX	0.40952	-2.63573	0.8885	0.3758
PCP	8.41770	5.07787	1.1673	0.2451
MPBV	9.91062	10.38626	-0.3650	0.7157
TrOut	0.33102	0.29641	0.8500	0.3968
AccmDp	0.59061	0.56880	1.0440	0.2983

NOTE: Group I is the acquisition group and Group II is the random sample from the general corporate population.

[a] Significant at the .01 level.
[b] Significant at the .05 level.
[c] T-test is two tailed.

All three variables in the leverage category represent statistically significant differences between the two groups. The debt ratio (DR) and the industry adjusted debt ratio (DRX) both indicate that acquired firms use less debt than other companies, both in general and within their own industry. The third ratio in this group indicates that the book value of debt to the market value of equity (BVDMVE) is higher for firms in the general group. This is due in large part to the lower debt carried by acquired firms, although it may also indicate a higher equity value compared to debt for the acquired group.

In the coverage group, the cash flow to total debt ratio (CFTD) has a level of significance less than .05. Generally, acquired firms have a higher cash flow when compared to debt than those companies in the general group, stemming from lower debt and perhaps a better cash flow situation.

The profitability group provides four significant variables. The return on assets (ROA) and the industry adjusted return on assets (ROAX) are both higher for acquired firms. Also, acquired firms appear to have a higher earnings before interest and tax to total assets ratio (EbitTA) and cash flow to total assets ratio (CFTA).

Both the sales (S) and total assets (TA) variables, which comprise the company size group, are significant at the .01 level. These two variables, which are highly correlated, indicate that firms that are acquired generally are smaller in size than the general population.

The final variable with univariate significance is average dividends, which is contained in the dividend policy group. Acquired firms paid a lower average dividend over the previous five years. This variable relates both to company dividend policy and company size. None of the variables in the company growth, variability, or market factors groups appear significant.

It is possible to anticipate the high rate of correlation among the variables included for study. This is unimportant in a univariate analysis, but is important to a multivariate analysis such as discriminant analysis. This is what causes dimension reduction to be such an important step in a model development. Many of the variables contain much of the same information and it is difficult to select the variable (or combination of variables) that gives the best explanation of this information. Unfortunately, in computing variables for study, most of which are obtained from the financial records of the firms involved, this type of business research makes it nearly impossible to avoid this problem.

Before turning to the multivariate analysis, there is one more type of t-test that is of interest. Each of the sixteen industry adjusted variables takes the firm's ratio and subtracts from it the appropriate industry average. Since the group of firms representing the general corporate population was drawn randomly from this identified population, the group averages will be different from zero. The expected value for the entire population, of course, would be zero since these are the firms comprising the industries used. Therefore, a better comparison for these industry adjusted variables would be a test of the hypothesis that each of the Group I (acquired firms) means is equal to zero. The t score and probability of obtaining a higher value of t are presented in Table 4.2.

TABLE 4.2

T-TEST OF HYPOTHESIS THAT MEAN = 0;
SIXTEEN INDUSTRY ADJUSTED VARIABLES FROM GROUP I

Variable	T Score	Prob>|T|[b]	Variable	T Score	Prob>|T|[b]
CRX	0.46881	0.64066	ROAX	1.55993	0.12329
CATAX	0.29949	0.76546	RONWX	-0.04581	0.96360
DRX	-2.80683	0.00648[a]	EbitTAX	0.94465	0.34809
TIEX	-1.12007	0.26651	EbitNWX	-1.24529	0.21718
CFIntX	-0.93533	0.35284	CFTAX	1.41500	0.16150
CFTDX	0.54723	0.58596	CFNWX	-0.90404	0.36908
NPMX	0.92729	0.35696	DPSEPSX	-2.59551	0.01150[a]
TATX	-0.84824	0.39920	PEX	0.16506	0.86937

[a]Significant at the .01 level.
[b]T-test is two tailed.

Only two of the variables are significant here at a level of .01 and there are none to add at the .05 level. The adjusted debt ratio (DRX) is still significant. Two changes in the results do occur however. The adjusted return on assets ratio (ROAX) is no longer significant. Another group difference is brought to light in that the adjusted dividends per share to earnings per share (DPSEPSX) now is significant. This reinforces the information provided by the average dividend variable which indicated the possibility that acquired firms generally paid out a smaller dividend.

This concludes the univariate results. The next section will begin the multivariate presentation beginning with the consideration of the underlying assumptions of DA.

Assumption of Multivariate Normality

One of the underlying assumptions of discriminant analysis is that multivariate normality exists in the distribution of study variables. A preliminary test of this assumption is to consider the normality of the distribution of each of the individual variables. Normality here does not in itself confirm the existence of multivariate normality, but it may confirm nonmultivariate normality. A Kolmogorov Test for normality for each of the forty-seven variables and both groups individually is presented in Table 4.3.

It is quite apparent that most of the variables are not normally distributed. Thus, the underlying assumption of multivariate normality has been violated. About one in three of the liquidity and leverage ratio distributions are not normal, and almost all of the ratios in the

TABLE 4.3

KOLMOGOROV TEST FOR NORMALITY OF
VARIABLE DISTRIBUTIONS: TWO GROUPS, FORTY-SEVEN VARIABLES

Variable	Group I		Group II	
	D Score	Prob>D	D Score	Prob>D
		Liquidity		
CashTA	0.15085	<0.010	0.20569	<0.010
NWC	0.10050	0.075	0.08520	>0.150
CR	0.08607	>0.150	0.20700	<0.010
CRX	0.11625	0.018	0.22633	<0.010
CATA	0.13578	<0.010	0.08707	>0.150
CATAX	0.05690	>0.150	0.11340	0.022
		Leverage		
DR	0.09819	0.088	0.08326	>0.150
DRX	0.06775	>0.150	0.11006	0.032
BVDMVE	0.23014	<0.010	0.23080	<0.010
		Coverage		
TIE	0.30481	<0.010	0.32279	<0.010
TIEX	0.26453	<0.010	0.47092	<0.010
CFInt	0.33777	<0.010	0.36532	<0.010
CFIntX	0.27410	<0.010	0.48761	<0.010
CFTD	0.12515	<0.010	0.22638	<0.010
CFTDX	0.11126	0.028	0.18474	<0.010
		Profitability		
NPM	0.20999	<0.010	0.19356	<0.010
NPMX	0.18257	<0.010	0.14653	<0.010
TAT	0.08755	>0.150	0.22058	<0.010
TATX	0.09314	0.129	0.14426	<0.010
ROA	0.75830	>0.150	0.23175	<0.010
ROAX	0.05284	>0.150	0.21489	<0.010
RONW	0.08788	>0.150	0.26004	<0.010
RONWX	0.09538	0.107	0.17983	<0.010
EbitTA	0.08908	>0.150	0.13758	<0.010
EbitTAX	0.10043	0.076	0.11918	0.013
EbitNW	0.07116	>0.150	0.16551	<0.010
EbitNWX	0.10068	0.074	0.12590	<0.010
CFTA	0.06347	>0.150	0.17539	<0.010
CFTAX	0.05933	>0.150	0.19419	<0.010
CFNW	0.12085	<0.010	0.24484	<0.010
CFNWX	0.12308	<0.010	0.23070	<0.010

TABLE 4.3-Continued

Variable	Group I D Score	Group I Prob>D	Group II D Score	Group II Prob>D
Company Size				
S	0.06061	>0.150	0.06330	>0.150
TA	0.07281	>0.150	0.07407	>0.150
Company Growth				
SGr	0.17397	<0.010	0.18475	<0.010
TAGr	0.17399	<0.010	0.17885	<0.010
EPSGr	0.35501	<0.010	0.28736	<0.010
Dividend Policy				
AvgDiv	0.27948	<0.010	0.37444	<0.010
DPSEPS	0.18793	<0.010	0.33164	<0.010
DPSEPSX	0.14025	<0.010	0.22616	<0.010
Variability				
SVar	0.10261	0.063	0.07500	>0.150
EPSVar	0.21198	<0.010	0.17110	<0.010
Market Factors				
PE	0.32275	<0.010	0.31964	<0.010
PEX	0.31901	<0.010	0.25203	<0.010
PCF	0.39539	<0.010	0.20297	<0.010
MPBV	0.19688	<0.010	0.24987	<0.010
TrOut	0.16498	<0.010	0.16854	<0.010
AccmDp	0.08552	>0.150	0.07630	>0.150

NOTE: Group I is the acquisition group and Group II is the random sample from the general corporate population.

coverage, profitability, company growth, dividend policy, and market factors groups exhibit this at a significance level of .01.

As is the case with most previous research using financial variables displaying nonmultivariate normality, it will be assumed that DA is robust enough to compensate for this violation of an assumption. Adequate model performance would be an indication of robustness. However, it is important to consider the effect of this violation. Unfortunately, little research has been conducted in this area. Pinches [1980, p. 433] summarizes the tentative conclusions that may be drawn,

> While much more empirical and theoretical work is needed, the presence of nonmultivariate normality indicates that 1) error rates are generally affected for both the linear and quadratic discriminant functions; 2) the quadratic is affected even more than the linear; and 3) correlation among the predictor variables may substantially influence classification results. The magnitude and direction of the impact is, in general, unknown but appears to be a function of the number of variables, the extent of the correlation between the variables, the distance between the k groups, the equality or inequality of the dispersion matrices, and the extent of the nonmultivariate normality.

Adjustments were made where possible to the individual variable distributions,[2] but for the most part, the nonnormality is difficult to correct. Many of the variables appeared to have normal distributions except for one or two outliers that fell many standard deviations from the mean. It is important to consider the nonmultivariate normality, but it is necessary to accept this as a condition and to rely on the robustness of the DA technique. The violation of this assumption is mitigated somewhat by the use of the Lachenbruch U method of classifying

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[2]These are already reflected in the tables and include lognormal transformation of the sales, total assets, and net working capital variables.

observations. This method does not assume normality. Based upon the sample data, it will provide an almost unbiased estimate of the classification accuracy that a particular model will achieve in the entire population.

It is interesting to note that the effect on the quadratic formulation of the model is more severe than it is for the linear model. The need to compare these two types of model formulation will arise again in the next section when considering the assumption of the equality of the population dispersion matrices.

