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BUSINESS FAILURE PREDICTION

AN ANALYSIS OF TYPE II PREDICTION ERRORS

BY

AHMED I. EL-ZAYATY

A Dissertation submitted to the Graduate Faculty in Business Administration in Partial Fulfillment for the Degree of Doctor of Philosophy, The City University of New York.

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This research project is dedicated to my country, EGYPT, for the love, respect, protection and support that it gave me during the course of my work. It is also dedicated to my late father, my mother, and my wife, who encouraged me to achieve my dreams.

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Table of Contents

LIST OF TABLES

CHAPTER I

INTRODUCTION

Importance of Business Failure Prediction

Predicting business failure is important from both the private and social perspectives. From the private point of view, early detection of probable business failure might encourage management, creditors, and shareholders to take actions that will deter possible future losses. From the societal point of view, probable business failure might indicate a misallocation of resources. Early detection of such misallocation could induce reallocation procedures or other actions to protect the social welfare.

Business Failure Prediction Models

Predicting the probable failure of financially distressed firms has been a recurring research topic over the past two decades. For example, Beaver (1966) used a univariate analysis of numerous financial ratios to determine if financial failure could be significantly predicted. Later, Altman (1968) and Deakin (1972) examined alternative ad hoc multivariable models using linear discriminant analysis to predict business failure. However, the use of the linear discriminant analysis in this research was criticized by Joy and Tollefson (1975) and Eisenbeis (1977). As a consequence, quadratic discriminant analysis was used by Altman and Eisenbeis (1977), Altman et al. (1977), and Deakin (1977) to develop additional ad hoc models. A more rigorous approach was used by Wilcox (1971, 1973), Vinso (1979) and Emery and Cogger (1981), who developed statistics that represent the probability that a firm will have a negative balance of funds during a specified time period. More recently, logit and probit analysis have been used as alternatives to discriminant analysis by White and Turnbull (1975), Ohlson (1980) and Zavgren (1982). A few reseachers, such as Blum (1974), Van Frederikslist (1978), and Zmijewski (1983a), have attempted to develop business failure prediction models on quasi-theoretical bases. The specification and predictive ability of these models, however, were similar to those of the ad hoc models. Stock return based variables have been proposed as possible predictors of bankruptcy by Beaver (1968b), Aharoney et al. (1980), and Zmijewski (1983b). Finally, recursive partitioning, which is a nonparametric classification technique based on pattern recognition, was used by Frydman, Altman, and Kao (1985), to predict business failure.

Potential Users of Business Failure Prediction Models

Foster (1986) listed the following parties as potential users of business failure prediction models:

1. Lenders

   Business failure prediction has relevance to lending institutions, both in deciding whether to grant a loan (and its conditions) and in devising policies to monitor existing loans.

2. Investors

Investors adopting an active investment approach may develop strategies based on the assumption that business failure prediction models can provide earlier warnings of financial problems than is implicit in the existing security price.

3. Regulatory Authorities

In certain industries, regulatory bodies are responsibile for monitoring the solvency and stability of individual companies. Financial institutions such as banks, insurance companies, and savings and loan associations are subject to overview by regulatory bodies in many countries. An important subset of the models mentioned above have been motivated by such regulation-based applications.

4. Government Officials

Government subsidies (bailouts) to financially distressed firms occur in many countries with varying degrees of frequency. Models that predict the likelihood of survival of a potential bailout candidate can be an important data item in weighing the economic, political, and social considerations in this area. The prediction of business failure is also important to government officials in antitrust regulation. One defense against violating U.S. antitrust laws is the failing company doctrine. The doctrine can apply where one of the two merging companies is likely to fail and where the "failing" company has received no offer to merge from a company with which a merger would not have violated existing antitrust guidelines.

5. Auditors

One judgment auditors must make is whether a firm is a going concern. This judgment determines which asset and liability valuation methods are appropriate for financial reporting. Business failure prediction models can be a useful aid to the auditor in making a going-concern judgment.

6. Management

Bankruptcy can mean that a firm incurs both direct and indirect costs. Direct costs include fees to professionals such as accountants and lawyers. Indirect costs include the lost sales or profits due to the constraints imposed by the court or the court-appointed trustee. Altman (1984) estimated that, for a sample of 19 industrial firms that went bankrupt, "bankruptcy costs ranged from 11% to 17% of firm value up to three years prior to bankruptcy" (p. 1087). It may well be that if early warning signals of bankruptcy were observed, these costs could be reduced. Managers could initiate corrective actions in their operating and/or financing policies that might turn around the financially distressed firm, arrange a merger with another firm, or adopt a corporate reorganization plan at a more propitious time.

Commercial Applications of Business Failure Prediction Models

Altman, Haldeman, and Narayanan (1977) developed jointly with a private financial firm the well-known ZETA business failure prediction model. This model is now being marketed by ZETA SERVICES, INC. (Mountainside, New Jersey). The ZETA model is a multivariate model which is based on the following seven variables:

1. Overall profitability: earnings before interest and taxes/total assets,

2. Size: total assets,

3. Debt service: earnings before interest and taxes/total interest payments,

4. Liquidity: current ratio,

5. Cumulative profitability: retained earnings/total assets,

6. Market capitalization: five-year average of market value of common equity/five-year average of market value of total capital (includes preferred stock, long-term debt, and capitalized leases), and

7. Earnings stability: normalized measure of the standard error of estimate around a ten-year trend in the overall profitability variable.

The coefficients on each variable are proprietary and are not disclosed.

Ex Post Classification Accuracy of Business Failure Prediction Models

Most of the business failure prediction models achieved a remarkable rate of correct classification that exceeded 90% for the estimation samples as well as for the validation samples. However, such a high rate of correct classification tended to be sample-specific and not generally attainable because of the methodological problems associated with this line of research. These include:

1. The sample selection criteria used in many studies make it difficult to draw inferences about the performance of these models for the general population. An extreme example is provided by studies that use samples of 50% failed and 50% nonfailed firms. In the Dun & Bradstreet (1985) survey of business failure in the 1925-1983 period, the failure percentages ranged from 1.54% in 1932 to .04% in 1945, while the 1983 rate was 1.1%. Therefore, misleading inferences about the ability of a model to predict business failure may occur when there is such a divergence between the samples prior of failed/non-failed firms used to estimate and validate a model and the population priors that describe the underlying population [Foster (1978), p. 478].

2. The requirement of some studies that a firm have at least five years of financial data available omits from the analysis newly formed firms for which the incidence

of corporate failure is relatively high. The Dun & Bradstreet (1985) survey noted that 47.0% of the failures that occurred in 1983 were businesses that had been in existence five years or less. This statistic suggests that age may well be an important variable when developing a model to predict business failure.

3. The retrospective or ex post nature of the analysis; that is, the estimation and validation samples both include firms that are known to have "failed" or not "failed" on a set date. Thus, it is possible in the research to compare the financial ratios of failed and nonfailed firms one year, two years, and so on prior to failure. Yet, in decision-making contexts, one knows neither which firms will fail nor the date on which they will fail. To demonstrate that the results of this research have direct applicability to actual decision contexts, it would be necessary to make predictions about the failure (and its timing) of firms currently nonfailed.

Because of these shortcomings and others, some researchers denied the predictive ability of such models. For example. Joy and Tollefson (1975) described the predictive ability of these models as ex post discrimination rather than ex ante prediction. Similarly, Benishay (1973), in his discussion of Wilcox's (1973) study, described the analysis as an "autopsy" of deceased firms rather than a prediction of which what firms might go bankrupt.

Ex Ante Prediction Accuracy of Business Failure Prediction Models

In judging the accuracy of business failure prediction models, two types of errors are usually observed. Type I error which occurs when failing firms are predicted as nonfailing, and Type II error which occurs when nonfailing firms are predicted as failing. The occurance of these two types of errors has been investigated when business failure prediction modesl are used on an ex post basis [e.g., Altman (1968), Deakin (1972), and Zmijewski (1983a)]. However, the occurance of these two types of errors, when such models are used on an ex ante basis, has received little attention in the literature.

Deakin (1977) was probably the first to examine this issue. He extended his 1972 analysis by developing a linear as well as a quadratic discriminant function with five independent variables that were selected based upon Libby's (1975) factor analysis. Using data two years prior to failure for a sample consisting of 63 failed and 80 nonfailed firms, Deakin's linear and quadratic discriminate functions were able to classify correctly 88.9% and 94.4% respectively of the failed firms, and 98.8% and 72.5%, respectively, of the nonfailed firms. Thus, while the linear function misclassified more failed firms (11.1% Type I error vs. 1.2% Type II error), the quadratic function misclassified more nonfailed firms (1.6% Type I error vs. 27.5% Type II error).

Puzzled over the difference in Type II error between the linear and the quadratic functions, and unable to resolve the trade-off between the costs of the two types of prediction errors, Deakin attempted to explore the extent to which Type II prediction error would occur if his model were used to predict firms currently nonfailed. He applied both the linear and the quadratic discriminant functions to the data of 1,780 firms, on the COMPUSTAT file for the fiscal year ending 1971. Then, he adopted the following decision rule:

1) classify as failing if both the linear and quadratic functions classify as failing.

2) classify as nonfailing if both the linear and the quadratic functions classify as nonfailing, and

3) classify as "investigate further" if the two functions produce conflicting results.

Based on the above decision rule, Deakin obtained the following results:

290 firms as failing,
1,317 firms as nonfailing, and
173 firms as "investigate further".

To determine the accuracy of the above predictions, Deakin followed the financial performance of the 290 firms predicted as failing and 100 firms of the 1,317 firms predicted as nonfailing. Unfortunately, he did not follow up on any of the "investigate further" group. Deakin's follow-up period extended from January 1972 to June 30, 1975. At the end of the three and one half year follow-up period, he found the following results:

1) Of the 290 firms predicted to fail, only 18 firms (6.2%) actually failed, and

2) All of the 100 firms that were followed-up from the 1,317 firms predicted as nonfailing continued to exist.

Confronted with this high rate of Type II prediction error, Deakin concluded that using these models to predict firms currently nonfailed should be limited to situations in which misclassification of nonfailing firms is not a costly matter.

Follow-up of Deakin's (1977) Study

As part of this research project, Altman's (1968) Z-score bankruptcy model was applied to the 1,225 firms' data on the COMPUSTAT file for the fiscal year ending 1979 (the characteristics of this model will be discussed in Chapter IV). The following predictions were obtained:

132 firms as failing (i.e. firms having a Z-score below the cutoff point of 2.675), and

1,093 firms as nonfailing (i.e., firms having a Z-score above the cutoff point of 2.675).

However, follow-up of the financial performances of the 132 firms predicted to fail for the period from January 1980 to October 31, 1983, shows the following:

firms bankrupt	2
firms liquidated	3
firms private	4
firms merged	11
firms still survive	112
Total	132

The three liquidated firms were investigated further to discover the reasons behind the liquidation decisions. One firm (Arcata Corporation) was liquidated without being financially troubled. The liquidation decision was made to sell the company's assets to investors (Wall Street Journal, 6/04/82, p. 21). However, the other two companies (Mansfield Tire and Rubber Company and Mclouth Steel Corporation) were financially troubled, and the liquidation decision was preferred to the bankruptcy decision. For example, the New York Times (September 20, 1980, p. L26) indicated that Mansfield Tire & Rubber had outlined a liquidation plan. Then, two days later, the Wall Street Journal (9/22/80, p. 46) reported that the company's reorganization bid failed, and liquidation of the company's assets was to begin.

Therefore, if we consider these two liquidated firms as business failure cases, then the number of firms that experienced business failure is four firms (two bankrupt and two liquidated due to financial difficulties) out of a total of 132 firms predicted as going to fail. Thus, the Type II prediction error rate is 97%.

The Research Question

The research question that will be addressed in this research project is why do business failure prediction models, when used to predict, on an ex ante basis, produce such a high rate of Type II prediction errors, or in other words, why do few firms predicted as going to fail not actually fail?

Objective of the Study

The objective of this research project is to investigate why many firms predicted to fail in the near future continue operating without going bankrupt. It is not clear whether this phenomenon is due to the inadequacy of business failure prediction models to predict, on an ex ante basis, firms currently nonfailed, or whether it is because of certain actions taken by interested parties, such as managers, creditors, or equity shareholders, to avoid bankruptcy and keep such financially distressed firms in business. Thus, the purpose of this research is to investigate the extent to which each of the following factors contributes to the observed high rate of Type II prediction error:

1) Inadequacy of business failure prediction models for use in real prediction situations.

2) Actions taken to avoid bankruptcy, by:

   a) Management,

   b) Creditors,

   c) Shareholders, and/or

   d) Government

Potential Contribution of the Study

By addressing the research question raised earlier, this study would potentially contribute to our understanding of the usefulness of business failure prediction models. As a consequence, better decisions could be made in different decision-making contexts. In other words, investors, lenders, and other users of these models will be able to make better decisions by understanding the expected predictive ability of these models.

Furthermore, the analysis of the possible reasons for the observed high rate of Type II errors would shed light on which factors are more important than others, and under what circumstances one might expect a recovery of a financially troubled firm.

Chapter II

Related Literature

An early prediction of business failure could have very important implications for the society as a whole as well as for individuals. On the societal level, an early prediction of business failure could lead to a better reallocation of national resources, and consequently an increase in the social welfare. On the individual level, early prediction of business failure could help creditors and shareholders to avoid substantial losses. For example, by monitoring the probability of failure, one or more of the following actions could take place. Managers could initiate corrective actions in their operating and/or financing policies that might turn around the financially distressed firm. Shareholders could attempt to avoid bankruptcy by offering more equity or seeking a merger with a healthy firm. Creditors might find that it is in their interest to keep the firm operating by extending sufficient credit, or to force the firm into bankruptcy, thereby initiating liquidation before further impairment of the firm's value.

Empirical Models of Business Failure Prediction

Given the importance of predicting imminent business failure, the topic has attracted the attention of a relatively large number of researchers over the past two decades. Although attempts to construct an articulated economic theory of financial distress have been meager and generally unsatisfactory because of the complexity and diversity of business operations and the lack of a well defined economic theory of the firm under uncertainty [Lev (1974)], there has been considerable research effort to develop empirically - derived models to predict imminent business failure. Such empirically derived models can be categorized into the following four broad categories:

1. Univariate Ratio Analysis

The ground-breaking work by Beaver (1966) is a good example of univariate ratio analysis. He analyzed numerous financial ratios to determine which ratios can be used to distinguish correctly between failing and nonfailing firms. The theory of ratio analysis employed by Beaver [1966] was a cash-flow model, which served as a framework for explaining the results of the tests on the ratios. The firm is viewed as consisting of a "reservoir of liquid assets, which is supplied by inflows and drained by outflows. The solvency of the firm can be defined in terms of probability that the reservoir will be exhausted" [Beaver (1966) pp. 79-80].