Assumption of Equal Dispersion Matrices

A second important assumption of discriminant analysis is that the population dispersion matrices are equal. If the matrices are not equal, then it is necessary to consider the usage of a quadratic formulation of the discriminant model. A first step is to consider the equality of dispersion between groups for each of the individual variables. These are presented in Table 4.4. Unfortunately, tests for the equality of dispersion are based upon an assumption of normality which, as noted previously, has been violated. Therefore, any conclusions concerning the equality of dispersion must weigh this factor.

An F-test of the equality between group variances for each of the individual variables was conducted. The hypothesis of equality is rejected at the .01 level of significance for a total of twenty-two variables. This hypothesis is rejected for four more variables at the .05 level. Given these results, it is highly probable that an overall test will reach the same conclusion.

TABLE 4.4

F-TEST OF EQUALITY
BETWEEN GROUP VARIANCES FOR FORTY-SEVEN VARIABLES

Variable	Standard Deviation		F Score	Prob>F
	Group I	Group II		
Liquidity				
CashTA	0.08256	0.08120	1.030	0.8901
NWC	0.64885	0.78035	1.450	0.1250
CR	1.20331	1.56805	1.700	0.0282[b]
CRX	1.11595	1.46093	1.710	0.0256[b]
CATA	0.21165	0.19561	1.170	0.5112
CATAX	0.12943	0.14423	1.240	0.3672
Leverage				
DR	0.13982	0.15098	1.170	0.5221
DRX	0.14257	0.14752	1.070	0.7760
BVDMVE	0.01645	0.02133	1.680	0.0314[b]
Coverage				
TIE	36.45000	30.48211	1.430	0.1371
TIEX	48.36097	117.08705	27.600	0.0001[a]
CFInt	30.14177	27.55598	1.200	0.4548
CFIntX	36.53280	121.71057	46.720	0.0001[a]
CFTD	0.25710	0.29587	1.320	0.2423
CFTDX	0.27083	0.26507	1.040	0.8577
Profitability				
NPM	0.07191	0.05966	1.450	0.1205
NPMX	0.06105	0.05576	1.200	0.4504
TAT	0.63676	0.99098	2.420	0.0003[a]
TATX	0.47321	0.66248	1.960	0.0055[a]
ROA	0.04413	0.07037	2.540	0.0001[a]
ROAX	0.04567	0.07337	2.580	0.0001[a]
RONW	0.07671	0.15289	3.970	0.0001[a]
RONWX	0.09221	0.16831	3.330	0.0001[a]
EbitTA	0.07741	0.09016	1.360	0.2045
EbitTAX	0.07636	0.09556	1.570	0.0626
EbitNW	0.14889	0.24037	2.610	0.0001[a]
EbitNWX	0.16610	0.25824	2.420	0.0003[a]
CFTA	0.05250	0.07417	2.000	0.0044[a]
CFTAX	0.05382	0.07523	1.950	0.0057[a]
CFNW	0.12096	0.26849	4.930	0.0001[a]
CFNWX	0.10563	0.26967	6.520	0.0001[a]

TABLE 4.4-Continued

Variable	Standard Deviation Group I	Standard Deviation Group II	F Score	Prob>F
		Company Size		
S	0.51330	0.75677	2.170	0.0014[a]
TA	0.50300	0.79380	2.490	0.0001[a]
		Company Growth		
SGr	0.19373	0.19681	1.030	0.8954
TAGr	0.14137	0.21178	2.240	0.0009[a]
EPSGr	0.72980	0.53893	1.830	0.0122[b]
		Dividend Policy		
AvgDiv	2.37773	35.29214	220.310	0.0001[a]
DPSEPS	0.24130	0.53692	4.950	0.0001[a]
DPSEPSX	0.27425	0.52370	3.650	0.0001[a]
		Variability		
SVar	0.20392	0.16788	1.480	0.1061
EPSVar	0.71023	0.74351	1.100	0.7026
		Market Factors		
PE	21.00491	20.00558	1.100	0.6844
PEX	20.90545	19.92684	1.100	0.6893
PCF	23.64004	4.72808	25.000	0.0001[a]
MPBV	6.44522	8.88904	1.900	0.0079[a]
TrOut	0.25657	0.22773	1.270	0.3206
AcmmDp	0.11978	0.12898	1.160	0.5372

NOTE: Group I is the acquisition group and Group II is the random sample from the general corporate population.

[a]Significant at the .01 level.
[b]Significant at the .05 level.

Almost all of the variable groupings contained members that yielded unequal dispersion. In particular, the profitability, company size, company growth, and dividend policy groups contained variables with unequal dispersion between the acquired and nonacquired samples. However, it is important to note that in many of the cases one or two outliers in one of the samples highly influenced the results.

To confirm the violation of this assumption, it is necessary to conduct an overall test. The multivariate analog of Bartlett's test for the homogeneity of variances is used to test this. The null hypothesis that the population dispersion matrices are equal is expressed below:

$$H_o: \Sigma_1 = \Sigma_2$$

$$H_a: \Sigma_1 \neq \Sigma_2$$

where:

Σ_1 = the true within covariance matrix of the variables of the acquired firms, and

Σ_2 = the true within covariance matrix of the variables of the general corporate population.

Test Chi-Square Value = 2914.259, Prob > Chi-Square = .0001.

The sample estimates of the dispersion matrices, of course, are used to test this hypothesis since the true matrices are unknown. The test statistic is distributed approximately as a Chi-Square distribution and the null hypothesis is rejected at the .0001 level. The violation of this assumption indicates the need to consider the quadratic formulation of the discriminant model.

Before accepting the change to a quadratic specification, Pinches [1980, p. 441] indicates that there are two issues to examine. First, the impact of nonmultivariate normality must be considered. Second, the impact of unequal dispersion matrices on the test for the equality of group centroids and model classification accuracy must be assessed. In addressing the first point, Pinches [1980, p. 441] concludes:

> . . . testing for unequal dispersion matrices in the presence of nonmultivariate normality yields biased results. The size and direction of the bias is apparently unknown, but prudence suggests researchers should only employ quadratic classification rules in cases where the test for the equality of the dispersion matrices presents overwhelming evidence of nonhomogeneity in the population.

In considering the impact on the test for the equality of group centroids, Pinches [1980, p. 42-43] summarizes the implications from previous research by stating,

> Studies indicate that quadratic rules produce more accurate estimates of classification accuracy when the sample is large relative to the number of variables, when the difference between the dispersion matrices is large, and when the data are multivariate normal. In other situations, linear rules may produce more accurate estimates of the probabilities of misclassification.

The choice of the quadratic classification rule is not clear in this case and there is little evidence to indicate that the linear rule would provide poorer results. Since, it is the research intent to build a simple model that can be used as a portfolio selection device, and since there are not sufficient grounds to incorporate the quadratic rule, the linear formulation of the discriminant model will be employed here.

With the implications from the violation of these two underlying assumptions in mind, the application of the DA technique to the research problem will be presented. In the next section, a test of the full variable model will be conducted to determine if there is significant discriminatory power contained within one, or a group, of the variables employed in the analysis.

Simultaneous Test of Mean Equality

Hotelling's T^2 statistic, which is analogous to the univariate t statistic except that it applies to all the variables simultaneously, is applied to test for a difference in group means. This hypothesis is expressed below:

H_o: $M_{1j} = M_{2j}$ for all j, where j equals the total range of variables.

H_a: $M_{1j} \neq M_{2j}$ for some variable j, or some group of variables.

where:

M_{1j} = the mean of Group I for variable j, and

M_{2j} = the mean of Group II for variable j.

$D^2 = 2.4628$, $T^2 = 87.43$, $F(47,94) = 1.249$, Prob > F = 0.1803

The T^2 statistic can be transformed to an F statistic, which indicates a significance of eighteen percent. This may not appear to imply much discriminatory power within the variables included for study, but this could be expected with such a large number of variables when compared to the sample size. Many of these variables do not have any discriminatory power and these are masking the subgroups of variables that do. In fact, the removal of twelve of the original variables yields an F statistic significant at the .01 level. Hotelling's T^2 is a specific case of the Wilks' Lambda statistic applicable to the two group problem. Wilks' Lambda will be used from now on to test the power of particular model candidates. When the overall discriminatory power has been determined, dimension reduction can begin.

Dimension Reduction

In order to build a workable model, a reduction of variables must occur. As shown in the previous section, elimination of twelve of the poorer variables provides a model with a very significant difference between group means. This indicates the existence of subsets of the variables that contain good discriminatory power. However, it is necessary to proceed with care during this elimination process, so that the most powerful subset is retained.

It is already apparent from the previous analysis in this chapter that much multicollinearity exists within the variables. Correlation between some of the variables is quite large, as would be expected given the variable definitions themselves. The highest positive correlation (.9978) is between the industry adjusted times interest earned and cash flow to interest ratios. The largest negative correlation exists between the industry adjusted debt and cash flow to total debt ratios, and is -.6865.

Multicollinearity is not as large a problem in DA as it is in the use of such techniques as regression. However, its effect on DA (and importance) is still not clear. Pinches [1980, p. 435] states:

> While, theoretically, multicollinearity may not cause problems in discrimination, in applied (i.e., sample-based) research a thorough review of the literature indicates there is a definite relationship between the degree of correlation among the predictor variables and the classification results.

The researcher should be aware of its existence, but should neither avoid nor ignore multicollinearity among the study variables. Principal components analysis, presented next, provides much insight into this problem by examining the relationships among the variables.

Principal Components Analysis

A principal components analysis was conducted utilizing the full forty-seven variable model. With standardized data, the total variance will equal the number of variables, and there will be forty-seven factors drawn from the data. Table 4.5 presents the variance accounted for by each of these factors, the percentage of the total variance, and the cumulative percentage. The first few factors explain a majority of the variance; the first ten account for over seventy-seven percent and the first twenty account for over ninety-three percent.

Only factors that explain large amounts of the variance need be retained. The procedure used here eliminated any factor with an eigenvalue less than one, the equivalent of the variance contributed by one variable. Thus, twelve factors were retained for further analysis. Of the factors removed all contributed very little to the total explanation of variance, with the highest being 2.1 percent. However, with the removal of thirty-five factors, the remaining twelve explain only 82.2 percent of the total variance.

TABLE 4.5

SUMMARY OF PRINCIPAL COMPONENTS ANALYSIS;
VARIANCE EXPLAINED BY EACH OF FORTY-SEVEN FACTORS

Factor	Variance	Percent Variance	Cumulative Percent
1	11.01	23.4	23.4
2	5.39	11.5	34.9
3	4.14	8.8	43.7
4	3.61	7.7	51.4
5	2.83	6.0	57.4
6	2.38	5.1	62.5
7	2.09	4.4	66.9
8	1.81	3.8	70.7
9	1.61	3.4	74.2
10	1.40	3.0	77.2
11	1.29	2.7	79.9
12	1.09	2.3	82.2
13	0.97	2.1	84.3
14	0.84	1.8	86.1
15	0.75	1.6	87.7
16	0.72	1.5	89.2
17	0.64	1.4	90.6
18	0.54	1.2	91.7
19	0.50	1.1	92.8
20	0.49	1.0	93.8
21	0.40	0.9	94.7
22	0.39	0.8	95.5
23	0.37	0.8	96.3
24	0.30	0.6	97.0
25	0.23	0.5	97.4
26	0.22	0.5	97.9
27	0.18	0.4	98.3
28	0.16	0.4	98.6
29	0.13	0.3	98.9
30	0.12	0.3	99.2
31	0.08	0.2	99.3
32	0.06	0.1	99.5
33	0.05	0.1	99.6
34	0.04	0.1	99.7
35	0.03	0.1	99.7
36	0.03	0.1	99.8
37	0.02	0.0	99.8
38	0.02	0.0	99.9
39	0.01	0.0	99.9
40	0.01	0.0	99.9
41	0.01	0.0	100.0
42	0.01	0.0	100.0
43	0.01	0.0	100.0
44	0.00	0.0	100.0
45	0.00	0.0	100.0
46	0.00	0.0	100.0
47	0.00	0.0	100.0

Retaining twelve factors, an orthogonal Varimax rotation was applied to the original factor matrix. The aim of this procedure is to simplify the explanation of the factors (columns). Table 4.6 presents the variance and percentage variance explained by each of the factors, of the total 82.2 percent of the original variance that remains. As can be seen, the first four factors explain over half of the variance.

Variables with high factor loadings on a given factor are grouped together to form an identification for that factor. One of the problems here involves where to cut off the membership in a factor based on these loadings. A cutoff of .7 was used since this generally provided a significant gap between clusters of variable loadings for each of the factors. It also divided the variables into identifiable groupings. Table 4.7 lists the factor loadings for each variable on each of the twelve factors.

Table 4.8 presents a summary of the factor compositions. The table lists the variables included and the variable names for each of the twelve factors. The naming of the factors based upon the variable composition was generally easy because of the common binds in most of the groups. However, the name chosen for several of the factors was difficult because of its variable membership, and thus, the names are not entirely appropriate.

Eight variables loaded onto the first factor which is by far the most important one in terms of variance explained. All the variables were from the profitability group, and given the large number of variables contained within this group, the importance of this variable is hardly surprising.

TABLE 4.6

SUMMARY OF PRINCIPAL COMPONENTS ANALYSIS:
VARIMAX ROTATION, TWELVE FACTORS RETAINED

Factor	Variance	Percent Variance	Cumulative Percent
1	8.97	23.2	23.2
2	4.49	11.6	34.8
3	3.04	7.9	42.7
4	3.15	8.2	50.9
5	2.83	7.3	58.2
6	2.82	7.3	65.5
7	3.32	8.6	74.1
8	2.10	5.4	79.5
9	1.88	4.9	84.4
10	3.23	8.4	92.8
11	1.57	4.1	96.9
12	1.25	3.2	100.0

TABLE 4.7

FACTOR LOADINGS: ORTHOGONALLY ROTATED
FACTOR MATRIX, VARIMAX ROTATION

Variable / Factor	1	2	3	4	5	6	7	8	9	10	11	12
CashTA	0.079	0.137	0.088	-0.010	0.108	0.051	0.762	-0.099	0.048	0.031	0.040	-0.072
NWC	0.076	-0.074	-0.036	0.880	0.147	-0.055	0.100	0.167	0.070	-0.117	0.134	0.093
CR	0.097	-0.005	-0.125	-0.105	0.117	-0.084	0.869	0.111	0.057	-0.116	-0.055	0.050
CRX	0.110	0.055	-0.048	-0.083	0.046	-0.041	0.880	0.039	-0.040	-0.114	-0.044	0.050
CATA	0.055	-0.105	0.014	-0.063	0.767	-0.169	0.274	0.108	0.002	0.012	-0.200	-0.003
CATAX	0.074	-0.078	-0.017	-0.083	0.781	-0.060	0.163	0.100	0.000	0.004	0.076	0.111
DR	-0.208	-0.278	0.177	0.065	0.180	-0.017	-0.451	-0.074	-0.384	0.579	0.030	0.045
DRX	-0.197	-0.332	0.088	0.058	0.230	0.005	-0.472	0.013	-0.244	0.565	0.014	0.139
BVDMVE	-0.241	-0.065	0.116	-0.014	-0.061	-0.002	-0.197	-0.117	-0.714	0.353	-0.006	-0.069
TIE	0.244	0.809	0.121	-0.022	0.068	0.006	0.242	-0.053	0.189	-0.027	-0.009	-0.028
TIEX	0.053	0.924	0.031	-0.027	-0.081	-0.010	-0.099	0.033	-0.073	-0.032	0.007	0.059
CFInt	0.216	0.868	0.084	-0.017	-0.005	0.002	0.228	-0.056	0.148	-0.011	0.005	-0.024
CFIntX	0.044	0.919	0.017	-0.032	-0.091	-0.009	-0.104	0.038	-0.083	-0.032	0.001	0.058
CFTD	0.530	0.597	-0.002	-0.074	-0.195	0.010	0.337	-0.014	0.249	-0.081	0.027	-0.088
CFTDX	0.549	0.602	-0.001	-0.021	-0.137	-0.036	0.402	-0.058	0.074	-0.099	-0.072	-0.137
NPM	0.611	0.362	0.035	-0.128	-0.366	0.036	-0.094	0.053	0.222	-0.190	0.051	-0.046
NPMX	0.681	0.391	0.003	-0.071	-0.238	-0.109	-0.015	-0.006	-0.046	-0.164	-0.146	-0.107
TAT	-0.114	-0.035	0.031	0.034	0.661	-0.034	-0.063	-0.219	-0.189	-0.053	-0.205	-0.281
TATX	-0.013	-0.038	-0.220	-0.051	0.659	0.081	-0.171	-0.120	0.178	0.011	0.216	-0.061
ROA	0.943	0.125	0.090	0.046	-0.014	-0.019	0.122	0.051	0.126	0.007	0.024	0.001
ROAX	0.932	0.120	0.058	0.033	0.008	-0.142	0.151	0.038	0.044	0.071	-0.023	0.099
RONW	0.926	0.001	0.079	0.082	-0.022	0.069	0.017	0.043	-0.034	0.190	0.069	0.009
RONWX	0.858	-0.005	0.057	0.046	0.033	-0.154	0.080	0.066	-0.016	0.263	0.015	0.174
EbitTA	0.923	0.115	0.120	-0.002	0.163	0.059	0.077	0.029	0.090	0.012	-0.038	-0.089
EbitTAX	0.916	0.122	0.065	0.008	0.169	-0.094	0.083	0.035	0.027	0.077	-0.074	0.051
EbitNW	0.718	-0.018	0.086	-0.050	0.126	0.072	-0.115	0.003	-0.044	0.594	0.005	-0.097
EbitNWX	0.518	-0.022	0.075	-0.079	0.173	-0.447	-0.064	0.123	0.079	0.582	-0.008	0.188
CFTA	0.854	0.174	0.041	0.039	-0.156	0.172	0.113	-0.028	0.104	0.112	0.090	-0.155
CFTAX	0.297	0.060	0.041	-0.123	-0.044	-0.724	0.110	0.143	0.200	0.207	0.070	0.205
CFNW	0.477	0.013	-0.027	-0.050	-0.162	0.146	-0.078	-0.054	0.068	0.769	0.087	-0.159
CFNWX	0.482	-0.047	-0.039	-0.024	-0.098	-0.022	-0.022	-0.018	0.094	0.807	-0.027	-0.056

TABLE 4.7-Continued

Variable / Factor	1	2	3	4	5	6	7	8	9	10	11	12
S	0.038	-0.055	-0.006	0.943	0.016	0.103	-0.133	0.014	-0.126	-0.006	0.101	-0.089
TA	0.043	-0.014	0.002	0.891	-0.248	0.179	-0.148	0.062	-0.062	-0.022	0.174	0.010
SGr	0.033	0.124	0.868	-0.103	0.024	0.190	-0.002	-0.030	0.020	0.104	0.074	0.103
TAGr	0.096	0.011	0.882	-0.030	-0.028	-0.050	0.002	-0.023	0.090	0.059	-0.022	-0.065
EPSGr	0.186	-0.029	0.225	-0.199	-0.073	0.274	0.103	0.057	-0.075	0.180	0.371	0.325
AvgDiv	-0.040	-0.001	-0.126	0.638	-0.114	-0.039	-0.069	0.090	0.206	0.115	-0.254	0.090
DPSEPS	0.066	-0.005	-0.114	0.156	-0.007	0.113	0.032	0.922	0.039	-0.023	-0.056	-0.070
DPSEPSX	0.073	-0.023	-0.053	0.112	-0.020	0.105	-0.001	0.935	0.061	-0.010	-0.018	-0.099
SVar	0.134	0.074	0.832	0.027	-0.002	0.034	-0.027	-0.048	0.024	0.017	0.087	-0.031
EPSVar	-0.157	-0.034	-0.156	0.245	-0.041	-0.110	-0.049	-0.150	-0.204	0.044	0.738	0.109
PE	0.042	0.012	0.135	0.044	-0.092	0.913	-0.006	0.189	0.111	0.092	-0.044	0.109
PEX	0.032	-0.001	0.146	0.043	-0.086	0.913	-0.009	0.165	0.093	0.065	-0.082	0.102
PCF	-0.078	0.013	0.042	0.094	-0.067	0.040	-0.029	-0.178	0.089	-0.083	-0.004	0.804
MPBV	0.078	0.128	0.326	0.059	-0.013	0.075	-0.035	0.030	0.773	0.306	0.026	0.082
TrOut	0.058	0.021	0.226	0.040	-0.004	-0.120	-0.049	0.034	0.208	-0.024	0.731	-0.095
AccmDp	0.144	-0.025	0.545	-0.077	-0.292	0.145	-0.128	-0.134	-0.044	-0.205	-0.028	0.159