From the concept of ratio analysis, these propositions were stated:

1. The larger the reservoir, the smaller the probability of failure.

2 The larger the net liquid-asset flow from operations (i.e. cash flow), the smaller the probability of failure.

3. The larger the amount of debt held, the greater the probability of failure.

4. The larger the fund expenditure for operations, the greater the probability of failure.

Beaver's analysis proceeded in three steps: a comparison of mean values, a dichotomous classification test, and an analysis of likelihood ratios. The original set of ratios were reduced to a set of six, each of which significantly classified firms as failed or non failed. These ratios were cash flow to total debt, net income to total assets, total debt to total assets, working capital to total assets, current ratio, and the no-credit interval. The best performing ratio was the ratio of cash flow to total debt.

Although Beaver's predictors performed fairly well, the main difficulty with his approach is that classification can take place for only one ratio at a time. The potential exists for finding conflicting classifications for any given firm according to various ratios. Moreover, the financial status of a firm is usually multidimensional, and no one single ratio would be capable of capturing all such dimensions.

2. Multiple Discriminant Analysis

Unlike the univariate analysis, which analyzes the predictive ability of single ratios, multiple discriminant analysis is a simultaneous consideration of several ratios in the prediction process. Altman [1968] pioneered the use of linear discriminant analysis for this application. The technique was adopted in order to assess whether ratio analysis is amenable to modern statistical techniques, whether a multivariate approach would improve the predictive ability of bankruptcy models, and whether the approach would be useful in practical application.

The accuracy achieved by Altman was higher than that achieved by Beaver with the univariate approach, especially for data for the first year prior to bankruptcy. However, Beaver was able to predict bankruptcy accurately five years prior to failure, whereas Altman's accuracy declines in years prior to the second year before bankruptcy.

The significance of Altman's model was that he introduced a technique for evaluating the ability of several ratios taken together to assess the financial health of a firm. As a result, several subsequent researchers have used multiple discriminant analysis to derive business failure prediction models [e.g., Deakin (1972, 1977), Blum (1974), Sinkey (1975), and Altman et al. (1977)].

However, the use of the linear form of the discriminant function was criticized by Eisenbeis (1971) and Joy and Tollefson (1975). As a consequence, the quadratic form of the discriminant function was used by Altman and Eisenbeis (1977), Altman et al. (1977), and Deakin (1977).

Recently, however, Ohlson (1980) criticized the use of the multiple discriminant analysis technique for business failure studies because of two major problems: (1) violation of the statistical assumption required for the use of the multiple discriminant analysis technique, and (2) the output of the application of a multiple discriminant analysis model is a score which has little intuitive meaning. Since such a score is basically an ordinal ranking device, it is not directly relevant for decisions that have complex payoff configurations. In other words, if the decision under consideration requires only the dichotomous classification of failure/nonfailure, then the discriminant analysis may be adequate. If the decision under consideration requires an evaluation of the financial risk associated with a specific investment, however, then an estimation of the probability of the firm's failure is required to estimate the appropriate risk premium.

Although discriminant analysis may be used to generate a probability, Martin (1977) provided evidence that the probabilities obtained from the discriminant function may be inaccurate, even though the classification accuracy may be high. When a population contains strongly asymetric proportions of groups, as in the case of bankruptcy, the classification results will exaggerate the size of the smaller group even though, by the maximum likelihood criterion, the discriminant function would be rejected. Thus, the use of a nonrepresentative group will bias the results of discriminant analysis. Since most discriminant analysis studies use equal-sized matched samples, their results are likely to suffer from this bias (Martin, 1977, P. 262).

3. Multivariate Conditional Probability Models

Reseachers have also examined the use of logit and probit analysis as alternatives to discriminant analysis [e.g. White and Turnbull (1975), Ohlson (1980) and Zavgren (1982)]. These models are used to estimate the probability of occurrence of a choice or an outcome, conditional on the attribute vector of the individual and the choice or outcome set that is available.

The coefficients resulting from these conditional probability models are the estimated representative effects of population parameters on the outcomes in the population. These coefficients are applied to the attribute vector of an individual firm in the sample. The resulting index is a measure of the "propensity to fail" or the "vulnerability" to failure, conditional on the firm's attribute vector [Koronow and Stuhr, 1975, pp. 157-65].

Ohlson (1980) and Zavgren (1982) developed logit models to provide a probabilistic measure of the financial risk of the firm and an evaluation of the significance of individual financial attributes in distinguishing failing and nonfailing firms. Each expected that the logistic model would improve the results since the data more nearly fit the assumption of the technique. The results of neither study bear this out, however. The significance of the estimated models, the pattern of significance of the financial attributes, and the information content of the probabilities as a financial risk measure appear to be the main contributions of this technique.

4. Recursive Partitioning

More recently, a new classification procedure called the "Recursive Partitioning Algorithm" has been used by Frydman et al. (1985) to classify financially distressed firms. A comprehensive exposition of the recursive partitioning algorithm is presented in the recent book by Breiman et al. (1984). This technique has attributes of both univariant and multivariant procedures. It is a nonparametric classification technique which is based on pattern recognition. The nonparametric, recursive partitioning algorithm is not vulnerable to the criticisms ascribed to parametric techniques, especially the violations of the underlying statistical assumptions.

Predictive Ability Evaluated and Compared

Direct comparison of extant business failure prediction models is difficult due to differences among individual studies with respect to statistical techniques employed, criteria used to assign firms to different categories, and samples examined. The Zmijewski (1983) study, however, considerably reduces these problems. Multivariate models based on variables used in prior studies were individually examined using a common statistical technique (probit analysis), a common definition of group categories (bankrupt/nonbankrupt), and a common sample (72 bankrupt and 3,573 non bankrupt firms [illegible] represent the actual population's prior probabilities of failure).

Zmijewski (1983) addressed the following questions: (1) Is there a superior model to use in predicting corporate bankruptcy?, (2) How similar are predictions from these models?, and (3) Could better models be developed? Examining a total of 13 models that were derived from extant empirical business failure prediction studies, Zmijewski concluded that most of the business failure prediction models produce similar probabilities of failure. There is no model that can be described as the "best". It is unlikely that additional models based on the same financial characteristics will produce better predictions of business failure. Based on these results, he urges researchers to apply these models in user-oriented decision processes to determine their usefulness.

Methodological Issues

While the various business failure prediction models developed in the literature appear to possess certain predictive power, most of the reported results are sample specific and do not perform as well on an ex ante basis. This could be attributed to one or more of the following circumstances:

1. Foster (1986) pointed out that in the absence of an economic theory to guide researchers to the important dimensions, researchers have undertaken extensive "searching exercises" with the object of discovering models with significant predictive power. The searching can occur in several areas:

a. Searching over N different models, for example, linear additive versus non-linear multiplicative,

b. Searching over N independent variables, for example, starting with 30 variables and choosing the subset that includes the "best" performers,

c. Searching over N firms, for example, starting with data for 100 firms over 10 years and then excluding firms/years for which the model performs worst (typically with an ex-post rationalization).

d. Searching over N estimation techniques, for example, linear discriminant analysis versus quadratic discriminant analysis.

Scott (1981) presented some links between theoretical models and the variables included in some empirical bankruptcy prediction studies. This link is still tenuous, however, and requires further exploration. In the absence of a theory that indicates the important dimensions, the practice of "searching exercises" mentioned earlier can lead to sample-specific results and to instability of the discriminant function.

2. One major limitation of these business failure prediction studies is the retrospective or the ex-post nature of the analysis used in developing and validating these models. That is, both the estimation and validation samples are based on firms that are known to have failed on a specific date. Due to the ex post nature of the analysis, Joy and Tollefson (1975) described the results obtained using these models as ex post discrimination rather than ex ante prediction. Foster (1978) pointed out that in a decision

making context, one knows neither which firms will fail nor the date on which they are going to fail. Thus, in order to assess the actual predictive ability of these models in decision - making contexts, it would be necessary to use these models to make ex ante predictions about the failure of firms currently nonfailed and the timing of their failure. Despite this obvious limitation of the extant business failure prediction models, little attention has been paid to examining the actual predictive ability of these models on an ex ante basis.

3. Zmijewski (1984) pointed out that estimating business failure prediction models on the basis of non-random sampling procedure creates two potential biases. The first bias, a choice-based sample bias, results when a researcher first observes the dependent variable and then selects a sample based on that knowledge, that is, the probability of a firm entering the sample depends on the independent variable's attributes. The second bias, a sample selection bias, results when only observations with complete data are used to estimate the model and incomplete data observations occur non-randomly. Both biases result in asymptotically biased parameters and probability estimates.

4. Zavgren (1983) pointed out that the limitation of the sample size also requires pooling of data of several years, which could confound the results significantly. If different years are characterized by widely differing incidences of

bankruptcy, the prior probabilities will be distorted.

Moreover, the usefulness of the data is further limited by alternative accounting methods in use. For example, the use of different depreciation methods would alter the value of some ratios, which may affect the predictive ability of the models.

5. The use of equal-size samples of failed and nonfailed firms causes problems with external validity using discriminant analysis, since prior probabilities in the sample are not the same as in the population. Misleading inferences about the ability of a model to predict business failure may occur when there is such divergence between the sample priors of failed/nonfailed firms used to estimate a model and the populations priors that describe the underlying population. Zimjewski (1983) represents a new direction which introduces the use of a sample that better approximates the general population.

6. The requirement of some studies that a firm must have at least five years of financial data available omits from the analysis newly formed firms in which the incidence of corporate failure is relatively high. The Dun & Bradstreet (1985) survey notes that 47.0% of the failures that occurred in 1983 were businesses that had been in existence five years or less (Foster, 1986).

7. The use of a paired-sample design, where firms are matched on size and industry criteria, effectively precludes these variables as indicators of financial distress. Yet there is considerable evidence that both size and industry groups contain important information on business failure likelihood.

Zmijewski (1984) provides further discussion of methodological issues in this area, with specific attention to "oversampling" of distressed firms and the deletion of firms when certain data items for them are not available.

Chapter III

Two Types of Prediction Errors

When business failure prediction models are used to make predictions about which firms are going to fail and which are not, a decision maker may commit either one of the following two types of errors.

Type I error = identifying a failed firm as nonfailed.

Type II error = identifying a nonfailed firm as failed.

Unfortunately, there is an inverse relationship between these two types of errors so that the decision-maker cannot reduce them simultaneously. However, the decision maker can set a cutoff point that reduces the probability of the more serious one. When the cost of both types of error is not the same, an optimal cutoff point would be the one that minimizes the total expected cost.

Expected Cost of Business Failure Prediction Errors

As mentioned above, two kinds of errors are possible when a business failure prediction model is used. If T_1 is the designation for the model predicting S_1 as the true state of nature (i.e., the firm under consideration will not go bankrupt), and T_2 is the designation for the model predicting S_2 as the true state of nature (i.e., the firm under consideration will go bankrupt), then, the error of T_1, given S_2, is the Type I error. The conditional probability of this error's occurrence is:

$$P\ (T_1/S_2)$$

Similarly, the error of T_2, given S_1, is the Type II error, and the conditional probability of its occurrence is:

$$P\ (T_2/S_1)$$

Since the expected cost of an error is the conditional probability of the error times the prior probability of the state of nature times the payment of that state [Tull and Hawkins (1980), p. 730], then the expected cost of each type of error can be expressed as:

$$\text{Expected Cost of Type I error} = P\ (T_1/S_2) \times P(S_2) \times V_2$$

$$\text{Expected Cost of Type II error} = P\ (T_2/S_1) \times P(S_1) \times V_1$$

where V_1 and V_2 are values of the payoffs for state of nature 1 and 2 respectively.

Costs of Type I vs. Costs of Type II Prediction Errors

When a decision maker uses a business failure prediction model to classify firms as failing or nonfailing, a cutoff point that minimizes the total expected cost (i.e., the expected cost of both Type I and Type II prediction errors) should be chosen. Such a cutoff point is a function of the decision-maker's prior probabilities and the payoff configuration. Thus, to the extent that the prior probability and the payoff configuration differs from one decision maker to another, there is no generalizable cutoff point. In other words, if we refer to

Type I Prediction error as Type I risk and Type II prediction error as Type II risk, then the cutoff point would be a function of each decision-maker's risk attitude and prior probability estimations.

It has been emphasized in the literature that the costs associated with Type I prediction errors are significantly higher than those associated with Type II prediction errors. For example, Diamond (1976) estimated the relative cost of Type I prediction errors to the cost of Type II prediction errors as having an upper bound of 20 to 1 and a lower bound of 38 to 1. Similarly, Altman et al. (1977), using survey data from small Southeastern regional banks, estimated that the relative cost of Type I prediction errors to the cost of Type II prediction errors is 35 to 1.

However, this does not imply that the costs associated with Type II errors are negligible. In fact, these costs are rarely considered based on the assumption that they are less significant. This is especially true when the decision is to classify a firm as failing or nonfailing - a case in which the decision problem has a payoff space that is partitioned into the binary status bankrupt versus nonbankrupt. If one considers a decision problem with a richer set of possible outcomes (e.g., a portfolio selection), costs associated with Type II prediction errors could be significant (i.e., in terms of opportunity cost). For example, this situation may occur when business failure prediction models are used to identify financially troubled firms for use as samples for research purposes. Research studies that have tested for stock market behavior around bankruptcy prediction dates [e.g., Altman and Brenner (1981) and Katz et al. (1985)], or that have investigated the merge/bankruptcy choice [e.g., Shrives and Stevens (1979) and Pastena and Ruland (1986)] dramatize this possible effect. If so many firms predicted to fail do not actually fail, the results of such studies are difficult to explain.

Ex-Post Discrimination and Error Rates

When business failure prediction models are used to classify a sample of firms that are known to be "failed" or "nonfailed" (i.e., ex post basis), the percentage of correct classifications is usually high and the difference between the rates of Type I and Type II prediction error is usually small. For example, Beaver (1966) used contingency tables to calculate Type I and Type II errors, and the results were 22 percent and 5 percent, respectively. Moreover, Type II error was stable over the five-year period, whereas Type I error increased substantially as the number of years prior to failure increased.