TABLE 4.8

FACTOR NAMES AND VARIABLE COMPOSITION:
TWELVE FACTORS RETAINED

1	2	3	4	5	6	7	8	9	10	11	12
Profitability	Coverage	Growth	Size	CATA	P-E	Liquidity	Div. Policy	Mkt. Value	CFNW	Mkt. Activity	PCF
ROA	TIE	SGr	NWC	CATA	CFTAX	CashTA	DPSEPS	BVDMVE	CFNW	TrOut	PCF
ROAX	TIEX	TAGr	S	CATAX	PE	CR	DPSEPSX	MPBV	CFNWX	EPSVar	
RONW	CFInt	SVar	TA		PEX	CRX					
RONWX	CFIntX										
EbitTA											
EbitTAX											
EbitNW											
CFTA											

The second factor contained four variables from the coverage group. Factor three contains both sales and total asset growth and will be considered the growth factor. Variables loading onto factor four are measures of size, including sales, assets, and net working capital. Factor six is a price-earnings factor and seven contains measures of liquidity. Factor eight is a measure of dividend policy and nine a measure of market value. Factor eleven contains the EPS variance and shares traded to outstanding variables and is difficult to classify.

The factors named so far may be considered common factors. The remaining three are unique factors since they essentially load only one variable (or a variable and its industry adjusted counterpart). Also, twelve variables did not load onto any of the factors. This occurred because of the elimination of factors previously and because these variables contain unique variances that are not shared commonly with any of the other variables.

The principal components analysis has been useful in describing common groupings of variance within the forty-seven variables. It is apparent that profitability, coverage, growth, and size are important dimensions within the data. This result provides insight into the composition of the final discriminant model. However, the variables identified with unique factors should not be overlooked because they may provide a good multivariate combination with the other variables. One factor representative from each factor is not selected either for the same reason. With these points in mind, the variables with poor discriminatory power are identified and removed, and the analysis continues with the reduced variable set.

Partial Dimension Reduction

Utilizing various stepwise discriminant methods, a number of variable models were developed. Forward, backward, and conditional techniques were applied, as were several different selection techniques, including contributions to the F-value, significance of that value, and the partial R^2. Various levels for each of these model building methods were set so that the difference in model development could be followed. This approach allows all variables to have the opportunity for interaction, and at the same time, it identifies variables that were never selected by any technique. These variables contribute little to discriminatory power and can be removed.

Twenty-two variables were identified from the various stepwise procedures as worthy of further consideration, and the rest were eliminated. The remaining variables are identified in Table 4.9 according to their factor membership. Also, a unique grouping has been added to identify variables that were not grouped into any factor previously.

At least one variable remained from each of the twelve factors, except for factors five, current assets to total assets, and seven, liquidity. Profitability and growth retained three variables each. Six variables remain in the unique category. Of the twenty-two variables, nine of the original sixteen industry adjusted ratios remain.

In order to examine the relationship among the remaining variables more closely, a principal components analysis was conducted. Eight factors remained this time. Table 4.10 provides the results from this analysis. These eight factors explained nearly eighty percent of the total variance contained in the twenty-two variables. Of this variance,

TABLE 4.9

PARTIAL DIMENSION REDUCTION:
TWENTY-TWO VARIABLES BY FACTOR GROUP

Profitability	Coverage	Growth	Size	P-E	Div. Policy	Mkt. Value	CFNW	Mkt. Activity	PCF	Unique
ROA	TIEX	SGr	NWC	CFTAX	DPSEPS	BVDMVE	CFNWX	TrOut	PCF	DRX
EbitNW		TAGr	S	PE						CFTDX
RONWX		SVar								NPM
										NPMX
										TATX
										EbitNWX

TABLE 4.10

SUMMARY OF REDUCED PRINCIPAL COMPONENTS ANALYSIS:
VARIMAX ROTATION, FACTOR NAMES AND COMPOSITION,
EIGHT FACTORS RETAINED

	1 ROI	2 NPM	3 Growth	4 Size	5 P-E	6 Mkt. Value	7 PCF	8 Activity	Unique
Variable Composition:	ROA EbitNW RONWX EbitNWX CFNWX	CFTDX NPM NPMX	SGr TAGR SVar	NWC S	CFTAX PE	BVDMVE	PCF	TATX	DRX TIEX DPSEPS TrOut
Variance:	3.96	3.47	2.59	1.94	1.75	1.60	1.08	1.11	X
Percent Variance:	22.6	19.8	14.8	11.1	10.0	9.1	6.2	6.3	X
Cumulative Percent:	22.6	42.4	57.2	68.3	78.3	87.4	93.6	99.9	

the first four factors explained nearly sixty-nine percent. Most of the factor identities were the same, but several important changes did occur. Factor one is better defined now as return on investment because a separate factor containing the net profit margin (factor two) has been created. The last factor, a unique one, is represented by the total asset turnover ratio and is therefore an activity factor. Five of the factors are common factors containing more than one ratio. Also, four variables did not identify with any of the eight factors and are listed in the unique grouping. Of the four factors that disappeared, one, the cash flow to net worth was combined into the ROI factor, and the other three were relegated to the unique grouping of variables.

Selection of a final model continued from among the twenty-two variables. Using the relationships identified in Table 4.10 as a guide, a number of model candidates were considered. Possible combinations were identified from the stepwise techniques, but it is necessary to consider the classificatory accuracy of the various candidates before completing the selection process. Many different model candidates were considered and this is summarized in the next section.

Final Model Selection

Once various model candidates were identified, each one's ability to classify observations had to be tested, as the final model's classification accuracy is critical. Six different models are presented in Table 4.11. The table includes the variable composition, classification results, overall classification accuracy, and statistics for each model. The approximate F-value for each of these models obtained from the

TABLE 4.11

DISCRIMINANT ANALYSIS MODEL PERFORMANCE:
CLASSIFICATION ACCURACY OF SIX MODEL CANDIDATES

Model One = NWC + DRX + TIEX + ROA

Actual		Predicted Acquired		Predicted General		Statistics
		%	#	%	#	
Acquired	71	63.4	45	36.6	26	Wilks' Lambda = 0.786
General	71	25.4	18	74.6	53	$F_{(4,137)}$ = 9.332
	142		63		79	Prob > F = <.001

Overall Classification Accuracy = 69%

Model Two = NWC + DRX + TIEX + ROA + NPMX

Actual		Predicted Acquired		Predicted General		Statistics
		%	#	%	#	
Acquired	71	69.0	49	31.0	22	Wilks' Lambda = 0.764
General	71	21.2	15	78.9	56	$F_{(5,136)}$ = 8.425
	142		64		78	Prob > F = <.001

Overall Classification Accuracy = 73.9%

Model Three = NWC + DRX + TIEX + ROA + CFTAX

Actual		Predicted Acquired		Predicted General		Statistics
		%	#	%	#	
Acquired	71	66.2	47	33.8	24	Wilks' Lambda = 0.776
General	71	26.8	19	73.2	52	$F_{(5,136)}$ = 7.845
	142		66		76	Prob > F = <.001

Overall Classification Accuracy = 69.7%

TABLE 4.11-Continued

Model Four = NWX + DRX + TIEX + NPM + ROA

Actual		Predicted Acquired		Predicted General		Statistics
		%	#	%	#	
Acquired	71	66.2	47	33.8	24	Wilks' Lambda = 0.778
General	71	28.2	20	71.8	51	$F_{(5,136)}$ = 7.755
	142		67		75	Prob > F = <.001

Overall Classification Accuracy = 69.0%

Model Five = NWC + DRX + TIEX + ROA + TATX

Actual		Predicted Acquired		Predicted General		Statistics
		%	#	%	#	
Acquired	71	64.8	46	35.2	25	Wilks' Lambda = 0.779
General	71	31.0	22	69.0	49	$F_{(5,136)}$ = 7.731
	142		68		74	Prob > F = <.001

Overall Classification Accuracy = 66.9%

Model Six = NWC + DRX + CFTDX + ROA + NPMX

Actual		Predicted Acquired		Predicted General		Statistics
		%	#	%	#	
Acquired	71	63.4	45	36.6	26	Wilks' Lambda = 0.751
General	71	33.8	24	66.2	47	$F_{(5,136)}$ = 9.012
	142		69		73	Prob > F = <.001

Overall Classification = 64.8%

NOTE: Model classification accuracy was based upon the Lachenbruch U classification scheme.

Wilks' Lambda indicates that all six models are statistically significant on the test of difference between the group centroids. This indicates that in each case the distance between groups could not have occurred by chance and that each model contains discriminatory power. However, this statistic is of little use in aiding in the selection of a model from among choices that all have discriminatory power.

In building a discriminant model in every case, the adjusted debt ratio (DRX) and the net working capital (NWC) variable were always first to enter the model. The adjusted times interest earned (TIEX) and return on assets (ROA) ratios were usually third and fourth. This is the composition of the first model. Its overall classification accuracy is sixty-nine percent, but its ability to identify acquired firms is much less (see Table 4.11).

The fifth variable to enter the model using a stepwise discriminant procedure was the adjusted net profit margin (NPMX), which added to model one was the basis for model two. This model's overall accuracy is 73.9 percent and its ability to select acquired firms is sixty-nine percent. In subsequent discriminant interations, the DRX, NWC, and ROA variables remain in the model. The TIEX and NPMX ratios both left under some stepwise specifications. Therefore, the three remaining variables were used as a foundation and other variables were combined with them to replace TIEX and NPMX. These three variables represent factors one and four, and one unique factor. Variables from other factors were included and were combined with this foundation, but as can be seen, none proved to be better than model two.

Model three attempted to improve results by adding in another variable from factor two instead of NPMX. Model four exchanged NPM for NPMX. Results deteriorated in both cases. Model five substituted the adjusted total asset turnover ratio (TATX) in for NPMX and model six substituted adjusted cash flow to total debt (CFTDX) in for TIEX. Neither of these two models were able to improve performance either. Many other combinations were considered in attempting to bring other ignored factors into the model. In each case, the results were inferior to those of model two. Model classification accuracy appears to peak with the five variables included in the model that was selected. It cannot be said that this is the optimal combination of variables, because all possible combinations were not considered. However, the model does meet the specifications set forth in this study, and it represents the best combination of variables that was discovered.

Before presenting the specific model selected, it is necessary to determine the significance of its discriminatory power. The model's classification results are better than those for any other model considered, and the distance between group centroids is also significant, but this does not mean that the model's selection ability is any better than that obtained by chance.

Utilizing the proportional chance model from Chapter Three yields a comparative statistic of .5; classification accuracy by chance alone should classify fifty percent of the firms accurately. The significance of the difference between classifications of .5 and .739 can be tested by computing a standardized normal Z score[4] in the following manner:

$$Z = \frac{\bar{y} - \pi}{\left[\frac{\pi(1-\pi)}{n}\right]^{\frac{1}{2}}} \tag{4.1}$$

where:

$\bar{y}$ = the proportion of observations correctly classified by the model,

π = the probability of classification by chance, and

n = the total number of observations in both groups.

In this case, the Z score is 5.696 and is significant well below the .001 level. The selected model contains good discriminatory power. In addition, it performs well on two other (conditional) dimensions. The 73.9 percent represents the total efficiency of the model. However, it is the acquired group that is of interest. Of all the acquired firms, the model classified 69 percent accurately. And even more importantly, of all the firms classified as acquired by the model, 76.6 percent were actually acquired. The latter two dimensions are measures of conditional efficiency and really are of more concern than total efficiency here, particularly the second conditional measure. All the models in Table 4.11 had more trouble classifying acquired firms than those in the general group. However, on the second dimension all the models had better

[4] This is not to be confused with the discriminant Z score.

success with the acquired firms.[5] This is significant since the model will be used as a portfolio selection device and the key to its success is its ability to select a high percentage of acquired firms within the group that it identifies as acquired. Model two outperformed the other models on these two dimensions, as well as in the total efficiency of classification. The specific model itself will be presented in the next section.

Discriminant Model

The model contains a total of five variables which includes: net working capital (NWC), the adjusted debt ratio (DRX), the adjusted times interest earned ratio (TIEX), the return on assets ratio (ROA), and the adjusted net profit margin (NPMX). Substituting the discriminant coefficients into equation 3.6 yields the following linear discriminant function:

$$Z_i = 0.72629 - 1.00353\ \text{NWC} - 5.13037\ \text{DRX} + 0.00184\ \text{TIEX} + 12.58367\ \text{ROA} - 8.86868\ \text{NPMX}$$

By placing the variable scores for a given firm into the equation, the firm's discriminant score is computed and the observation can be classfied into one of the two groups. The logarithm of the prior odds does not enter the constant because the a priori odds were specified as .5 for both groups in the model building phase. When the model is applied

[5] Conditional discriminatory power for both conditional dimensions was also statistically significant for model two. Of the acquired firms, sixty-nine percent were classified correctly, yielding a standardized Z score from equation 4.1 of 3.202. Of the firms predicted acquired by the model, the conditional classification accuracy is 76.6 percent (49/64), yielding a Z score of 4.483. Both are significant at well below the .01 level.

in later phases, it will be necessary to adjust the constant by the change that occurs in this logarithm.

The discriminant coefficients provide insight into the group differences determined by the model. Acquired firms generally have less net working capital and below industry average debt ratios compared to firms in the general population. The industry adjusted times interest earned ratio and the return on assets ratio are higher for the acquired group. Finally, the model indicates that the industry adjusted net profit margin is lower for acquired firms on a multivariate basis.

A caveat to these interpretations is in order. The discriminant model is the result of a multivariate analysis and, therefore, all the variables must be considered simultaneously. The DRX, NWC, and ROA ratios had univariate significance and, as a result, may be interpreted separately. However, in making statements about TIEX or NPMX, the result of the interaction of the other four variables in the model is a conditional factor of that interpretation.

Given the univariate results presented earlier, the model composition and the group differences are not surprising. The NWC, DRX, and the ROA variables were all found to have very high univariate significance in explaining group differences. However, the TIEX and NPMX variables had very little univariate significance, but become important in a multivariate model. Given that the return on assets for the acquired group was higher, the negative effect of the adjusted net profit margin may seem surprising. However, the adjusted total asset turnover, the other dimension of ROA, was higher for acquired firms in the equation developed for model five (see Table 4.11). The relative importance of these group differences will be discussed next, after which the discussion will proceed into phase two of the study.

Variable Importance

There is no definitive measure of variable importance. Therefore, five separate measures will be computed to see if there is any consistency in their rankings of the variables. The rankings and measure scores are provided in Table 4.12. The univariate F value is the first measure listed. The second measure, the scaled coefficient, is based on the discriminant coefficient times the standard deviation for each of the variables included. Two other measures consider F values. One is the conditional F obtained by removing each variable individually from the model and testing its significance. The other is the Forward F value that obtained entrance originally for the variable into the model. The final measure, the Mosteller-Wallace coefficient, is a test of the variable's contribution toward the total separation between the two groups.

The measures are fairly consistent in their rankings. Four of five select the adjusted debt ratio as the most important variable. Net working capital is the second most important variable. Return on assets ranked third on four of the five measures. These three variables were all significant on a univariate basis. The adjusted net profit margin and the adjusted times interest earned ratio ranked fourth and fifth respectively.

TABLE 4.12

IMPORTANCE OF INDIVIDUAL VARIABLES:
FIVE VARIABLES, COMPARISON OF FIVE METHODS

Variable Name	Univariate F		Scaled Coefficients[a]		Conditional F		Forward F		Mosteller-Wallace[b]	
	F-Value	Rank	Coefficient	Rank	F-Value	Rank	F-Value	Rank	Percentage	Rank
NWC	8.68	2	-0.721	3	16.55	1	9.60	2	28.79	2
DRX	13.32	1	-0.744	1	16.04	2	13.32	1	36.85	1
TIEX	0.78	5	0.337	5	2.85	5	5.63	4	4.02	5
ROA	6.75	3	0.739	2	10.18	3	6.06	3	23.97	3
NPMX	0.81	4	0.521	4	3.99	4	3.99	5	6.37	4

[a]The scaled coefficients are equal to $b_j\sigma_j$, where b_j is the discriminant coefficient and σ_j is the standard deviation for variable j.

[b]The Mosteller-Wallace coefficient is based upon bj $(\bar{x}_{j1}-\bar{x}_{j2})$, where $\bar{x}_{j1}-\bar{x}_{j2}$ is the difference between group means for variable j. The coefficient represents the contribution of each discriminant variable to the total separation between the two groups. The score above represents the percentage contribution of each variable to this separation.

In general, it can be hypothesized that acquiring firms seek takeover targets that offer latent debt capacity, and are smaller and maintain lower liquidity. In addition, given the aforementioned characteristics, firms with higher times interest earned coverage compared to industry norms and higher returns on assets are sought. Finally, companies experiencing lower net income to sales compared to their respective industries were attractive, perhaps because the acquiring firms identified an inefficiency that was felt to be correctable; given the other factors, such as the higher return on assets of acquired firms.

The model building phase is now complete. The model selected has exhibited strong ex post validity which compares favorably to other studies. Stevens [1973] obtained an overall classification accuracy of 67.5 percent during the same phase of his research, ex post validation, in which he utilized a holdout sample to test this validity. The model's ability to perform on an intertemporal basis is tested during the next phase of research.

Phase Two: Intertemporal Validation

The model selected in phase one has shown ex post validity, but it must also be valid on an intertemporal basis for it to be utilized as a portfolio selection device. A total of 1967 firms from the general population was available for use at the beginning of 1978. During the subsequent two-year period, 171[6] of these firms were actually acquired on an

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[6]Two of these firms are actually classified as liquidations. However, in each case, the company management felt that the stock was underpriced, actively sought an acquisition offer, and profitably liquidated the company by selling it in segments. Thus, it was felt that these two firms aligned more closely with the acquired group.

ex post basis. These firms comprise 8.69 percent of the population. Acquisition activity increased substantially during the second two-year period.

Substituting the variable scores for each firm into Equation 4.2 yielded the predicted group membership for each company. The constant in the equation is adjusted by the change in the logarithms of the ratio between the group a priori probabilities to .0869 and .9131, from the specification of .5 for both groups in the model building stage. The classification results are presented in Table 4.13.

Ninety-four firms are predicted to belong to the acquired group, of which thirteen actually do belong on an ex post basis. The model's overall classification accuracy is 87.85 percent. A random chance selection would provide an average of 87.36 percent. Converting the difference statistically to a standardized normal Z score indicates that the probability of a larger separation is 25.65 percent. This does not appear overly promising, but it should be indicated that prediction of the general group was poorer than that of the acquired group. The intent here is to provide a model that will identify enough acquired firms so that superior portfolio performance is provided. Therefore, the entire acquired group need not be identified. Consideration of the conditional classification accuracy of the acquired group seems sufficient to provide an adequate assessment of the model's ability.