When Altman (1968) applied his Z-score model to the initial sample of 33 bankrupt firms and 33 nonbankrupt firms, the model was able to classify 95% of the total sample correctly. The Type I error was only 6% and Type II error was only 3% [Altman (1983), p. 112]. Thus, Type II prediction errors tended to be less than Type I error, and the difference between the rates of the two types of errors is relatively small.

Ex Ante Prediction and Error Rates

In the ex post discrimination, Type II error rates tended to be less than Type I error rates. However, in an ex ante prediction setting, where business failure models are used to make predictions about the failure (and its timing) of firms currently nonfailed, Type II prediction error rates tend to be significantly high. For example, Deakin (1977) extended his 1972 analysis by developing a linear as well as a quadratic discriminant function with five independent variables that were selected based upon Libby's (1975) factor analysis. Using data two years prior to failure for a sample consisting of 63 failed and 80 nonfailed firms, Deakin's linear and quadratic discriminant functions were able to classify correctly 88.9% and 94.4%, respectively, of the failed firms, and 98.8% and 72.5%, respectively, of the nonfailed firms. Thus, while the linear function misclassified more failed firms (11.1% Type I error vs. 1.2% Type II error), the quadratic function misclassified more nonfailed firms (1.6% Type I error vs. 27.5% Type II error).

Puzzled over the difference in Type II prediction error between the linear and quadratic functions, and unable to resolve the trade-off between the costs of the two types of prediction errors, Deakin attempted to explore the extent to which Type II prediction error occurs if his model were used to predict firms currently nonfailed. He applied both the linear and the quadratic discriminant functions to the data of the 1,780 firms on the COMPUSTAT file for the fiscal year ending 1971. Then, he adopted the following decision rule:

1) classify as failing if both the linear and quadratic functions classify as failing.

2) classify as nonfailing if both the linear and the quadratic functions classify as nonfailing, and

3) classify as "investigate further" if the two functions produce conflicting results.

Based on the above decision rule, Deakin obtained the following results:

290 firms as failing,
1,317 firms as nonfailing, and
173 firms as "investigate further".

To determine the accuracy of the above predictions, Deakin followed-up the financial performance of the 290 firms predicted as failing and 100 of the 1,317 firms predicted as nonfailing. Unfortunately, he did not follow up on any of the "investigate further" group. Deakin's follow-up period extended from January 1972 to June 30, 1975. At the end of the 3 1/2 year follow-up period, he found the following results:

1) Of the 290 firms predicted to fail, only 18 firms (6.2%) actually failed, and

2) All of the 100 firms that were followed-up from the 1,317 firms predicted as nonfailing continued to exist.

Confronted with this high rate of Type II prediction error, Deakin concluded that using these models to predict firms currently nonfailed should be limited to situations in which misclassification of nonfailing firms is not a costly matter.

Possible Reasons for Observing High Rate of Type II Error

The observed high rate of Type II prediction error, when business failure prediction models are used to predict firms currently nonfailed, could be attributed to either the inadequacy of these models to make valid predictions and/or to the effect of certain actions taken by interested parties such as management, stockholders, creditors, or even the government. The following is a brief discussion of these possibilities, which are summarized in Illustration (2).

Possible Inadequacy of Business Failure Prediction Models

In their review of bankruptcy studies, Ball and Foster (1982) pointed out that such studies used an empirical approach to choose the independent variables used to develop what they refer to as business failure prediction models. Since an underlying theoretical rationale was not used to justify the selection of such variables, the ex post classification accuracy achieved by these models tended to be sample specific and not capable of making real predictions. Joy and Tollefson (1975) described the predictive ability of these models as an ex post discrimination rather than an ex ante prediction. Similarly, Benishay (1973), in his discussion of Wilcox's (1973) study, described the analysis as an "autopsy" of deceased firms, rather than a prediction of which firms might go bankrupt.

Business failure prediction models could be inadequate to make reliable predictions on an ex ante basis for one or more of the following reasons:

a) Inadequate cutoff point to discriminate between failing and nonfailing firms. An efficient cutoff point, which minimizes the expected total cost of misclassification (i.e., the total costs of Type I and Type II errors), is a function of the prior probability and the cost of misclassification [Joy and Tollefson (1975)]. Therefore, to the extent that these two factors are user specific, there is no generalizable cutoff point. However, some researchers established what they call a "practical" cutoff point for their models. For example, Altman (1968) established a cutoff point for his Z-score model of Z = 2.675 as a practical cutoff point. Therefore, it is possible that the observed high rate of Type II prediction errors is due to the inadequacy of such practical cutoff points.

b) Nonstationarity of the predictive ability of business failure prediction models because of the changes over time in certain macroeconomic variables such as the rate of inflation, the level of interest rates, and the business cycle. For example, Rose et al. (1982) reported that macroeconomic conditions influence the business failure of individual firms. The business failure rate increases during periods of recession and decreases during periods of expansion. Mensah (1984) presented evidence that the predictive accuracy of business failure prediction models differs across different economic environments. Moyer (1977) re-examined Altman's (1968) model, and indicated that the model is not generally suitable when applied to a sample of firms outside the original sample period.

c) Inadequate representation of the model for certain firm sizes or industries. Business failure prediction models are usually developed based upon certain financial ratios of a sample of firms that are taken from a certain industry or industries and have sizes that fall within a specific range. For example, the Altman (1968) Z-score model is developed based upon five financial ratios of a sample of manufacturing firms whose mean asset size is $6.4 million, with a range of between $0.7 million and $25.9 million. Therefore, when this model is used to predict firms in different industries or having different asset sizes, prediction errors are expected. Although Altman

(1968) attempted to control for the size effect by scaling his financial variables by total assets, Lev and Sunder (1979) argued that such scaling controls for size only under highly restrictive conditions. If these conditions are not met, size is not adequately controlled for and the resulting estimate is biased. The amount of bias varies with the size; it is large for small firms and relatively small for large firms. Similarly, Altman (1968) attempted to control for possible industry effects by limiting his sample to only manufacturing companies. Gupta and Huefner (1972), however, found that cross sectional differences in many financial ratios were primarily related to industry characteristics. Therefore, to the extent that the manufacturing firms included in Altman's sample belong to nonhomogeneous industries, there might be industry effects that would inhibit the predictive ability of the Z-score model. For example, the ratio of Sales/Total Assets (which is X_5 in the Z-score model) should be significantly different between firms in capital-intensive industries (e.g., steel industry) and firms in receivable intensive industries (e.g., textile industry). Therefore, if the sample used by Altman (1968) included more firms from capital-intensive industries, then it would be expected that the model produces more mispredictions in receivable-intensive industries than it would in capital-intensive industries.

Possible Actions by Interested Parties

Ohlson (1980) pointed out that the dichotomization of bankrupt versus nonbankrupt by business failure prediction studies ignores the many other options available to financially troubled firms. These options include debt restructuring, divestment of unprofitable operations, and/or merging with a healthy firm. The theoretical literature suggests that the interests of management, equity shareholders, and creditors of a financially troubled firm are usually promoted by avoiding bankruptcy. Since real costs are associated with bankruptcy, there are always parties who have incentives to avoid it. However, the actual avoidance of bankruptcy depends upon which party or parties have the controlling power to act and make decisions in certain situations. Such actions could be taken by management, creditors, or equity shareholders. A brief discussion of these possible actions follows:

1) Possible Managerial Actions

Altman (1983) indicates that management may use a business failure prediction model as an "early warning system." In such a case, management may deliberately attempt to influence the model's measurements and, as a consequence, "control" its prediction. As evidence for such use, Altman mentioned that the management of GTI Corporation made a series of decisions over a five-year period to foil his (1968) Z-score model's prediction of bankruptcy. This series of decisions, many of which were specifically motivated by considering their effect on the financial ratios in the model, led to the recovery of the company. These managerial decisions included eliminating GTI's excess assets, freezing all capital expenditures, restructuring debt, structural reorganization, selling off entire plants, and closing some divisions. As a consequence of these decisions, the Z-score (i.e., the index of bankruptcy) has continued climbing until it reached the safe zone (i.e., above the critical point of Z = 2.675). Altman (1983, p. 205) comments on the case of GTI Corporation as follows:

> "We believe that certain predictive models offer opportunities to be used as management tools. Supporting that view, GTI's employment of the Z-score bankruptcy predictor has been described as a specific illustration of how an ordinary passive model can be used actively with substantial success.
>
> ....
>
> It is quite conceivable that a large number of firms presently in a distressed situation can learn from and perhaps be put on the road to recovery by the strategies used by GTI Corp."

It is more realistic to assume that the management of a financially distressed firm will concentrate on improving operating and financing policies rather than simply focusing on improving given ratios. However, if we assume that improving such operating and financing policies has the effect of improving those ratios included in the Z-score model, then it would be expected that the observed high rate of Type II prediction erros is due, at least in part, to such managerial activities.

2) Possible Creditors' Actions

Creditors may recognize that they will have to absorb a large loss should the firm go bankrupt. If they believe that the firm could be made viable by restructuring debt, they may agree to convert debt to equity, forgive some debt, reduce some debt to very low interest rates, or extend debt repayment over a longer time period. For example, Bibeault, in his book Corporate Turnaround (1982), states:

> "Debt restructuring is a key to turnaround success to those companies in serious trouble. Certainly Bank of America's help was key to Memorex Corporation's turnaround. The bank agreed to convert $30 million of its debt into preferred stock and convinced other lenders to exchange an additional $10 million of debt for preferred stock........................Finally, Bank of America provided Memorex with a new $35 million line of credit. As one analyst said, Bank of America provided the financial framework to turn the company around." (Page 271)

In addition, Bulow and Shoven (1978) demonstrated that when there are asymmetrical claimants (i.e., asymmetric in their negotiating and controlling abilities), a negative net worth is not a sufficient condition to force a firm into bankruptcy. The authors present a case in which a firm continues operating even though its liquidation value exceeds its present expected ongoing value. Thus, it might be in the interest of the controlling creditors to save a failing firm from bankruptcy by extending sufficient credit to keep it in business, regardless of the other parties' interests.

The above mentioned creditors' behavior toward financially distressed firms might explain, in part, the observed high rate of Type II prediction error of the business failure prediction models.

3) Possible Shareholders' Actions

Since the equity shareholders are the residual claimants, and in most cases they suffer a loss should the firm ultimately be liquidated, they have strong incentives to seek alternatives to bankruptcy. For example, Bulow and Shoven (1978) indicate that in a financial crisis, shareholders tend to convince the firm's major bank to keep the firm in business by offering enough of the equity position to make the bank's claim with the firm continuing in business more valuable than if it goes bankrupt.

Merger with a healthy firm also has been considered a viable alternative to bankruptcy. Bulow and Shoven (1978) also demonstrated that because of the asymmetry in the tax system (where negative taxes are not permitted, while loss deductions may be carried forward), there are cases in which the only way that a financially distressed firm can use all current loss deductions immediately is to merge with another firm. In addition, Shrieves and Stevens (1979) set forth possible reasons for shareholders to prefer merger over bankruptcy:

a) Avoidance of the legal and administrative costs of bankruptcy,

b) Possible loss of tax loss carryforwards, in bankruptcy,

c) Going concern equity value is greater than its liquidation value in the event of bankruptcy, and

d) The adverse effect of declaring bankruptcy on sales and income because potential customers might fear that the firm will be unable to honor its contracts, provide future service, or replace parts for its products.

The authors also found that a significant number of merged firms were near bankruptcy at the time they were merged.

In a more specific study, Pastena and Ruland (1986) examined the bankruptcy versus merger alternative for financially distressed firms. The authors found that financially distressed firms show a greater tendency to merge when the concentration of ownership is relatively high.

Again, to the extent that equity shareholders of financially distressed firms are able to avoid bankruptcy, Type II prediction error will increase. That is, whenever a financially distressed firm is predicted to fail by a business failure prediction model, such prediction will not materialize if the equity shareholders are able to save the firm from bankruptcy.

In summary, when business failure prediction models are used to predict firms currently nonfailed, Type II prediction error (i.e., firms predicted to fail do not actually fail) might be relatively high because of one or more of the following reasons:

1) Inability of business failure prediction models to predict on an ex ante basis.

2) Managerial actions to avoid bankruptcy,

3) Creditors' actions to bail out some financially distressed firms and keep them in business, and

4) Actions taken by equity shareholders to avoid bankruptcy by seeking sufficient funds to keep the firm operating or by seeking a merger with a healthy firm.

Chapter IV

RESEARCH METHODOLOGY AND EMPIRICAL RESULTS

The objective of this research project is to investigate why many firms predicted to fail in the near future continue operating without going bankrupt. This phenomenon may be due to the inadequacy of business failure prediction models to predict on an ex ante basis. On the other hand, corrective actions taken by interested parties (e.g., managers, creditors, equity shareholders, or government) that enable certain financially distressed firms avoid bankruptcy may provide an equally plausible explanation for that phenomenon.

In this research project, the Altman (1968) Z-score model is used to investigate the above mentioned phenomenon. This specific model is chosen for the following reasons:

First: This model has been used in many studies to identify study samples of firms presumably going to fail [e.g., Shrieves and Stevens (1979), Altman and Brenner (1981), Katz, Lilien, and Nelson (1985), and Pastena and Ruland (1986)] and seemed to be useful. Therefore, the results of the current study may have direct implications for the conclusions drawn from these previous studies.

Second: This model has been widely cited in both trade publications and financial management texts [e.g., Bolton (1976), Reed et al. (1976), and Van Horn (1974)] as a basis for predicting financial distress, as a tool to assist in credit evaluation, as a tool to assist in portfolio selection, and as an early warning system.

Third: Collins (1980) compared the predictive ability of the simple Altman (1968) Z-score model type to the more sophisticated model type developed by Meyer and Pifer (1970). He found that the simpler Altman's model type performs as well as or better than the more sophisticated model.

Fourth: Hamer (1983) demonstrated that the predictive ability of business failure prediction models is not particularly sensitive to the specific set of independent variables, nor the choice of specific statistical techniques employed in their development. In a more rigorous study, Zimjewski (1983) empirically compared the performance of 13 business failure prediction models derived from the extant empirical literature. One of his objectives was to answer the question: "Is there a best model?" The results indicated that most of the extant business failure prediction models predicted equally well and that the estimated bankruptcy probabilities were highly correlated.

Fifth: Since the methodology of this study requires the application of a business failure prediction model to a large number of firms, using more than one model will complicate the analysis and might obscure the results. That is, since it has been evidenced that most of the extant business failure prediction models produce similar predictions [Zmijewski (1983)], there is no need to use more than one model or a more complex model for the purpose of this study.