Conditional classification considers one of two dimensions, model performance within the acquired group, and within the predicted acquired group. The important conditional dimension is the ability of the model to identify ex post acquired firms within the total group of firms that

TABLE 4.13

OVERALL CLASSIFICATION ACCURACY FOR DISCRIMINANT MODEL USING THE GROUP A PRIORI PROBABILITY SELECTION SPECIFICATION

Actual			Predicted					
			Acquired			General		
Group	Number	Percent	Cond. %	Number	Total %	Cond. %	Number	Total
Acquired	171	8.69%	13.84%	13	0.66%	8.44%	158	8.03%
General	1796	91.31%	86.17%	81	4.12%	91.56%	1715	87.19%
Total	1967	100.00%	100.00%	94	4.78%	100.00%	1873	95.22%

Overall Classification Accuracy = .0066 + .8719 = .8785

Random Chance Classification = .0478 (.0869) + .9522 (.9131) = .8736

$$Z = \frac{.8785 - .8736}{\left[\frac{.8736\ (1.0 - .8736)}{1967}\right]^{\frac{1}{2}}} = 0.654, \qquad \text{Probability} > Z = 25.65\%$$

Conditional Classification Accuracy (Acquired) = .1383

$$Z = \frac{.1383 - .0869}{\left[\frac{.0869\ (1.0 - .0869)}{94}\right]^{\frac{1}{2}}} = 1.769, \qquad \text{Probability} > Z = 3.85\%$$

it places in the acquired category. On a random basis, 8.69 percent of these firms have the potential to be subsequently acquired. The model selected 13.83 percent. The probability of obtaining a larger percentage difference is 3.85 percent. The model displays a significant ability to select acquisition targets within the portfolio of firms that is identified.

A second method of evaluating the model's performance is through the placement of the correct number of firms in each of the respective groups. Therefore, the first 171 firms from the ranking provided by the discriminant scores are placed in the acquired group. These results are provided in Table 4.14.

Using this method of evaluation the model's performance improves. Of the firms identified as acquired, twenty-four are ex post acquired, for a conditional percentage of 14.04. The overall performance in this case is 85.05 percent, and given that a random chance model would provide 84.13 percent, the probability of obtaining a larger distance in accuracy would be 13.20 percent. Of the firms identified as acquired, the probability of obtaining a larger percentage of ex post acquired firms is less than one percent. Both methods of evaluation illustrate the significant conditional performance achieved by the model.

This completes the intertemporal validation of phase two. The model displays a powerful predictive capacity in identifying ex post acquired firms from among a large number of possible firm candidates. The model appears to perform significantly well in a realistic environment similar to that faced by a small investor in making portfolio selection choices. As such, discriminant analysis shows much promise as a predictive tool in

TABLE 4.14

OVERALL CLASSIFICATION ACCURACY FOR DISCRIMINANT MODEL USING THE CORRECT GROUP NUMBER SELECTION SPECIFCATION

Actual			Predicted					
			Acquired			General		
Group	Number	Percent	Cond.%	Number	Total	Cond.%	Number	Total
Acquired	171	8.69%	14.04%	24	1.22%	8.18%	147	7.47%
General	1796	91.31%	85.96%	147	7.47%	91.82%	1649	83.83%
Total	1976	100.00%	100.00%	171	8.69%	100.00%	1796	91.31%

Overall Classification Accuracy = .0122 + .8383 = .8505

Random Chance Classification = $(.0869)^2 + (.9131)^2 = .8413$

$$Z = \frac{.8505 - .8413}{\left[\frac{.8413\ (1.0 - .8413)}{1967}\right]^{\frac{1}{2}}} = 1.117,$$ Probability >Z = 13.20%

Conditional Classification Accuracy (Acquired) = .1404

$$Z = \frac{.1404 - .0869}{\left[\frac{.0869\ (1.0 - .0869)}{171}\right]^{\frac{1}{2}}} = 2.484,$$ Probability >Z = 0.65%

the merger and acquisition area. There is enough conformity between acquisition targets to allow this statistical technique to identify group differences and use this information in a predictive capacity.

There is one source of bias in the performance evaluation of the discriminant model. The firms comprising the ex post acquired group represent those firms that were merged or acquired during the two year period of investigation. Care was taken with the original sample to insure that there was a dominant firm in the combination so that the potential for stockholder gains would be present. When two firms of similar size merge, the respective gains are not as clearly defined. These types of mergers are, however, included in the acquired group and provide a downward bias on the results by increasing the size of the acquired group without adding any substance. No attempt was made to eliminate these firms because they were identified from the same source as the other members of the group, and any ex post evaluation of their group membership introduces the possibility of a judgmental bias that is best left out of the analysis. Even with this conservative estimate of acquired group membership, the model provides a significantly improved performance.

One final step remains in order to complete the study. The model appears to improve the prediction of acquired firms over that achieved by chance. However, this still is not an indication that the model offers a valid portfolio selection device. To do so, it must identify enough acquired firms so that the positive abnormal benefits, granted by the market to the stockholders of acquired firms, combine with the return from the remainder of the portfolio to provide superior performance. The final section of this chapter describes phase three and considers this aspect further.

Phase Three: Portfolio Selection

The discriminant model has an ability to select more acquisition targets among the firms that it identifies as acquired than does a random chance selection. However, this ability may not be strong enough to influence the entire portfolio return positively. In addition, this ability has not been shown to be uniform across the range of portfolio sizes that investors may decide to accept. The discriminant model provides a ranking of the firms from the most likely to the least likely to be acquired. On an ex ante basis there is no way of determining the optimal portfolio size, so it is necessary to evaluate the performance of portfolios selected from the ranking, starting with a small portfolio and increasing its size. There are two considerations here. First, it must be determined if the selected securities can provide superior performance. Second, the marginal performance of each increase in portfolio size must be considered so that a determination of the consistency of model performance across portfolio size can be evaluated.

A lack of consistency across portfolio size might indicate that the model is not a valid portfolio selection device. Varying specifications of the a priori probability of the acquired group within the total sample will be selected arbitrarily to determine the portfolio composition. An investor faced with a ranking of choices must cut off investment at some point and this method allows the range in portfolio size to be altered for evaluation purposes. The first portfolio comprises firms selected as acquired with an a priori probability specification of .03. This is near the actual probability in the model building sample. Table 4.15 provides the portfolio makeup at each a priori specification, as well as the conditional probability and statistical significance of the selection of actual acquired firms. With groups of greatly different size, the discriminant model is likely to select fewer firms for the group than the probability specified. Each increase in portfolio size is determined by increasing the a priori specification of the acquired group by one percent. This was discontinued at .10 because 117 firms had been selected at this point, and larger portfolios would represent unrealistic situations under the research focus of this study.

At a specification of .03, eighteen firms are placed in the portfolio, two of which are ex post acquired. The portfolio composition and the statistical significance of each of these portfolios is presented in Table 4.15. At a specification of .04, the portfolio size increases by ten firms to a total of twenty-eight. One additional acquired firm is identified. Eighteen firms from the acquired group are selected with the a priori specification set at ten percent.

The conditional percentage of ex post acquired firms begins at eleven percent for the first portfolio. This percentage drops to nine percent at the .05 level and then begins to increase gradually to thirteen percent with the larger portfolios. Although the predictive ability is uneven, in each case the conditional percentage is higher than that provided by random chance. The significance of the selection of acquired firms does not become acceptable until the portfolio increases to eighty-seven firms at the .08 level. The lack of statistical significance for

TABLE 4.15

PORTFOLIO SELECTION OF PREDICTED ACQUIRED FIRMS
BASED UPON INCREASING A PRIORI PROBABILITY
SPECIFICATION OF ACQUIRED GROUP MEMBERSHIP

A Priori Probability	Ex Post Acquired	Total Firms	Cond. %	Z Score	Signif.
.03	2	18	11.11%	0.364	35.79%
.04	3	28	10.71%	0.379	35.24%
.05	3	33	9.09%	0.082	46.73%
.06	7	52	13.46%	1.221	11.10%
.07	8	67	11.94%	0.944	17.26%
.08	12	87	13.79%	1.689	4.66%
.09	14	101	13.86%	1.845	3.25%
.10	18	117	15.38%	2.569	0.51%

the smaller portfolios is not disturbing because of the limited sample size. Statistical significance for the smaller portfolios would require a very large percentage difference in classification accuracy between the model and a random selection. Therefore, since each of the portfolios contains a larger than expected conditional percentage of actual acquired firms, the return performance of each of these portfolio specifications will be considered.

The marginal and cumulative performance of the selected securities is presented in Table 4.16. In addition, the performance during each of the two years of study is presented. The performance of the two subgroups - acquired and general population firms - is provided also. At the .03 level the entire portfolio return is nearly seventy percent, compared to the Standard and Poor 500 Index return of twenty-four percent. Generally, the larger the portfolio becomes, the lower the cumulative return. The marginal performance of the higher a priori specifications declines from the seventy percent obtained at the .03 level; however, the return of the largest portfolio is still quite good at fifty-seven percent. The marginal performance of the actual acquired members in a portfolio does much toward providing this high overall return. The cumulative performance of this group remains consistently high, beginning at seventy-eight percent and gradually dropping to sixty-nine percent.

One interesting contrast does emerge. As the portfolio becomes larger, the statistical significance of the model's predictive ability improves, until leveling off at the higher a priori specifications. At the same time, it is observed that the portfolio return performance declines with size. This contrasting result is caused partly by the sample

TABLE 4.16

MARGINAL, CUMULATIVE PORTFOLIO PERFORMANCE:
FIRST YEAR, SECOND YEAR, AND COMBINED
PERIOD BY INCREASING A PRIORI
SPECIFICATION

A Priori Prob.	Cumulative Performance				Two Year Performance					
	First Year		Second Year		Acquired		General		Total	
	Acq.	Gen.	Acq.	Gen.	Mar.	Cum.	Mar.	Cum.	Mar.	Cum.
.03	.7123	.2770	.0707	.4889	.7808	.7808	.6885	.6885	.6988	.6988
.04	.7462	.2017	.0731	.4670	.8919	.8178	.4815	.6140	.5225	.6358
.05	.7462	.2206	.0731	.3919	---	.8178	.3081	.5630	.3081	.5861
.06	.5504	.1565	.3325	.3618	.9286	.8811	.3119	.4793	.4417	.5333
.07	.4443	.1385	.3726	.3822	-.0078	.7670	.5459	.4951	.5090	.5279
.08	.3178	.0954	.4031	.3872	.4415	.6585	.3255	.4589	.3487	.4867
.09	.2741	.1645	.4086	.3446	.4265	.6254	.7611	.5006	.7133	.5181
.10	.3440	.1601	.3816	.3933	.9204	.6909	.8944	.5483	.9009	.5702

NOTE: For the first year, 1978, the return for the Standard and Poor 500 Stock Composite Index was .0627, and for 1979 the return was .1793. For the combined two year period, the index return was .2438. The returns include dividends and are comparable to the returns listed above.

size involved, since it is much more difficult for the smaller portfolios to achieve statistical significance. This still does not explain the conditional percentage of acquired firms increasing (with portfolio size) from around eleven to fifteen percent. Perhaps the explanation for this lies with the nonacquired segment of the general population that is selected. Theoretically, these firms have been identified as attractive to acquisition. It is possible that the general firms identified first are attractive and can provide superior performance, but as the number of these firms continues to increase, this condition becomes less pronounced.

The marginal performance of the general segment of the portfolio is not as good as that of the acquired segment, but it is still much higher than that of the surrogate return measure for the population from which it was drawn. This rather interesting finding is considered further later in the chapter. It is sufficient to note that the returns from this segment are more than twice that of the Standard and Poor 500 Index.

The performance of the acquired segment stock is quite good during the first year. The S&P 500 Index return is around six percent for the year. The ex post acquired firms included at the .03 specification provide a return of seventy-one percent, due to the premiums paid to stockholders for these issues. As more ex post acquired firms are added at each a priori specification, this return declines to thirty-four percent. The general group's performance ranges downward from twenty-seven at the .03 level to sixteen percent at the final level.

In the second year, the general (nonacquired) segment's performance improves to a range of cumulative returns that begins at forty-nine percent and gradually drops to thirty-nine percent. The S&P 500 Index return also improves to eighteen percent for 1979. The cumulative performance of the acquired segment in the second year approximates that of the first year at the .10 level; however, this is not true for the smaller portfolios. This low performance of the smaller portfolios is misleading. The money invested in an acquired company's stock was assumed to be reinvested in a Treasury Bill until the end of the two year period. The low return of the acquired group in the second year is partially a result of the low return on these government securities. Most of the acquired firms selected in the lower a priori specification portfolios were acquired during the first year and this T-bill reinvestment assumption is reflected in the second year returns.

The performance of the nonacquired group, as noted above, is an interesting factor. Theoretically, these firms should be those that are attractive acquisition targets because of the similarities between these firms and those that were acquired in the model building sample. This results in their being selected for inclusion in the portfolios. A consideration of pertinent news items concerning these firms provides insight into the attractiveness of this group. Of these ninety-nine firms, five received unsuccessful offers, ten issued tender offers (intracompany) for their own shares, and three had very large block transactions occur in their stock. Unsuccessful tender offers may result in large abnormal positive gains for the stockholders of the target companies (Dodd and Ruback [1977]), so it is not necessary for the acquisition to be con-consummated for the portfolio to benefit (see Chapter Two). An intracompany tender offer may reflect management's opinion that the company stock is undervalued on the market. Many of these firms that made offers for shares sustained a large positive increase in stock price over the period of study, perhaps a result of the market reassessing its value for the stock, or the tender offer itself having a positive impact on the stock value. Large block transactions could reflect similarities to an intracompnay tender offer if the purchaser is the company itself. Alternatively, it could indicate the preliminary activity of an acquisition offer if the transaction is between two other parties. Two companies purchased large blocks of their own stock and one company experienced a sale between third parties unrelated to the company. All of this activity lends credence to the hypothesis that this nonacquired group has a profile of acquisition attractiveness.

The risk implied by this investment strategy is also of concern. The marginal and cumulative average portfolio betas are presented in Table 4.17. The portfolio investment is equally weighted among the securities. The beta coefficients are consistent over the range of portfolios and they indicate that the risk involved is higher than that of the market average.

Higher risk implies higher average returns. These portfolios would be expected to provide higher returns than the market. On a preliminary risk-adjusted basis, these portfolios still provide superior performance. Treynor's [1967] portfolio performance measure (T_p, see Table 4.17) provides a means for comparison between the portfolio returns obtained by the model and that of the market. This measure adjusts all portfolio risk premiums to a comparable basis - the risk premium that the market would have achieved had it been able to provide performance equivalent

TABLE 4.17

PORTFOLIO BETA ESTIMATES AND RISK-ADJUSTED RETURNS

A Priori Probability	Stocks		Avg. Beta		Risk Premium[a]	T_p[b]
	Mar.	Cum.	Mar.	Cum.		
.03	18	18	1.091	1.091	.5257	.4819
.04	10	28	1.453	1.220	.4627	.3793
.05	5	33	1.147	1.209	.4130	.3416
.06	19	52	1.240	1.220	.3602	.2952
.07	15	67	.849	1.136	.3548	.3124
.08	20	87	1.446	1.208	.3136	.2596
.09	14	101	1.087	1.191	.3450	.2897
.10	16	117	.867	1.146	.3971	.3465

[a]The risk premium is derived from $\bar{r}_p - R$, where $\bar{r}_p$ is the average rate of return on portfolio p (taken from the last column in Table 4.16) and R is the risk free rate. R is the average return on 90-day Treasury Bills for the years of 1978 and 1979, and is .1731. Therefore the market risk premium for this period is .0707.

[b]T_p is compared to the market risk premium and this provides a comparison of risk-adjusted portfolio performance. T_p represents Treynor's [1967] portfolio performance measure and is defined $T_p = \frac{\bar{r}_p - R}{bp}$, where bp is the beta coefficient for portfolio p ($\bar{r}_p$ and R are defined in note a).

to the portfolio under consideration. The market risk premium for the 1978-79 period is about seven percent. The risk-adjusted portfolio returns range from forty-eight to twenty-six percent. This measure provides preliminary evidence that the DA model is able to identify portfolios capable of achieving superior performance.

The discriminant model's ability to select likely acquisition targets appears to be quite good. It was used to select more actual ex post acquisitions than a random chance model could be expected to provide, and a profile of the nonacquired general population subgroup indicates that many of these companies are, or have been, candidates for acquisition. The portfolio return from both subgroups is considerably better than that provided by a comparable market index. Therefore, it appears that the DA technique is a viable portfolio selection tool, and that it holds much promise as a vehicle for the prediction of acquisition targets and the subsequent use of this predictive capacity in providing superior portfolio performance.

Chapter Five provides a summary of the conclusions and implications of this research. In addition, the chapter will discuss the limitations of the study and indicate promising avenues for further research.

Chapter Summary

This chapter has presented the results from the three phases of research. Phase one provided the development of a five variable discriminant model that is capable of selecting acquired firms significantly better than a random chance model, on an ex post validation basis. These variables include the industry adjusted debt ratio, net working capital, the return on assets ratio, the adjusted net profit margin, and the adjusted times interest earned ratio. The importance of these ratios to the model is in the descending order provided above.

Phase two tested the intertemporal validity of the model, and was able to provide evidence that the validity of the model's predictive capacity is quite good. In the simulated portfolio selection setting the model performed well in that it was able to select a higher percentage of ex post acquired firms than could be achieved by random chance. Previous studies have used the technique to identify firms intertemporally, and the classification results were good, but none had tested the predictive ability of discriminant analysis through its application to a sample of firms that contained appropriate a priori group membership.

Phase three attempted to evaluate the portfolio selection ability of the discriminant model. As the number of firms increased in the portfolio, the predictive ability of the model continued to improve, until leveling off when a large portfolio of 117 securities was obtained. In any case, the conditional selection ability of the model was better than a chance occurrence. Also, the returns achieved through this selection device were consistently higher on a risk-adjusted basis than that achieved by the Standard and Poor 500 Stock Composite Index. The marginal performance of the portfolio declined as the total portfolio increased in size, but the returns remained substantially above that provided by the index. Finally, the profile of firms in the nonacquired group selected for investment by the model indicated that these firms are similar to actual acquired firms in their attractiveness as acquisition targets even though an actual, successful offer had not been made during the period of study.

CHAPTER FIVE

STUDY CONCLUSIONS, LIMITATIONS, AND EXTENSIONS

Introduction

This study has attempted to assess the predictive ability of Discriminant Analysis (DA) when applied to the identification of likely acquisition targets and based upon a model developed from selected financial variables. In order to be considered successful, this model's predictive power needed to be sufficient to identify enough acquired firms, so that an investor could utilize the DA model as a portfolio selection device that would outperform the market. It is not necessary that the model identify all acquisitions, nor a large percentage of them. The only necessity is that enough of these securities be identifed so that the portfolio will be the beneficiary of the large positive abnormal returns that the market grants to the stockholders of acquired firms, and that these returns will be large enough to provide superior performance for the overall portfolio.

The DA technique offers much promise as a predictive tool in the merger and acquisition area. The intertemporal test conducted in phase two indicated that the best model produced results significantly better than those that could be obtained by random chance. Phase three utilized the model in a simulated portfolio setting. The risk-adjusted performance obtained by the identified portfolios was substantially better than the market performance as measured through the Standard and Poor 500 Stock Composite Index.

The following section summarizes the conclusions and implications of the research. A subsequent section discusses the limitations underlying the study, and the final section considers further extensions of work in this area.

Conclusions and Implications

The model building stage developed a five variable model that included net working capital, the industry adjusted debt ratio, the adjusted times interest earned ratio, the return on assets ratio, and the adjusted net profit margin. It is interesting to note that three of the five variables were adjusted for industry effects. Previous research has ignored this aspect,[1] (except Austin and Fishman [1969] in a univariate study) even though it is widely held that the market would implicitly account for this influence.

The variables themselves indicate group differences and provide insight into the factors that acquiring firms seek in acquisition targets. The most important variable in the model is the adjusted debt ratio. The study provides evidence that acquired firms have below average amounts of debt. Therefore, latent debt capacity is an important attraction for acquiring firms. The net working capital variable may represent differences in size or liquidity, it is difficult to separate these two factors. However, it appears that smaller firms are attractive to offers and there is evidence to indicate that firms with lower liquidity are attractive as well. The return on assets ratio is

[1] Simkowitz and Monroe [1971] suggest this as a possible improvement to their multivariate analysis.

higher for the firms in the acquired group and is indicative of the attractiveness of this factor to an acquiring firm as it searches for possible target companies.