Based on the above, this study will be focused on Altman's (1968) Z-score model, which is a linear function of five weighted variables:

$$Z = 1.2\ X_1 + 1.4\ X_2 + 3.3\ X_3 + .6\ X_4 + X_5 \qquad (1)$$

Where:

Z = the discriminant score

X_1 = the firm's working capital divided by its total assets,

X_2 = the firm's retained earnings divided by its total assets,

X_3 = the firm's earnings before interest and taxes divided by its total assets,

X_4 = the market value of the firm's equity and preferred stock divided by its liabilities at book value, and

X_5 = the firm's sales divided by its total assets.

The sample used by Altman consisted of thirty-three manufacturers that filed for bankruptcy during the period 1946 - 1965. The nonbankrupt sample was an equal number of firms, selected randomly from manufacturing firms, stratified by asset size and industry, which were still in existence after 1966. Data was compiled one year prior to bankruptcy for the firms in the bankruptcy sample and for the same period for the firms in the nonbankrupt sample.

The variables included in Altman's study were chosen on the basis of their (1) popularity in the literature, and (2) potential relevancy to the study. The variables included in the function were chosen by a criterion of improvement of the discriminating power of the function.

The discriminant function was validated in both a descriptive and a predictive sense. For the former, the cases in the sample from which the function was developed were classified using the discriminant function. Both Type I and Type II errors were evaluated. The classification of the original sample resulted in a Type I error rate of 6 percent and a Type II error rate of 3 percent. Predictive validation was performed using two different secondary samples. First, the developed discriminant function was used to classify a secondary sample of 25 bankrupt firms whose asset size range is similar to that of the original sample of bankrupt firms. The classification of this secondary sample of bankrupt firms resulted in a Type I error rate of only 4 percent. Second, the developed discriminant function was used to classify another secondary sample of nonbankrupt firms that suffered losses in the previous two or three years. These firms were selected regardless of their asset size. The classificaiton of this secondary nonbankrupt sample resulted in a Type II error rate of 21 percent.

By observing those firms which have been misclassified by the discriminant function, Altman chose the Z-score value that resulted in the minimum number of misclassifications as a cutoff point. This cutoff score is Z = 2.675. Firms having a Z-score below that cutoff point are classified as "bankrupt," while firms having a Z-score above the cutoff point are classified as "healthy".

The cutoff point of the Z-score should be selected so as to equate the probability of Type I and Type II prediction errors with the ratio of the explicit cost of accepting a failure to the opportunity cost of rejecting a success. However, choosing the cutoff point as the Z-score that minimized the number of misclassifications assumes that the expected costs of both types of errors are equal. Because of that assumption, the cutoff point of the Altman's Z-score (i.e., Z = 2.675) is of a generalized nature.

Three Phases of Analysis

To address the research question raised in this research project, the empirical analysis will be conducted in the following three phases:

Phase I: Identification of the Study Sample

Altman's (1968) Z-score business failure prediction model will be used to identify firms predicted to fail on an ex ante basis. Then, these firms will be followed-up to determine their current status (i.e., went bankrupt, liquidated, merged, still survive).

Phase II: Investigating the Adequacy of the Z-score Model.

The adequacy of business failure prediction models, when they are used to predict the failure of firms currently nonfailed, will be examined. The objective of this phase is to explore the extent to which the observed high rate of Type II prediction error could be explained by a possible inadequacy of these business failure prediction models to make real predictions (i.e., on an ex ante basis).

Phase III: Survey of Preventive Actions

In this final phase, possible actions taken by the firm's managers, creditors, and shareholders will be examined to explore the extent to which the observed high rate of Type II prediction errors could be explained by the effect of certain actions taken by interested parties.

Detailed Analysis of Each Phase and its Empirical Results

Phase I: Identification of the Study Sample

This phase represents the sample selection procedure through which firms that will be used as a sample for the analysis in phase II and III will be identified. The Altman (1968) Z-score was computed using the 1979 data for the 1,225 manufacturing firms on the 1980 version of the COMPUSTAT tape.

The 1980 version of the COMPUSTAT was used for two reasons; first, to avoid the effect of the updating process in which the bankrupt, liquidated, or merged firms are deleted from the more recent versions of the COMPUSTAT tape. Second, it is the earliest version available to this research and allows maximum time to follow-up the financial performance of firms predicted to fail that are still in existence as of 1983.

A total of 132 firms having a Z-score below the cutoff point of 2.675 were identified as going bankrupt the following year (i.e., during 1980). However, these 132 firms were traced from 1979 to 1983, using the following sources of information about corporations:

a) Industrial Annual Research Tape

This is a COMPUSTAT tape that has data for 20 years for those companies deleted from the Annual Industrial Tape for one of the following reasons:

1. Acquisition or merger,
2. Bankruptcy,
3. Liquidation,
4. Now a private company, and
5. Other (no longer files with the S.E.C., etc.).

b) Predicasts F & S Index (United States Annual Edition)

This index covers company, product and industry information from over 750 financial publications, business-oriented newspapers, trade magazines and special reports. The F & S INDEX contains information on corporate acquisitions and mergers, new products, technological developments and socio-political factors. It summarizes analyses of companies by securities firms, forecasts of company sales and profits made by company officers and reports on factors influencing future sales and earnings such as price changes, government antitrust actions, sales and licensing agreements and joint venture arrangements. It also reports on new capacity by company, and factors affecting future product demand. Each entry in the F & S Index contains a brief description of the contents of the articles, standard abbreviation for the publication from which the entry was abstracted, and the date and page on which the entry appeared.

c) Financial Stock Guide Service (Directory of Obsolete Securities)

The annual edition of this directory contains a brief profile of companies whose original identities have been lost as a result of one or more of the following actions:

1. Change of name,
2. Merger,
3. Acquisition,
4. Dissolution,
5. Reorganization,
6. Bankruptcy, and/or
7. Charter Cancellation

The listing for each company indicates the manner in which the company's identity was lost, the new name of the company (if any), and the year in which the action occurred.

d) Moody's Industrial Manual

This manual presents financial information including income accounts, balance sheets, and financial and operating ratios.

Each listing has a detailed description of the company's business, including a complete list of subsidiaries and office and property locations. A special capital structure section at the beginning of the company report provides the details on capital stock and long term debt, with bond and preferred stock ratings and two year stock and bond price ranges. There is also an extensive presentation of material from the company's annual report, including letter of the chief executive to shareholders, report of independent public accountants, general notes to financial statements, and financial review of management.

e) Moody's Industrial News Reports

Moody's Industrial News Reports are published on Tuesday's and Friday's of each week and contain data subsequent to the publication of Moody's Manual. Information contained therein includes interim financial statements, personnel changes, information on new plants or products, merger proposals, descriptions of new debt and stock issues, security offerings and announcements of new financing.

f) The Wall Street Journal Index (Corporate News)

This contains the annual indexes for the Wall Street Journal. The index for the Wall Street Journal is divided into two sections, Corporate News and General News.

Each entry gives a brief abstract of the article followed by a four figure citation for locating the article.

g) The Value Line Investment Survey

This includes a complete list with latest prices, Timeliness and Safety ranks, Betas, estimated earnings and dividends, and reference to pages in Ratings and

Reports carrying latest full-page reports.

h) Other corporate news in the financial press such as the New York Times (Business Day Section), Barrons, Business Week, Fortune Magazine, etc.

A full investigation of the above listed sources of information revealed the following distribution of the 132 firms predicted as going to fail:

firms bankrupt	2
firms liquidated	3
firms became private	4
firms merged	11
firms still survive	112
Total	132

The three liquidated firms were investigated further to discover the reasons behind the liquidation decisions. One firm (Arcata Corporation) was liquidated without being financially troubled. The company's assets were sold to investors (Wall Street Journal, 6/04/82, p. 21). However, the other two companies (Mansfield Tire and Rubber Company and McLouth Steel Corporation) were financially troubled. Apparently the liquidation decision was preferable to a bankruptcy decision. For example, the September 20, 1980 issue of the New York Times (p. L26) indicated that Mansfield Tire & Rubber had outlined a liquidation plan. The Wall Street Journal (9/22/80, p. 46) later stated that the company's reorganization bid failed and the liquidation process was to begin.

If these two liquidated firms are considered cases of business failure, then the number of firms that experienced actual business failure is four firms (two bankrupt and two liquidated due to financial difficulties) out of 132 firms predicted as going to fail. Thus, the Type II prediction error rate is 97%.

The empirical investigation in the remaining two phases of analysis will be based on the 112 firms that are still in existence as publicly held companies as of December 31, 1983. Firms that merged or went private will not be included in the analysis due to the lack of publicly available data.

Phase II: Investigating the Adequacy of the Z-Score Model

It has been shown in Phase I that when Altman's (1968) Z-score business failure prediction model was used on an ex ante basis, the Type II prediction error rate was 97%,. This level is significantly higher than that of only 3% reported by Altman (1968), when the model was used to classify the initial sample, and of only 21%, when the model was used to classify a secondary sample. The question now is why do we observe such a high rate of Type II prediction error when the model is used on an ex ante basis? It has been suggested in Chapter III that this phenomenon might be attributable to the model's inability to make "real" predictions(i.e., predicting the failure of firms currently nonfailed), and/or the effects of preventive measures that have been intentionally taken by certain interested parties (e.g., management, creditors, shareholders, and/or government) to bail out certain ailing firms.

This phase of the study is concerned with investigating the possibility that the model is inadequate to make ex ante predictions. This issue of the model's inadequacy will be investigated in two different ways: (1) investigating the ability of the Z-score to capture the financial conditions of firms currently nonfailed, and (2) investigating the influence of the individual independent variables on the predictive ability of the Z-score.

The Ability of the Z-score to Predict on An Ex Ante Basis

Foster (1986, p. 560) pointed out that due to the lack of an economic theory of business failure, individual researchers have undertaken extensive "searching exercises" to discover models with significant classificatory power. Such "searching exercises," coupled with the ex post nature of the analysis (i.e., the estimation and the validation samples include only firms that are known to have "failed" or "not failed" on a set date), can lead to sample-specific results. As a consequence, the predictive ability of these business failure prediction models might fall sharply when they are used to predict the failure of firms currently nonfailed.

One way to judge the predictive ability of a business failure prediction model is to examine the financial status of the firms predicted to fail during the period in which the failure was expected to take place. For an accurate prediction model, firms predicted to fail in a given year either will fail or at least will show signs of financial trouble during that year. Since Altman's (1968) Z-score model was developed to predict business failure within a year, the financial condition of the 112 firms that were predicted in 1979 as going to fail within a year but that did not were examined during 1980. If the model is an accurate predictor, it would be expected that most of these 112 firms would show signs of financial distress in 1980.

To judge the financial condition of these firms, and consequently the predictive ability of the Z-score model, the following procedure were followed:

First: Consulting Investment Advisory Publications

The following two well-known investment advisory publications were consulted to determine the financial strength of each of the 112 firms during 1980:

1. Bond Ratings

Both Moody's Investor Service and Standard and Poor's Corporation rate a wide variety of debt instruments. Corporate bond ratings measure credit risk, that is, the probability of occurrence of developments adverse to the interest of creditors. The judgment of credit worthiness is expressed in a series of symbols that show the degrees of risk. The top four ratings grades (e.g.. AAA, AA, A, and BBB by Standard and Poor's) are generally referred to as "investment grade", and those ratings grades that follow the top four are generally referred to as "speculative-grade" ratings, where payments of debt are uncertain [Standard and Poor's Ratings Guide (1979) p. 5). These ratings have been found to be highly correlated with the financial condition of the issuing firm [see for example, Harold (1938), Burrell (1947), and Hickman (1958)].

Investigating both Moody's Bond survey and Standard and Poor's Corporate Bond Guide during 1980 showed that only 39 companies (of the 112 companies predicted as going to fail) received bond ratings during that year.

2. The Value Line Relative Financial Strength Ratings

The Value Line Investment Survey, which is one of the largest and best known investment advisory publications, follows and reports on about 1,700 companies. A full page report, comprising historical data, financial analysis, and written comments, is published quarterly for each company under review. In the lower right hand-corner of each review is a rating of the financial strength of the company in question. There are nine relative financial strength ratings that range from A++ (highest) down to C (lowest).

Investigating this publication showed that only 66 firms from the 112 firms under consideration were rated by this agency.

Second: Comparing Key Solvency Ratios with Industry Norms

The principal purpose of financial analysis is to identify irregularities that could help in assessing the financial strength of a given firm. These irregularities can be identified by looking at the differences between the industry norms and the key ratios of a specific firm. However, such a comparison should be interpreted with great care because industry means are usually computed using a relatively small sample (in relation to the total number of firms in a given industry) that is not selected by a statistically reliable method (Robert Morris Associates' 1980 Annual Statement Studies, p. 2.). Furthermore, Lev (1974) pointed out that the significance of deviation of an observed ratio from the industry mean depends not only on the extent and direction of deviation, but also on the dispersion and "shape" of the distribution of ratios from which the mean was calculated.

Taking this limitation into consideration, the following three popular solvency ratios were computed for each of the 112 firms and compared to the mean of their industry counterparts:

1) Current Ratio - This ratio is computed by dividing total current assets by total current liabilities. Current assets include cash, accounts and notes receivable (less reserves for bad debts), inventories, and marketable securities. This ratio measures the degree to which current assets cover current

liabilities. The higher the ratio, the more assurance exists that the retirement of liabilities can be made. The current ratio measures the margin of safety available to cover any possible shrinkage in the value of current assets. A ratio of 2 to 1 (2.0) or better is often considered to be adequate.

2) Times Interest-Earned Ratio: This ratio is computed by dividing earnings before interest expense and income taxes by annual interest expense. This ratio is a simple version of a more comprehensive fixed charge coverage ratio that measures the relationship between debt related fixed charges and the earnings available to meet these charges [for full discussion and analysis of this issue, see Bernstein (1983), pp. 569-580]. This simple version of the earnings-coverage ratios was used because of its availability for the industry level comparison.

On the industrial level, this ratio is published only by Robert Morris Associates and only for selected industries. Unfortunately the industries of many of the firms included in this study are not presented in that publication. Therefore, the ability to compare this ratio to its industry norms was limited. To overcome this problem, however, this ratio was evaluated based on how it is used in the process of rating industrial bonds. Sherwood (1976) revealed that:

> "For a company's bond to be candidate for a triple-A rating, earnings should be seven or eight times as large as interest and rental charges after taxes; for a double-A rating, four or five times as large, fo a single-A rating, more than three times; and for a triple-B rating, more then two times." [Sherwood (1976), p. 35].