The fourth and fifth variables do not represent dimensions of importance equivalent to the first three variables. However, they are included in the model and indicate distinct multivariate group differences. The adjusted times interest earned variable represents the coverage factor and indicates that acquired firms have a higher coverage of fixed interest charges than firms in the general corporate population. The adjusted net profit margin for acquired firms is lower in relation to the respective industries. Removal of this inefficiency may be a motive in the acquisition process. An important caveat to the interpretation of these last two model variables is in order. The three more important model variables also were significantly different on a univariate basis. This makes the interpretation of group differences concerning these variable much less difficult than for the last two variables. Each of the first three may be interpreted separately. However, the adjusted times interest earned ratio and the adjusted net profit margin must be considered in their multivariate context. Conclusions concerning group differences based upon these variables are tentative at best and must be considered in relation to the entire five variable model. For example, the tentative conclusion that acquired firms generally have higher adjusted net profit margins, recognizes that acquired firms generally had lower net working capital, a lower adjusted debt ratio, and a higher return on assets.

This model meets the goal of a workable model in that it provides substantially higher returns from selected portfolios, and yet it uses only five input variables. Thus the model is of potential aid to small investors in the selection of investments. The variables specified are readily available from annual reports and industry averages in publications carried by most libraries. All that is necessary is that the model be applied to a sufficiently large number of securities which are then ranked according to attractiveness. The investor can decide on the number of securities to include from this list. A cautionary note here is that the investment horizon specified for this study was composed of firms generally available from the New York and American Stock Exchanges. The applicability of the model to smaller Over-The-Counter securities was not tested, and this is both a study limitation and a suggestion for further research. In addition, a preliminary consideration of risk indicates that the portfolios selected by this investment approach offer above average risk, but it appears that the portfolio performance is superior to that of the market on a risk-adjusted basis.

This model and its variables are somewhat consistent with previous work done in the area; the model ratios vary, but the dimensions they represent are similar. There are important differences however. Stevens [1973] developed a four variable model, which indicated that group differences were related to measures of leverage, liquidity, profitability, and asset turnover. Three of these four dimensions appear in the present study, and the fourth, asset turnover, appears implicitly because of the presence of profitability and return on investment in the model. On a univariate basis, Stevens reports, that leverage is lower for acquired firms, and there is some indication that liquidity is higher. Given the latter, it is possible that the net working capital variable represents size since it would indicate lower liquidity, the opposite of Stevens' findings. Previously in this study, it had been difficult to determine if the net working capital variable indicated size or liquidity, or both. Singh [1971] and Simkowitz and Monroe [1971] both indicate that size is an important dimension.

One difference between the Stevens study and the present one is that coverage has been entered into the model, a dimension not reported previously. Also, tentative conclusions concerning the return on investment would differ between these two studies.

Simkowitz and Monroe report four dimensions in their discriminant model, including price-earnings, dividend payout, size, and growth. Only one of these dimensions appears in the present model-size. Singh also confirms that smaller firms are more attractive acquisition targets. In the present study, lower dividend payout does have univariate significance, but it does not appear in the final model. Also, price-earnings and growth were represented, but did not enter the model. A lower price-earnings ratio was an important acquired firm characteristic during the merger activity of the late 1960's. Simkowitz and Monroe disavow the importance of liquidity and profitability; although they do acknowledge the importance of leverage.

It seems likely that leverage and size are important dimensions in the identification of acquisitions. Profitability also appears to be important. The present study has indicated that coverage too may be important, although it is one of the weaker discriminant variables, and did not appear in previous studies. Finally, dividend policy is a promising dimension even though it did not enter the model provided here.

The ability to develop a discriminant model able to identify acquired firms and use this model in a predictive capacity to achieve superior portfolio performance, raises questions about the validity of the efficient markets hypotheses, in particular the semi-strong efficient hypothesis. This research has shown that prior, publicly available financial information can be used to imporve the prediction of acquisitions. The investment performance of companies identified by the discriminant model as "attractive" to acquisition indicates that the market also anticipates the probability of acquisition attempts by bidding up the price of these companies' stocks. However, this still does not answer the basic question concerning the present model's ability to identify this anticipation of acquisition in advance as well.

The model does use published financial information. However, when this information is used in a multivariate model, it can be contended that a complex reformulation of the data has taken place and that the information is no longer public or readily available to the market. As soon as the market becomes aware of the procedure, then it will react to bring security prices into a new equilibrium to reflect this. Firth [1976, p. 7] states:

> ...it is suggested that technical analysis would uncover any substantial dependence existing in historical data and that investor action would then nulify it, i.e. investors react to discount a rule such that it is no longer profitable. Successful technical analysis rules would thus, if widely publicized, lead to a more efficient market, the analysis in fact highlighting inefficiency.

Given the past research in this area, the results of this study and its implication to efficient market findings may still seem puzzling. Perhaps, investors are unconvinced that identification of group differences can lead to systematic superior portfolio performance. Perhaps the lack of overall consistency between studies has not been sufficient to show that this technique is a valid security selection device. Possibly, there is a lag in time between academic research and market reaction to it because of some inefficiency in the system. In any case, the issue is unresolved and deserves further consideration.

The next section discusses limitations of the study, after which, a discussion of possible extensions is presented.

Study Limitations

There are several limitations related to this study, its results, and conclusions. First, the conclusions drawn from phase three can be considered tentative at best. They do provide a preliminary view of the risk-return aspect of this portfolio selection device. This is all that was intended. Care must be taken in interpreting these results because of their tentative nature. The use of Treynor's portfolio performance measure was intended solely for this preliminary consideration of risk. This measure, and others similar in nature, has been criticized by Roll [1978] in its use as a direct measure of portfolio performance.

Even so, the performance exhibited by the portfolios is so great that it is highly likely that a more sophisticated form of analysis would yield the same result.

A second limitation arises from the simple buy and hold strategy of portfolio investment. The model was allowed to select securities only at one point in time, the beginning of the two year period. Perhaps a more complex set of trading rules that allows the discriminant model to accept new information and revise portfolio holdings would give a better indication of the model's performance.

A third limitation of the study concerns the specification of the time frame to be used. The selection of two year ex post and intertemporal model validation periods is somewhat mechanical in nature, in that a longer time period would have resulted in a larger segment of the population becoming acquired. The two year period was selected so that enough observations would be available, yet not so long that major shifts in merger motives might occur. The major impact is on the a priori probabilities and the researcher must be aware of this in specifying a time period for either model building or intertemporal validation of the model.

The last limitation to be discussed here involves the type of firms used in the study. The investment population of general corporate stocks involves the use of stocks from the New York and American Stock Exchanges. It was hypothesized that this population is a realistic investment population for many small investors. However, the study has dealt with larger firms and the results may not be generalizable to other investment populations, such as securities sold over the counter.

This is particularly important because one of the statistically significant variables relates to this dimension of size.

Many of the limitations just mentioned, also suggest avenues for further research. These and other suggestions are presented in the final section.

Suggested Research Extensions

As with any study of this scope, more issues are raised than confronted. The intent here is to summarize briefly some of these issues pertinent to this study and to the area of mergers and acquisitions.

Several suggestions can be drawn directly from the limitations discussed in the previous section. Given that the investment population was restricted to larger firms, this research approach could be extended to smaller firms to determine the similarities and differences between the two groups.

A second suggestion is to develop a much more complex set of trading rules for the portfolio selection device and to submit the model to more rigorous and realistic usage. Also, the performance of the portfolios could be extended into a residual analysis to attempt to resolve the issue concerning the ability of the model to provide portfolios able to outperform the market on a risk-adjusted basis.

Three other suggestions relate generally to the issue of timing. First, an interesting extension would be to determine the length of time the model remains able to identify acquired firms on a statistically significant basis. This would provide information concerning the stability of the model variables. It would also allow comparisons with previous periods to highlight differences in merger and acquisition characteristics during differing time periods. Second, the effect of a firm being identified as "attractive" to an offer on the stationarity of its security beta could be investigated. Third, the model could be subjected to performance in differing investment climates to differentiate performance between bull and bear markets, if any.

This research has indicated two other areas that deserve additional consideration. First, the model was able to select firms that were not acquired, but that were able to assist portfolio performance almost as well as the actual acquired companies. These firms were labeled attractive to acquisition offers, indicating the hypothesis that these firms are considered to be attractive acquisition candidates that have not yet been approached by an acquiring firm. This phenomenon deserves more careful development. Second, the issues concerning the impact of this type of research on the efficient markets hypotheses needs to be considered more fully and addressed in greater detail.

Finally, alternate statistical approaches to discriminant analysis are available and can be considered for their ability to perform in this type of research. Both the Logit and Probit statistical techniques hold promise for this type of future application.

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THE PREDICTIVE ABILITY OF DISCRIMINANT ANALYSIS
TO IDENTIFY TAKEOVER TARGETS FOR PORTFOLIO SELECTION

by

Mitchell Andrew Fields

(ABSTRACT)

This study utilizes the discriminant analysis technqiue in the development of a model able to predict acquisition targets. The model is tested in a portfolio selection setting to determine its ability to identify portfolios capable of performance superior to that of the market.

The sample in the model building phase is composed of seventy-one firms acquired during the years of 1976 and 1977. Another seventy-one firms were drawn randomly from the general corporate population of firms identified for the study. A total of forty-seven variables were considered, including sixteen industry adjusted variables. The variables themselves are financial ratios available in company annual reports.

A five variable model is developed which includes the adjusted debt ratio, net working capital, the return on assets ratio, the adjusted net profit margin and the adjusted times interest earned ratio. There is evidence to indicate that acquired firms use less debt, are smaller, and obtain a higher return on assets than firms in the general population. The model itself achieved an overall classification accuracy of 73.9 percent. The model then was subjected

The model then was subjected to an intertemporal test of validity during the subsequent two year period. A total of 1967 firms were classified, of which 171 represented actual acquired firms. These firms represent an appropriate investment population for a small investor confronted with portfolio investment choices. The model's performance in selecting acquired firms among those that are identified as acquired is significantly superior to that provided by a random chance model.

In selecting portfolios, the model is able to identify securities that provide risk-adjusted returns superior to those obtained by the market. Increasing the portfolio size indicated that the model is able to consistently provide superior portfolio performance. One interesting finding is that the performance of the nonacquired segment of the portfolio is superior to the market as well. It is hypothesized that this group represents firms that are attractive to acquisition.