3) Total Liabilities to Net Worth - This ratio is computed by dividing total liabilities by net worth. In general, total liabilities shouldn't exceed net worth. Otherwise, creditors would have more at stake than owners.

Third: Scanning the Financial Press for News

The 1980 editions of the following financial publications were scanned to locate articles and/or news that will assess the financial condition of each of the 112 firms under consideration:

1) Moody's Industrial News Reports,

2) The Value Line Investment Survey,

3) Financial Stock Guide (Directory of Obsolete Securities),

4) The Wall Street Journal Index, and

5) All other sources referred to in the U.S. Annual editions of the Predicasts F & S Index (e.g., The Daily News, Bu3iness Week, Barrons, Fortune, and The New York Times).

Based on the information obtained from the above mentioned sources, the 112 firms under consideration were classified into three categories:

1. Firms that are apparently financially healthy,

2. Firms that are apparently financially distressed, and

3) Firms that are in the "gray area".

This classification was made in three steps:

Step 1: Classification Based on Bond Ratings, Value Line Ratings, Key Solvency Ratios, and Financial Press News

Of the 112 firms under consideration, 39 firms had bond ratings in 1980. Of those 39 firms, apparently financially healthy firms were identified as those having:

a) "Investment grade" bond ratings (i.e., 'BBB' or better),

b) Value Line Financial Strength Ratings of 'B' or better,

c) Solvency ratios that are comparable to the industry norms, and

d) Nothing in the financial press indicating that the firm was suffering any financial problems.

Apparently financially distressed firms were identified as those having:

a) "Speculative-grade" bond ratings (i.e., less than 'BBB'),

b) Value Line Financial Strength Ratings of C+ or less,

c) Solvency ratios that deviate significantly from industry norms, and

d) At least one financial publication indicating that the firm was facing financial problems at the time.

Firms that have conflicting ratings by bond rating agencies and/or the Value Line Financial Strength system were classified into the "gray area" category.

Step 2: Classification Based on Value Line Ratings, Solvency Ratios, and Financial Press News

Of the 112 firms under consideration, 31 firms received Value Line ratings but did not receive bond ratings. These 31 firms were classified according to their Value Line ratings, solvency ratios, and financial press news. Guided by the Step 1 classification, apparently financially healthy firms were identified as those having:

a) Value Line Financial Strength Ratings of 'B' or better,

b) Solvency ratios that are comparable to the industry norms, and

c) Nothing in the financial press indicating that the firm was suffering any financial problems.

Firms were classified as apparently financially distressed based on the following criteria:

a) Value Line Financial Strength Ratings of C+ or less,

b) Solvency ratios that deviate significantly from industry norms, and

c) At least one financial publication indicated that the firm was facing financial problems at the time.

Firms having solvency ratios that are in conflict with the Value Line Financial Strength ratings were classified into the "gray area" category.

Step 3: Classification Based on Solvency Ratios, and Financial Press News

Of the 112 firms under consideration, 56 firms had neither bond ratings nor Value Line ratings. Classification of these 56 firms were guided by the classification in Steps 1 and 2. Apparently healthy firms were identified as those having:

a) Solvency ratios that are comparable to the industry norms, and

b) Nothing in the financial press indicating that the firm was suffering any financial problems.

Apparently financially distressed firms were idenified as those having:

a) Solvency ratios that deviate significantly from industry norms, and

b) At least one financial publication indicating that the firm was facing financial problems at the time.

Firms having conflicting solvency ratios were classified into the "gray area" category.

The above classification procedure resulted in the following distribution of the 112 firms under consideration:

Firms that are apparently financially healthy	45
Firms that are apparently financially distressed	34
Firms that are in the "gray area"	33
Total	112

Thus, of the 112 f' - :redicted by Altman's (1968) Z-score as going to fail in 1980, only 34 firms (30%) showed signs of financial distress in that year. The remaining 78 (70%) firms are either healthy or not in notable financial distress. To better judge the adequacy of the Z-score as a predictor of financial distress, Table (1) compares the Z-scores with the other solvency measures (i.e., bond ratings, Value Line Financial Strength ratings, and key solvency ratios) used in the above classification. As can be seen from Table (1), the Z-score is inadequate as a predictor of financial distress. Of the 35 firms receiving both bond and Value Line ratings, 19 firms (54%) are apparently financially healthy. Although these firms have Z-scores below the cutoff point (2.675), they received "investment-grade" bond ratings, relatively high Value Line Financial Strength ratings, and they have solvency ratios that are comparable to their industry norms.

Furthermore, Table (1) shows that the value of the Z-score is inconsistent with the other solvency indicators. For example, U.S. Steel Corporation, has a Z-score of 1.694, but has or a bond rating of AA- and a Value Line rating of A+. While United

Table (1)

Comparing the Z-score with Bond Ratings, Value Line Financial Strength Ratings, and Certain Key Solvency Ratios

(For Companies that Have Both Bond Ratings and Value Line Financial Strength Ratings)

	Z-score	Bond Rating	V.L. Rating	Current Ratio			Times Inter. Earn. Ratio			Debt/Equity Ratio		
				Co.	Inds.	Deviation (Inds.-Co.)	Co.	Inds.	Deviation (Inds.-Co.)	Co.	Inds.	Deviation (Inds.-Co.)
Group I: Apparently Healthy Firms												
1. Shell Oil Co.	2.425	AAA	A++	1.0	1.2	0.2	13.0	NR	-	1.0	1.7	0.7
2. International Paper Co.	2.642	AA-	A+	1.9	2.1	0.2	6.2	NR	-	0.7	1.0	0.3
3. U.S. Steel Corp.	1.694	AA-	B++	1.5	1.2	(0.3)	2.9	NR	-	1.3	1.7	0.4
4. Inland Steel Co.	2.568	AA-	A	1.6	2.0	0.4	1.1	NR	-	1.3	0.8	(0.5)
5. Westinghouse Electric Corp.	2.061	AA-	B++	1.3	2.1	0.8	6.3	NR	-	1.6	0.9	(0.7)
6. Dow Chemical	2.638	A+	A+	1.6	2.1	0.5	5.3	NR	-	1.6	0.8	(0.8)
7. Owens-Illinois Inc.	2.412	A	A+	1.8	2.0	0.2	4.2	NR	-	1.3	1.1	(0.2)
8. Bethlehem Steel Corp.	2.636	A	B+	1.7	2.0	0.3	2.4	NR	-	1.2	0.8	(0.4)
9. Republic Steel Corp.	2.647	A	B++	1.7	2.0	0.3	9.4	NR	-	1.0	0.8	(0.2)
10. Continental Group	2.348	A	A+	1.4	2.1	0.7	3.5	NR	-	1.4	0.9	(0.5)
11. Combustion Engineering Inc.	2.592	A	B+	1.2	1.9	0.7	14.2	5.9	(8.3)	1.2	1.1	(0.1)
12. RCA Corp.	2.359	A	A	1.5	1.9	0.4	2.9	4.5	1.6	2.2	1.3	(0.9)
13. ITT Corp.	2.220	A	B++	1.4	2.0	0.6	NR	NR	-	1.5	1.0	(0.5)
14. Macmillan Inc.	2.452	A-	B+	2.2	2.4	0.2	3.6	3.6	-	1.4	0.7	(0.7)
15. Ideal Basic Industries Inc.	2.460	A-	A	1.9	2.0	0.1	4.1	NR	-	1.1	1.0	(0.1)
16. Allis-Chalmers Corp.	2.597	A-	A-	1.5	2.0	0.5	3.2	NR	-	1.6	0.8	(0.8)
17. McGraw-Edison Co.	1.855	A-	A+	2.3	2.1	(0.2)	1.9	NR	-	1.6	0.9	(0.7)
18. Federal Paper Board Co.	2.579	BBB	B	2.3	2.1	(0.2)	4.4	NR	-	1.2	1.0	(0.2)
19. Williams Companies	2.239	BBB-	B	1.9	2.1	0.2	4.2	NR	-	1.3	0.8	(0.5)
Average Deviation from Industry Norms for Group I						0.3						(0.3)
Group II: "Grey Area" Firms												
20. UNC Resources	1.818	BB	C++	2.8	2.1	(0.7)	1.1	NR	-	1.3	0.8	(0.5)
21. Insilco Corp.	2.574	BB	B++	2.0	2.0	-	3.1	NR	-	2.4	0.8	(1.6)
22. Talley Industries Inc.	2.352	BB	C++	3.1	2.2	(0.9)	0.9	NR	-	1.2	0.9	(0.3)
23. Cooper Laboratories	2.620	B	C--	1.5	2.3	0.8	9.1	6.0	(3.1)	2.5	0.8	(1.7)
24. Nortek Inc.	2.397	B	C+	2.7	2.0	(0.7)	2.2	5.0	2.8	1.8	0.8	(1.0)
Average Deviation from Industry Norms for Group II						(0.3)						(1.0)
Group III: Apparently Financially Distressed Firms												
25. Singer Co.	2.374	BB-	C+	1.5	2.1	0.6	2.3	NR	-	2.6	0.9	(1.7)
26. APL Corp.	1.900	B	C+	1.1	1.2	0.1	0.3	NR	-	1.9	1.7	(0.2)
27. Gulf & Western Industries Inc.	2.110	B	C+	1.9	1.9	-	3.1	NR	-	2.3	1.2	(1.1)
28. NVF Corp.	1.555	B	C+	2.3	2.0	(0.3)	1.0	NR	-	4.2	0.8	(3.4)
29. Fedders Corp.	1.180	B	C	2.0	2.0	-	(3.7)	NR	-	4.1	0.8	(3.3)
30. Fischer & Porter Co.	2.338	B	C	2.5	2.0	(0.5)	1.6	5.5	3.9	1.7	1.2	(0.5)
31. Chrysler Corp.	1.564	B-	C	1.0	1.6	0.6	(5.1)	3.6	8.7	15.4	1.6	(13.8)
32. Farah Manufacturing Co.	1.832	CCC	C	2.9	1.9	(1.0)	2.2	NR	-	2.9	1.2	(1.7)
33. National Homes Corp.	1.119	CCC	C	1.4	1.9	0.5	0.9	NR	-	2.7	0.8	(1.9)
34. Grolier Inc.	1.720	CCC	C	2.5	2.4	(0.1)	1.9	3.6	1.7	10.4	0.7	(9.7)
35. United Merchants & Manufacturers Inc.	2.282	D	C	2.8	2.0	(0.8)	(1.3)	NR	-	7.4	0.9	(6.5)
Average Deviation from Industry Norms for Group III						(0.2)						(4.2)

* NR: Not Reported.

Merchants and Manufacturers Inc., has a higher Z-score (2.282), but has a bond rating of D and Value Line rating of C.

However, Table (1) also indicates that most of the financially healthy firms have, in general, a higher Z-score than do the financially distressed firms. This could indicate that the Z-score might be useful, to some extent, in detecting potentially financially distressed firms, but the location of the cutoff point might be inappropriate. This issue will be investigated below.

Inappropriate Cutoff Point

It has been shown earlier that Altman (1968) chose a cutoff point of Z = 2.675 to minimize the total number of misclassifications in his sample [Altman (1983) pp. 119 - 120]. Since this cutoff point is based on the estimation sample, it might be a sample-specific cutoff point; different samples may require different cutoff points. For example, this cutoff point may be applicable only to small firms similar to those used by Altman (1968), and for data based on economic conditions similar to what prevailed at that time. To investigate this possibility, the Z-scores of all 132 firms that the model predicted would fail were ranked from the lowest to the highest to see how the different firms appear on such ranking. Table (2) shows the ranks of the 132 firms. As can be seen from Table (2), most of the apparently financially distressed firm rank low, while most of the apparently healthy firms rank high. Thus, the model seems to be relatively useful in identifying financially distressed

Table (2)

Ranking of the Z-score of the 132 Firms Predicted as Failing

No.	Z-score	Status	No.	Z-score	Status	NO.	Z-score	Status
1	(0.093)	Private	45	2.145	Merged	89	2.436	Bankr.
2	0.148	Liquid.	46	2.153	Merged	90	2.452	Distres.
3	0.779	Merged	47	2.162		91	2.459	*
4	.888	Private	48	2.163	Private	92	2.460	
5	1.088	*	49	2.169	Merged	93	2.463	Merged
6	1.119	Distres.	50	2.205	Distres.	94	2.464	
7	1.141	Bankr.	51	2.218	*	95	2.485	Distres.
8	1.180	Distres.	52	2.220		96	2.490	*
9	1.300	Distres.	53	2.223	*	97	2.498	Distres.
10	1.318	*	54	2.239		98	2.505	Merged
11	1.381	Distres.	55	2.257	Distres.	99	2.515	Distres.
12	1.533	*	56	2.264	Distres.	100	2.522	
13	1.550	Distres.	57	2.270	Distres.	101	2.524	*
14	1.564	Distres.	58	2.272	*	102	2.534	*
15	1.694	*	59	2.275	*	103	2.544	*
16	1.704	Distres.	60	2.275		104	2.546	*
17	1.720	Distres.	61	2.282	*	105	2.555	Distres.
18	1.723	*	62	2.286		106	2.568	
19	1.756	Distres.	63	2.295		107	2.571	Merged
20	1.766	Distres.	64	2.299	Distres.	108	2.572	*
21	1.771	Distres.	65	2.299		109	2.573	Private
22	1.818	Distres.	66	2.305		110	2.573	*
23	1.832	Distres.	67	2.322	*	111	2.573	
24	1.839	*	68	2.323	Distres.	112	2.574	Distres.
25	1.855		69	2.338	*	113	2.574	
26	1.871	Distres.	70	2.345	Distres.	114	2.578	
27	1.875		71	2.348		115	2.579	
28	1.900	Distres.	72	2.352	*	116	2.580	
29	1.915	Distres.	73	2.359		117	2.592	
30	1.922	Distres.	74	2.360	Merged	118	2.592	
31	1.935	Distres.	75	2.374	*	119	2.596	
32	1.948	*	76	2.380	Distres.	120	2.597	
33	1.953		77	2.388		121	2.603	*
34	1.981	Merged	78	2.397	*	122	2.612	
35	1.986	*	79	2.401	Merged	123	2.620	*
36	2.007		80	2.410	Distres.	124	2.623	*
37	2.012	Distres.	81	2.410		125	2.633	Merged
38	2.016	Distres.	82	2.412		126	2.636	
39	2.036	*	83	2.413	Distres.	127	2.638	
40	2.041		84	2.425		128	2.642	
41	2.070		85	2.425		129	2.646	
42	2.085	*	86	2.429	Liquid.	130	2.646	
43	2.091		87	2.429	*	131	2.649	Liquid.
44	2.110	Distres.	88	2.433		132	2.651	

* Firms "in between".
Healthy firms are left blank.

firms. As previously mentioned, the liquidated firm that ranks at the top (Arcata Corporation) was apparently healthy when shareholders cleared a plan of liquidation and sale of assets to investors on June 4, 1982 (Wall Street Journal, 6/04/82, p. 21). A cutoff point of Z = 2.437 would have not misclassified any of the bankrupt firms, and would have reduced the number of nonbankrupt firms misclassified by 42 firms (i.e., reducing the Type II prediction error by 32%).

Thus, the analysis indicates that about 32% of the Type II prediction error is due to the inappropriate cutoff point of Z=2.675. However, the analysis also suggests that despite the low ability of the Z-score to predict bankrupt firms, its predictive ability to identify financially distressed firms is relatively high. As can be seen from Table (2), a cutoff point of Z = 2.575, would identify all financially distressed firms. Thus, it seems that the Z-score model could be useful in situations where the objective is to predict financially distressed firms. In such a case, establishing a cutoff point that considers the expected costs of both Type I and Type II prediction errors would be desirable. However, to the extent that the trade-off between the two types of prediction errors is decision-maker-specific, a generalizable cut-off point is only useful as a benchmark that can be adjusted by different users.

Random Fluctuation in the Z-score of Some Firms

The Z-score for some companies may not be stable over time. If the Z-score of some firms fluctuates over time, then those firms would be predicted as failing in the years during which the Z-score falls below the cutoff point. If this is the case, then Type II prediction error may be partially due to the effect of such random fluctuations in the Z-score of these firms. Table (3) shows the behavior of the Z-score over the eight-year.period 1975 - 1983 for a random sample of firms with a Z-score below the cutoff point of 2.675 in 1975.

As shown in Table (3), of the 20 randomly selected firms listed in that table, 15 firms, identified by asterisks in the last column, have a Z-score that fluctuates above and below the cutoff point over time. For example, the first company in Table (3), Cognitronics Corporation, showed a negative Z-Score in 1975 of 0.084 then changed to a positive score in 1976 of 0.783 and continued to have a Z-score far below the cutoff point until 1979. However, in 1980, it showed a very high score of 6.234, while in 1981 it showed a Z-score of only 2.733. Then, in 1982, its Z-score went down to only 1.736, which is far below the cutoff point of 2.675. Surprisingly, in 1983 it showed a Z-score of 9.778. Thus, it seems that the Z-score of some firms tends to fluctuate over time. Such fluctuation might explain the low Z-scores of those firms that did not experience financial distress. If such is the case, it might explain, in part, the observed high rate of Type II prediction errors.

Table 3

A Random Sample of Firms Having Z-scores Below the Cutoff Point (2.675) in 1975

COGNITRONICS CORP	-0.094	0.783	0.488	1.395	2.270	6.234	2.733	1.736	9.778	***
RECOGNITION EQUIPMENT INC	2.136	2.937	3.321	2.356	2.790	2.805	1.798	1.098	2.889	
COMPUTERVISION CORP	0.926	2.961	3.700	4.763	7.136	14.099	9.097	2.797	8.259	***
LUNDY ELECTRONICS & SYSTEMS	1.562	1.892	1.595	1.313	2.490	2.819	2.689	2.447	4.015	
COMPUTER CONSOLES	2.108	1.099	2.427	3.634	4.489	13.862	7.627	2.196	3.145	***
ELECTRONIC MEMORIES & MAGNET	2.596	3.919	3.585	3.355	3.571	4.132	4.415	3.800	3.941	
ARMATRON INTERNATIONAL INC	2.448	3.296	2.513	1.921	2.809	4.165	4.858	3.547	6.277	***
CHRYSLER CORP	2.396	3.245	2.972	2.522	1.564	0.567	1.535	1.616	2.443	
CONDEC CORP	2.160	2.601	2.401	2.371	2.085	2.274	2.274	1.702	1.720	
HONDA MOTOR LTD-ADR	2.254	2.673	2.490	2.208	2.425	3.220	2.990	2.657	3.534	
RIBLET PRODUCTS CORP	2.105	3.171	3.522	3.777	4.178	3.228	4.279	3.280	4.803	
ARVIN INDUSTRIES INC	2.480	3.650	4.270	3.604	3.573	3.122	3.698	2.965	4.041	
FRUEHAUF CORP	2.206	2.626	2.758	2.790	2.847	2.332	2.225	1.663	2.281	***
SMITH (A.O.) CORP-CL A	2.600	3.238	3.499	2.731	3.618	2.563	2.696	2.243	3.300	
SUNDSTRAND CORP	2.374	3.055	3.062	3.369	3.943	4.730	4.138	2.538	4.073	
FAIRCHILD INDUSTRIES INC	2.496	2.695	3.183	3.761	4.497	3.062	3.131	2.261	2.234	
AERONCA INC	1.753	0.748	1.122	2.312	2.413	3.649	3.347	2.608	3.101	
MACRODYNE INDS	-0.746	2.356	0.911	0.745	1.381	2.639	2.456	0.850	1.155	
ROHR INDUSTRIES	2.457	2.138	2.328	2.944	2.983	2.620	3.181	3.164	4.039	
SIGNAL COS	2.390	2.746	2.870	3.101	3.398	3.290	3.437	2.539	2.858	

To investigate the above possibility, the time-series behavior of the Z-score was examined. Serial correlation analysis was used to see whether Z-scores, in general, tend to fluctuate over time. The jth-order serial correction coefficient (r_j) measures the extent to which the Z_t and Z_{t+j} observations move together. If a higher (lower) than average observation tends to be followed by another higher (lower) than average observation j periods later, then the Z_t and Z_{t+j} observations are said to be positively serially correlated. On the other hand, if a higher (lower) than average observation tends to be followed by a lower (higher) than average observation j periods later, then the Z_t and Z_{t+j} observations are said to be negatively correlated. The jth-order serial correlation coefficient is estimated as:

$$r_j = \frac{(1/T) \sum_{t=1}^{T-j} \left[(Z_t - \bar{Z})(Z_{t+j} - \bar{Z}) \right]}{S_o}$$

where:

$\bar{Z}$ = the mean of the time series,

T = the number of observations in the time series, and

S_o= the variance of the time-series observations.

The range of r_j for j=1 to T-j is from -1 to +1, with r_j=o, means that there is no correlation among the time-series observations.

Serial correlation analysis has been used frequently in recent years to examine the time series behavior of accounting variables [e.g., Beaver (1970), Ball and Watts (1972), Foster

(1977), and Cogger and Ruland (1982)]. Serial correlation coefficients can be used to identify certain time-series properties of the variable under consideration. For example, Beaver (1970) stated that under the assumption of mean reversion, the first order serial correlation coefficient of the original series will be zero, but the first-order serial correlation coefficient of the first differences in the series is 0.5 [Beaver (1970), P. 67]. Under the assumption of pure random walk, however, the first serial correlation coefficient of the original series will be positive and will approach one as the time-series increases, and the first-order correlation coefficient of the first differences is zero [Beaver (1970), P. 67].

Serial correlation analysis is used to examine the time-series behavior of the Z-score of the sample firms over the 20 year period 1964 - 1983. This 20 year period was chosen because it provided enough observations to conduct test statistics.

The test statistics used in this study is the one used initially by Ball and Watts (1972), and modified by Cogger and Ruland (1982). The null hypothesis to be tested, according to the latter, is that firms, "on average", exhibit independent changes in Z-score. That is:

$$H_o : \sum_{i=1}^{N} \rho_i = 0 \tag{1}$$

Cogger and Ruland (1982) showed that, under the above null hypothesis, the expected value and the variance of the computed average serial correlation coefficients are:

$$E(\bar{r}) = -1/(T-1) \qquad (2)$$

and

$$V(\bar{r}) = \frac{1}{N(T+1)} - \frac{(T-1)(T-3)}{N^2(T+1)^2(T+3)} \sum_{i=1}^{N} \rho_i^2 \qquad (3)$$

Where:

$\bar{r}$ = Average serial correlation coefficients of a sample,

n = Number of firms in the sample,

t = Number of successive changes in the time series.

Following a conservative approach, in the sense of increasing the chance that H_o will not be rejected, Cogger and Ruland (1982) set all the ρ_i in (3) equal to zero, and this results in the following test statistic:

$$Z = \left[\bar{r} + \frac{1}{(T-1)}\right] \sqrt{N\ (T+1)} \qquad (4)$$

where Z is the standardized normal score for the test statistic [Cogger and Ruland (1982), P. 736].

Table (4) reports the results of the serial correlation analysis. Of the 112 firms, only 41 firms having complete data over the period 1964 - 1983 were included in the analysis. As can be seen from Table (4), the mean of the serial correlation coefficients for the original series is 0.518 and for the first

Table (4)

Distribution of Serial Correlation Coefficients
(Z-score Observations For the Period 1964-1983)

Serial Correlation Coefficients for:	Mean	Deciles								
		.1	.2	.3	.4	.5	.6	.7	.8	.9
1. Original Series	0.518	.138	.355	.456	.508	.554	.615	.666	.689	.767
2. First Difference (Z-statistic*)	-0.045 0.302	-.339	-.279	-.230	-.184	-.114	-.040	.097	.192	.285

* This is the standardized normal score for testing the null hypothesis that firms "on average" exhibit independendt changes in Z-score (i.e., $H_0 : \sum_{i=1}^{n} \rho_i = 0$). As can be seen from the table, the null hypothesis cannot be rejected at any reasonable level of significance.

differences is -0.045. Using the standardized normal Z statistic proposed by Cogger and Ruland (1982), the mean of the serial correlation coefficients for the first differences is insignificantly different from zero. That is, the null hypothesis that firms, "on average", exhibit independent changes in the Z-score cannot be rejected at any reasonable level of significance. The positive mean serial correlation coefficients of the original series coupled with a mean that is insignificantly different from zero for the first differences suggests that the Z-score series of the sample "on average" can be described by a pure "random walk" model [see Beaver (1970), P. 67].

The above conclusion is based upon the results of the mean of a relatively small sample. To investigate whether specific firms are outliers, the time series of the Z-score of each firm of the sample was investigated separately. Table (5) reports the results of the serial correlation analysis for individual firms. Foster (1978) suggests a general rule of thumb that states if the serial correlation coefficient of the original series is no more than two standard errors from zero, one cannot reject the null hypothesis that the serial coefficient of the population is zero at the 95% confidence level. Consequently, the series can be described by the random-walk model [Foster (1978), P. 85]. As shown in Table (5), 11 firms (identified by asterisks in the remarks column) have Z-score series that can be described by the random-walk model based on the above rule of thumb.

Table (5)

Time Series Serial Correlation Coefficients
For Companies Having 20 Observations (1964 - 1983)

Company	Serial Correl. Coeffic. (level)	Serial Correl. Coeffic. (changes)	Remarks
1. Valmac Industries Inc.	0.818	-0.118	
2. Gulf & Western Inds. Inc.	0.645	-0.231	
3. National Homes Corp.	0.798	-0.110	
4. APL Corp.	0.547	-0.084	
5. Bowater PLC-ADR	0.687	0.042	
6. Federal Paper Board Co.	0.729	-0.120	
7. International Paper Co.	0.613	0.296	
8. Southwest Forest Industries	0.694	0.138	
9. Grolier Inc.	0.402	-0.509	***
10. Allied Corp.	0.468	0.285	
11. Dow Chemical	0.479	0.316	
12. UNC Resources Inc.	0.370	0.115	***
13. Del Laboratories Inc.	0.645	0.108	
14. Sun Chemical Corp.	0.619	-0.082	
15. Coastal Corp.	0.248	0.333	***
16. Murphy Oil Corp.	0.386	-0.031	***
17. U. S. Steel Corp.	0.493	0.042	
18. Dunlop Holdings PLC	0.667	-0.108	
19. Uniroyal Inc.	0.565	-0.021	
20. Walter (Jim) Corp.	0.682	0.224	
21. Owens-Illinois Inc.	0.582	0.204	
22. Ideal Basic Industries Inc.	0.689	0.201	
23. Arundel Corp.	0.539	-0.159	
24. General Refractories Co.	0.489	0.009	
25. Wheeling-Pittsburgh Steel	0.538	-0.173	
26. Lehigh Valley Industries	0.559	-0.317	
27. Kaiser Aluminum & Chem. Corp.	0.476	0.264	
28. Handy & Harman	0.154	-0.267	***
29. Insilco Corp.	0.668	-0.004	
30. Continental Group	0.481	0.268	
31. Allis-Chalmers Corp.	0.329	-0.324	***
32. Harnischfeger Corp.	0.373	-0.278	***
33. Combustion Engineering Inc.	0.460	-0.300	
34. Selas Corp. of America	0.183	-0.461	***
35. Westinghouse Electric Corp.	0.685	-0.367	
36. RCA Corp.	0.759	0.231	
37. Sony Corp. ADR	0.318	-0.192	***
38. ITT Corp.	-0.073	-0.019	***
39. Curtiss-Wright Corp	0.180	-0.348	***
40. ACF Industries	0.545	0.122	
41. Rymer Co.	0.729	-0.269	
Mean Serial Corr. Coefficients	0.518	-0.045	

*** The Serial Correlation Coefficient of the Original Series is Within Two Standard Errors (± 0.404).

Thus, the results of the serial correlation analysis suggest that the time series of Z-scores, for some firms, can be described by the random-walk model. This model implies that the best forecast (in the sense of the minimum mean-square forecast error) of Z_t is Z_{t-1} [Foster (1978), P. 83]. In addition, as shown in Table (4), the mean and median of the first differences is negative, which indicates that successive changes in Z-scores tend to alternate on different sides of the overall mean [Chatfield (1984), P. 27]. This tendency to alternate might explain, in part, why so many financially healthy firms were predicted as going to fail (as a consequence Type II prediction error increases). That is, the fluctuation in Z-score from one period to another causes the Z-score, for those firms, to fall below the cutoff point in certain periods regardless of the financial conditions of such firms. Possible sources of such fluctuations will be examined in the following section.

The Association Between the Changes in Z-score and the Changes in the Independent Variables

Given such fluctuations in the Z-score, a relevant question is: Are the changes in the Z-score attributable to similar changes in all the independent variables or to specific changes in specific independent variables? The answer to this question may provide an explanation of the observed fluctuation in the Z-score. For example, if the changes in the Z-score are associated with specific changes in specific independent variables, further investigation of the changes in such independent variables would reveal the reasons behind the changes in the Z-score.

To investigate the above issue, the association between the relative changes in the Z-score and the relative changes in the weighted independent variables was examined. The correlation between the relative changes in the Z-score and the relative changes in the independent variables was computed using the same 20-year period used in the serial correlation analysis (1964 - 1983). The relative changes in the Z-score were computed as follows:

$$Y_t = \frac{\Delta Z_t}{Z_{t-1}} = (Z_t - Z_{t-1}) / Z_{t-1} \qquad T = 1, 2, \ldots\ldots, 20$$

The relative changes in the weighted independent variables were computed as follows:

$$S_{jt} = \frac{\Delta X_{jt}}{X_{jt-1}} = (bX_{jt} - bX_{jt-1}) / bX_{jt-1}$$

where:

Y_t = relative change in Z-score in year t,

S_{jt} = relative change in the independent variable j in year t,

b = the coefficient of the j independent variable in the Z-score model,

X_j = the j independent variable in the Z-score model

j = 1, 2, 3, 4, and 5, and

t = 1, 2, 3, ... , 20

Table (6) presents the correlation coefficients between the relative changes in the Z-score (Y_t) and the relative changes in the weighted independent variables (S_{jt}) for the 41 firms having complete data over the 20-year period (1964 - 1983). From Table (6), one can determine, for each firm, the extent to which changes in the Z-score are associated with changes in each of the independent variables. For example, for Valmac Industries, the first company, sales to total assets, variable X_5, has the highest correlation coefficient of 0.800. This is followed by X_4, the market value of total equity to the book value of total debt, with a correlation coefficient of 0.397. Variable X_2, retained earnings to total assets, has the lowest correlation which is -.086. These correlations suggest that the relative changes in the Z-score for Valmac Industries over the period 1964 - 1983 are attributable mainly to the relative changes in X_5 and X_4. That is, the main source of the change in the Z-score for that company are the changes in the ratio of sales/total assets and the ratio of market value of equity/book value of total debt.

In order to draw general conclusions from Table (6), the independent variables for each company were ranked according to their correlation coefficients. Table (7) summarizes the frequency of the cases in which each independent variable has the highest and the lowest correlation coefficient.

As can be seen from Table (7), X_4, the market value of equity to the book value of total debt, has the highest correlation coefficient in 24 of the 41 cases analyzed (i.e.

Table (6)

Correlations Between the Relative Changes in the Z-score and the Relative Changes in the Weighted Independent Variables

Company	X_1	X_2	X_3	X_4	X_5
Valmac Industries	.303	(.086)	(.187)	.397	.800
Gulf & Western Ind.	.451	.209	.685	.793	.736
National Homes Corp.	(.039)	.121	(.120)	.737	.604
APL Corp.	.050	.521	.146	.754	.631
Bowater PLC-ADR	.064	.072	.753	(.043)	.828
Federal Paper Board Co.	.595	.479	.442	.672	.767
International Paper Co.	.273	.555	.467	.768	.451
Southwest Forest Ind.	.384	.691	.523	.723	.891
Grolier Inc.	.945	(.294)	(.134)	(.843)	.164
Allied Corp.	.506	.314	.547	.673	.473
Dow Chemical Co.	.224	.365	.374	.864	.288
UNC Resources Inc.	.260	.662	.591	.781	.108
DEL Laboratories Inc.	.135	.271	(.260)	.893	.146
Sun Chemical Corp.	.317	.725	.720	.779	.669
Coastal Corp.	.121	.221	.170	.739	.333
Murphy Oil Corp.	.414	.423	.363	.899	(.046)
U. S. Steel Corp.	.705	.872	.344	.569	.420
Dunlop Holdings PLC	.309	.226	.523	.570	.524
Uniroyal Inc.	(.084)	.683	(.147)	.570	.069
Walter (JIM) Corp.	.354	.545	.725	.559	.774
Owens-Illinois Inc.	.592	.732	.636	.812	.729
Ideal Basic Ind. Inc.	.042	.734	.346	.934	.668
Arundel Corp.	(.082)	.855	.650	.709	.598
General Refractories Co.	.473	.769	(.074)	.844	.310
Wheeling Pittsburgh Steel	.067	.652	(.293)	.547	.877
Lehigh Valley Ind.	.843	(.006)	(.308)	(.129)	.423
Kaiser Aluminum & Chem. Co.	.368	.693	.578	.322	.817
Handy & Harman Co.	.651	.800	.893	.837	.968
Insilco Corp.	.361	.608	.649	.878	.657
Continental Group	.506	.817	.539	.858	.632
Allis-Chalmers Corp.	.671	.449	(.131)	.548	.477
Harnischfeger Corp.	.668	.229	.538	.671	.469
Combustion Engineering Inc.	.283	.317	.574	.680	.636
Selas Corp. of America	.876	.884	.034	.692	.588
Westinghouse Electric Corp.	.043	.671	.673	.916	.619
RCA Corp.	.641	.284	.763	.832	.727
Sony Corp. ADR	.334	.392	.602	.959	.309
ITT Corp.	.663	.378	.373	.856	.306
Curtiss Wright Corp.	.260	.748	.252	.888	.039
ACF Ind.	.320	.648	.330	.536	.530
Rymer Co.	.405	(.153)	.261	.029	.158

Table (7)

Frequency of Cases in Which the Variables Have
the Highest (the Lowest) Correlation Coefficients

Cases \ Variables	X_1	X_2	X_3	X_4	X_5
Number of cases in which the variable **has** the highest correlation	4	5	0	24	8
Number of cases in which the variable **has** the lowest correlation	13	7	6	2	7

56%). This is followed by X_5, sales to total assets, which has the highest correlation coefficient in 8 cases (20%). However, X_1, working capital to total assets, has the lowest correlation coefficient in 13 cases (i.e., 32%), but X_4, the market value of equity to the book value of total debt, has the lowest correlation coefficient in only two cases.

The above results suggest that the relative changes in the Z-score are highly associated with the changes in the independent variables X_4, the market value of equity to the book value of total debt, and X_5, sales to total assets. Since both the market value of equity and sales change with the overall economy, it would be expected that the Z-score, for certain firms, might change without actual changes in the firm's long-run competitive and financial condition.

The implication of the above is that, to the extent that changes in the firm's X_4, the market value of equity to the book value of total debt, and X_5, sales to total assets, are caused by non-firm-specific factors (e.g., macroeconomics factors), the firm's Z-score will experience similar changes that might not be directly related to the firm's financial condition. As a consequence, whenever such changes cause the firm's Z-score to fall below the cutoff point, the firm will be classified as going to fail without actually being financially distressed. This could explain, in part, why such a high rate of Type II prediction errors is observed.

Substitution Among the Independent Variables

Another problem stems from the fact that Altman's (1968) Z-score model is an additive linear combination of five independent variables. The independent variables may substitute for one another without restictions. For example, an increase in a firm's working capital may be due to unfavorable factors (e.g., slow-moving inventory items and/or an increase in uncollectable receivables that are not written off in a timely manner, accompanied by a decrease in accounts payable because suppliers refuse supplying the firm on credit). If in total assets remains unchanged, X_1, working capital to total assets will increase. Such an increase in X_1 could compensate for a similar decrease in other independent variables, such as X_2, retained earnings to total assets, or X_3, income before interest and income taxes to total assets. Such substitutions would produce a misleading Z-score. As a result, the model's tendency to make false predictions increases.

To clarify the above problem, six financially trouble firms were randomly chosen; each firm was matched with another financially healthy firm as to Z-score. Table (8) presents these six pairs of firms. Both firms in each pair have approximately the same Z-score , but the first firm is apparently financially troubled and the second is apparently financially

Table (8)

Pairs of Healthy and Financially Troubled Firms
Having the Same Z-score in 1979

Company	Z-score	$1.2(X_1)$	$1.4(X_2)$	$3.3(X_3)$	$.6(X_4)$	X_5	Total Assets	Status
Lehigh Valley	2.410	.308	(.644)	.465	.201	2.077	53	T *
Sun Chemical	2.410	.246	.311	.396	.269	1.188	395	H
Lockheed	2.574	.174	.119	.201	.158	1.920	2,113	T
Inland Steel	2.572	.108	.546	.264	.324	1.330	2,726	H
Aeronica Inc.	2.413	.516	(.658)	(.066)	.522	2.110	26	T
Owens Ill.	2.412	.168	.476	.297	.258	1.212	3,072	H
New Park Res.	2.345	.276	.224	.396	.648	.801		T
Continental Gr.	2.348	.120	.350	.264	.396	1.218	3,653	H
LSB Lab.	2.299	.384	.155	.297	.162	1.299	50	T
Allied Corp	2.295	.079	.280	.528	.384	1.024	4,209	H
Rymer Corp.	2.257	.477	.139	(.964)	.214	2.391	49	T
Williams Cos.	2.239	.157	.358	.306	.498	.920	2,012	H

* H : Healthy Firm.
T : Financially Troubled Firm.

healthy [according to the criteria used in this study (see pp. 60-62)]. Comparing the weighted independent variables for each pair shows that X_1, working capital to total assets, multiplied by its weight of 1.2, tends to be higher for the financially troubled firms than for the financially healthy firms. Also, X_5, sales to total assets, multiplied by its weight of 1, tends to be higher for the financially troubled firms than for the financially healthy firms. However, X_2, retained earnings to total assets, multiplied by its weight of 1.4, tends to be higher for the financially healthy firms than for the financially troubled firms. This suggests that the independent variables substitute for each other within the model. Such substitution might obscure the Z-score and inhibit the predictive ability of the model.

To address the above issue, a portfolio of the apparently financially distressed firms was matched by the Z-score for each individual firm with another portfolio of apparently financially healthy firms. The test included 28 pairs of firms with a maximum difference in the Z-score of about 5%. Then, Hotelling's T^2 was used to test the following hypothesis:

$$H_o: \ U_1 = U_2 \qquad \text{vs. } H_1: U_1 \neq U_2$$

Where: U is a 1x5 vector of the means of the weighted independent variables included in the Z-score model, and 1 and 2 refer to the first and second portfolio respectively.

Table (9) reports the results obtained from Hotelling's T^2 statistic. It is quite clear from Table (9) that the means of the weighted independent variables are significantly different between the apparently healthy firms portfolio and the apparently financially distressed firms portfolio. The null hypothesis of equal means can be rejected at .0004 level of significance.

In addition, the 28 apparently financially distressed firms were also matched on their Z-scores with another portfolio of 28 firms from the "gray area" category identified earlier. Then, the Hotelling's T^2 was used to test the equality of the means of the weighted independent variables for both portfolios. Table (10) reports the results of that test. Again, the null hypothesis of equal means for the two portfolios can be rejected at .01 level of significance.

Thus, the results from the multivariate Hotelling's T^2 test statistic suggest that both financially troubled and financially healthy firms can have the same low Z-score but for different reasons. A question arises as to which independent variables tend to differ between financially troubled firms and financially healthy firms, and how these independent variables differ between the two types of firms. To examine this issue, the univariate t-test statistic is used to test the following null hypothesis for each of the five independent variables.

Table (9)

HOTELLING T^2

Differences Among the Means of the Five Independent Variables of Altman's Z-score Model

28 Healthy Firms vs. 28 Financially Troubled Firms

Mahalanobis D^2	2.1024
Hotelling T^2	29.4331
F Value	5.4506
Degrees of Freedom	5, 50
P-Value	0.0004

Table (10)

HOTELLING T^2

Differences Among the Means of the Five Independent Variables of Altman's Z-score Model

28 Firms of the 'Gray Area' vs. 28 Financially Troubled Firms

Mahalanobis D^2	1.2353
Hotelling T^2	17.2947
F Value	3.2027
Degree of Freedom	5, 50
P-Value	0.0138

$$H_0: \quad U_{1i} = U_{2i}$$

where;

U_{1i} = the mean of the independent variable i for the of financially troubled firms portfolio,

U_{2i} = the mean of the independent variable i for the nontroubled firms portfolio, and

i = 1, 2, 3, 4, 5.

Table (11) presents the results of the above univariate test statistic. The comparison includes the means of the individual independent variables for the three portfolios of financially troubled firms, financially healthy firms, and firms in the "gray area". As can be seen from Table (11), both X_1, working capital to total assets, and X_5, sales to total assets, tend to be significantly higher for financially troubled firms. However, X_2, retained earnings to total assets, tends to be significantly higher for the financially healthy firms.

The above findings could be explained as follows:

First: Financially troubled firms could have higher X_1, working capital to total assets, for one or more of the following reasons:

a) They may have large amounts of slow-moving or obsolete inventory items, which inflate the inventory and consequently raise the total current assets.

Table (11)

Comparison of the Means of the Individual Independent Variables
(Three Portfolios of Firms Having Approximately the Same Z-score)

Portfolio	Z-score	X_1	X_2	X_3	X_4	X_5
Financially Troubled (28 Firms):						
Mean	2.023	0.320	(0.094)	0.126	0.289	1.382
St. D.	0.418	0.203	0.472	0.324	0.227	0.422
Financially Healthy (28 Firms):						
Mean	2.030	0.224	0.257	0.237	0.337	0.976
St. D.	0.415	0.130	0.204	0.188	0.250	0.234
Firms in the "Gray Area" (28 Firms):						
Mean	2.194	0.302	0.197	0.237	0.305	1.152
St. D.	0.201	0.183	0.206	0.153	0.235	0.296
t-statistic* (Portfolio 1 vs. 2):	0.06	(2.10)	3.60	1.56	0.75	(4.46)
p-value	0.96	0.04	0.0007	0.12	0.46	0.0001
t-statistic** (Portfolio 1 vs. 3):	1.94	(0.35)	2.99	1.64	0.27	(2.36)
p-value	0.057	0.729	0.004	0.107	0.788	0.022

* Test-statistic for the difference between the means of the financially troubled portfolio and the financially healthy portfolio.

** Test-statistic for the difference between the means of the financially troubled portfolio and the firms in the "gray area" portfolio.

b) They may have a large balance of accounts receivable due to either poor collection policies or loosened credit criteria to increase sales.

c) They may have low current liabilities because suppliers are unwilling to extend credit to a financially troubled firm and instead require cash on delivery.

d) The company may operate in a low capital-intensive industry, and consequently has a relatively low total assets figure.

It is noteworthy that Table (1) on page (64) indicates that financially troubled firms (Group III in that table) show current ratios with less unfavorable deviations from industry averages than do financially healthy firms. This could be attributable to one or more of the above mentioned reasons or to some "window dressing" activities by management.

Second: Financially troubled firms could have higher X_5, sales to total assets, because they may follow what is called an inventory "Fire-Sale" policy to bring in badly needed cash. Sloma (1985) described such a policy as follows:

> "Sometimes considerable cash can be obtained by severely marking down inventory and dumping it on the market ....
> ....
> The greater the general use of the product, the easier it is to move it in a 'Fire-Sale.'" [Sloma (1985), p. 137].

Third: Financially troubled firms could have low X_2, retained earnings to total assets, simply because they have either low or negative retained earnings.

Implication

It has been shown that the Z-score allows the independent variables to compensate for one another, and such compensation could obsure the meaning of the Z-score as a financial profile. Favorable (unfavorable) independent variables compensate for unfavorable (favorable) independent variables. Such compensation among the independent variables produces, for some companies, an overall misleading Z-score. Two similar Z-scores may be obtained, but for very different reasons. Therefore, the Z-score is not necessarily an accurate discriminator between financially healthy firms and financially troubled firms. To the extent that a low Z-score is obtained for reasons other than financial difficulties, Type II prediction errors will occur. Thus, the above findings could explain, in part, the observed high rate of Type II prediction errors.

Phase III: Survey of Preventive Actions

This phase of the study addresses the question of to what extent Type II prediction errors are attributable to preventive actions taken by interested parties (e.g., management, creditors, shareholders, or the government). In other words, how often do actions taken by interested parties prevent financially troubled firms from failing?

The theoretical literature suggests that the interests of management, creditors, shareholders, and society as a whole are promoted through the avoidance of bankruptcy. Various corrective actions have been suggested to preserve financially troubled firms. Altman (1971) suggests the following actions by which financially troubled firms might avoid bankruptcy.

1. Changes in product line and/or management personnel,

2. Sale of unprofitable equipment and/or entire unprofitable divisions.

3. Altering the firm's capital structure, and

4. Merger with a financially sound company.

The first three actions are recommended when the threat of failure is clear but not necessarily imminent. The fourth action, however, is recommended when the danger of failure is imminent [Altman (1971), p. 95].

Similarly, Platt (1985) suggests strategies that might help near-bankrupt firms. He classifies such strategies into three categories:

1. Asset Maneuvers

   This involves the following possible actions:

   a) Collateralize a new loan using assets, and

   b) Sell off an unsuccessful division or, if necessary, a successful one.

2. Liability Maneuvers

This involves the following possible actions:

a) Sell new shares of common stock,

b) Obtain a loan guarantee from the government or an interested third party, and

c) Negotiate an extension and/or a composition plan with lenders.

3. Company Maneuvers

This includes the following possible actions:

a) Develop a new company strategy,

b) Remove the management team that shepherded the firm into trouble,

c) Pressure the labor force and suppliers for concessions, and

d) Merge with another company.

Platt (1985) comments on such strategies as follows:

> "It is never too late to try to save a company. The endless variety of asset, liability, and company maneuvers that exist provides opportunities for the entrepreneur's creativity and endurance." [Platt (1985), p. 105].

Nevertheless, the literature is almost void of empirical evidence that shows what financially troubled firms actually do. This may be due to the fact that the specific problems which beset a specific firm are in some way unique to that firm. However, it would be beneficial to investigate empirically the extent to which such suggested actions are taken by financially troubled firms. This phase of the current study is concerned with investigating this issue.

Because of the lack of prior empirical research on this issue, this phase of the study is exploratory in nature. The objective is to develop an initial understanding of the nature of those actions that are actually taken by financially distressed firms. Exploratory research is indicated when the commonalities, and the categories of variables which play a part in a situation are uncertain, and where we are trying to formulate a new framework within which controlled experiments may later be performed [Zikmund (1982), p. 100]. That is, the objective of the research in this phase is to help formulate the problem and clarify concepts rather than to reach conclusive evidence.

Formal research design is conspicuous by its absence in exploratory studies. The imagination of the researcher is the key factor in such studies [Boyd, Westfall, and Stasch (1981), p. 37]. However, exploratory survey design is regarded as appropriate for investigating the research question at hand. Manheim and Rich (1981) described exploratory surveys as follows:

> "Exploratory surveys help us acquire information that can be helpful in formulating research questions and hypotheses more precisely when we know little about a phenomenon we consider worthy of study." [Manheim and Rich (1981), p. 107].

Similarly, Jones (1985) described the objective of the survey research as follows:

> ".......The third objective for which survey research is sometimes used is EXPLORATION, exploratory analysis of an issue or problem area.....................
> .....The goal is to find out as much as you can about the issue and the subissues, the dimensions and the ramifications of the problem area." Jones (1985) p. 173.

In sum, a survey of firms will be used in this phase of the study to explore what actions have been taken by interested parties to avoid imminent business failure, and consequently to cause the predictions made by the Altman's (1968) Z-score to fail to materialize.

Selection of Survey Firms

To identify those actions that might have been taken intentionally to bail out a financially troubled firm, survey firms are chosen from the three categories identified in Phase II (i.e., apparently financially distressed firms, apparently healthy firms, and firms in the "gray area"). Although the apparently financially distressed firms are the focus of this study, the other two categories are included in the investigation to determine whether similar actions are taken by firms in other categories. The fifteen firms that have the lowest Z-scores in each category were chosen for investigation. That is, a total of 45 firms were included in this exploratory survey.

Data Collection

In the absence of a prior knowledge of what actions might have been taken to bail out financially distressed firms, it is desirable to collect as much data as possible about all actions that could have been taken to keep a financially troubled firm alive. However, since there exists an endless variety of such actions, the survey in this exploratory study will concentrate first on those actions suggested by Altman (1971) and Platt (1985), above. Thus, the actions included in the survey are the following:

1. Sale of property, plant, and equipment,
2. Divestiture of an entire division or a subsidiary,
3. Restructure of debt (e.g., an extension and/or reduction plan with creditors),
4. Obtain a loan guarantee from the government,
5. Sell new shares of common stock,
6. Request relief from labor unions,
7. Develop a new company strategy (e.g., concentrating on specialty markets, changing product line(s), withdrawing from certain overseas operations, etc.), and
8. Change the top management team that shepherded the company into trouble.

The merger option could not be examined in this survey because only surviving firms have been included in this study.

Information about the above actions was collected by scanning the following sources over the 5-year period 1979-1983:

1. Financial Statements,

2. Moody's Industrial News Reports,

3. The Value Line Investment Survey,

4. Financial Stock Guide Service (Directory of Obsolete Securities),

5. The Wall Street Journal Index, and

6. All other sources referred to in the U.S. Annual editions of the Predicasts F & S Index (e.g., The Daily News, Business Week, Barrons, Fortune, and The New York Times).

Data Analysis and Results of Survey

Tables (12) presents the results of the survey. The results can be summarized into the following:

A. Actions taken by financially troubled firms only:

1) Restructuring of debt,

3) Obtaining governmental guaranteed loans, and

4) Requesting relief from labor unions.

Table (12)

Survey of Actions Taken by Firms with Different Financial Condition

	Sale of PEE	Sale of Division or Subs.	Restructuring of Debt	Govern. Guarant. Loans	Issue of new Equity	Labor Unions Relief	Strategy Changes	Top Management Changes
Financially Troubled Firms:								
1. Orange-Co. Inc.,	X	X			X	X		
2. International Proteins	X	X						
3. Texfi Industries	X							
4. Farah MFG Co.	X			X				
5. National Homes Corp.	X	X				X		
6. APL Corp.	X	X						X
7. Grolier Inc.,	X		X				X	
8. International Banknote	X		X					
9. Ronson Corp.	X	X	X				X	
10. Buckhorn Inc.,	X				X			
11. Massey Ferguson Ltd.	X	X	X	X	X		X	
12. Fedders Corp.	X	X						
13. Chrysler Corp.	X	X	X	X		X	X	
14. The Singer Company	X	X	X				X	
15. NVF Corp.	X	X						
Total	15	10	6	3	3	3	5	1
Firms in the "Gray Area":								
1. Valmac Industries Inc.,	X	X						
2. Concord Fabrics Inc.,	X							
3. After Six Inc.,	X	X					X	
4. UNC Resources Inc.,	X	X			X			
5. ICN Pharmaceuticals Inc	X	X			X		X	
6. Dunlop Holdings PLC								
7. Moore McCormack	X						X	
8. Puerto Rican Cement Co.	X							
9. Arundal Corp.	X	X						
10. Sharon Steel							X	
11. Sterling Extruder Corp.	X							
12. Superscope Inc.,	X						X	
13. Acton Corp.	X	X			X		X	
14. Nortek Inc.,	X							
15. Talley Industries Inc.,	X	X						
Total	13	7			3		6	1
Financially Healthy Firms:								
1. Allied Corp	X	X						
2. Coastal Corp.	X	X			X			
3. U. S. Steel Corp.	X	X					X	
4. Gifford-Hill & Co.		X			X			
5. Genstar Corp.	X	X					X	
6. Inland Steel Co.	X							
7. Handy & Harman					X		X	X
8. Westinghouse Electric Co.		X						
9. McGraw-Edison Co.	X	X			X		X	X
10. RCA Corp.	X	X					X	X
11. Sony Corp. ADR								
12. ITT Corp.	X							
13. Honda Motor Ltd. ADR								
14. ACF Industries	X	X					X	
15. Compudyne Corp.	X				X			
Total	10	9			5		6	3

B. Actions taken by firms in the three categories with approximately the same frequency.

1) Sale of property, plant, and equipment,

2) Divestiture of entire divisions or subsidiaries, and

3) Strategic changes.

C. Actions taken more often by nontroubled firms:

1) Issuance of new common stock, and

2) Top management changes.

Those actions taken by financially troubled firms only are those that have been suggested by Altman (1971) and Platt (1985). The actions taken by firms in all three categories with approximately the same frequency, however, must be explained. Both healthy firms and financially troubled firms may take the same actions for different reasons. For example, a healthy firm might sell assets or an entire division or subsidiary, use the proceeds to buy or build another division or subsidiary, and thereby increase the firm's diversification. On the other hand, a financially troubled firm can sell assets or an entire division or subsidiary and use the proceeds to pay due debts and/or finance current operations (i.e., payment for labor and materials).

The following two excerpts from comments by the Value Line Investment Survey clarify that point.

- Genstar Ltd., (a financially healthy firm):

> "Go West (and South), young man". In the past two years, Genstar has sold or liquidated $100 million of property in eastern Canada to concentrate on the U.S. Sunbelt and western Canada. The company is investing heavily in Canada's booming western provinces, where it makes cement, fertilizer, and chemicals, and develops residential land, shopping centers, and industrial projects. (Value Line Investment Survey, 5/19/1980, p. 872).

- Ronson Corp. (a financially troubled firm):

> The debt burden is receding. Ronson's economy measures have freed up land and buildings that management is selling for cash. (Capital gains on property sales may account for a third of 1979 earnings.) To give the company time to negotiate property sales, its bankers have agreed to extend loan repayments to late 1979. Ronson met its quota of property disposals in 1978 and used the proceeds to retire $6 million of debt. If more time is needed to complete pending transactions, Ronson's lenders would likely cooperate.

Similarly, the actions taken more often by non-troubled firms can be explained in the same fashion. Both healthy firms and financially troubled firms issue new common stock or change top management but for different reasons. Unless these reasons are disclosed, no conclusion can be made with respect to these actions.

Other Actions by Financially Troubled Firms

In addition to the actions suggested by Altman (1971) and Platt (1985), the results of the survey revealed that financially troubled firms took other actions, including the following:

1. Converting debt into common equity. For example, Massey-Ferguson Limited, in its 1983 annual report, Financial Review Section, p. 15, disclosed the following:

> "On March 7, 1983 the Company concluded agreements with its lenders which basically comprised a combination of interest or principal conversion and forgiveness.......................... ....The agreement by the lenders to accept Common Shares and other securities convertible into or exchangeable for Common Shares of the Company in settlement of part of the outstanding and unpaid interest at March 7, 1983 and for interest accruing to January 31, 1983 and for part of the principal at March 7, 1983..........."

2. Operating under strict cash conservation measures. For example, Massey-Ferguson Limited, in its 1983 annual report, Financial Review Section, p. 15, disclosed the following:

> "The Company has operated under strict cash conservation measures since 1981. While this has adversely affected the Company's operating results, it has improved liquidity. Primarily as a result of these measures, the Company was able to generate positive cash flow from operations of $44.8 million in fiscal 1983 and $21.4 in 1982."

3. Sale - Leaseback of property: Sale-leaseback is used to improve the company's debt to equity ratio. The Value Line Investment Survey's comment on Farah Manufacturing Company (3/16/1979, p. 1607) provides an example:

> "Farah sliced its long-term debt by more than half last month. It arranged for the sale-leaseback of approximately 70 acres of land and three buildings at the company's Gateway West Complex, its home office and primary manufacturing facility in El Paso, Texas. Management used $14.8 million of the $18 million sale price to pay off back debt, essentially leaving only $9.9 million of 5% convertible debentures on the long-term liability line and considerably improving the company's debt-equity ratio."

Also, the sale-leaseback decision could be taken to improve reported net income. An example of this is given by Buckhorn, Inc., in its 1981 annual report, Note H:

> "On October 30, 1980, the Company sold its distribution, warehouse and maintenance facilities in Columbus, Ohio for $5 million ($3.75 million in cash and debt assumptions and $1.25 million in notes receivable). In conjunction with the agreement, the Company is leasing back the property from the buyer for seven years. During 1981, $250,000 was paid on the notes receivable and $1 million is due in 1987. The gain on the sale of $2 million is being taken into income ratably over the lease term."

4. Cutting common dividends: The Value Line Investment Survey on APL Company (8/8/1980, P. 930) comments as follows:

> "The dividend has been cut, just as we thought it would be. Directors omitted the July payout in an attempt to conserve cash and working capital. Considering APL's meager profit prospects over the coming year, we doubt the dividend will be restored soon."

5. Improving profitability: This includes improving production methods, aggressive advertising, inventory control, and improving plant utilization. Following are two such examples

as reported by The Value Line Investment Survey:

- Fedders Corp. (2/9/1979, p. 872):

> "Fedders is expected to have a profitable year.......................................
> Although sales gains may not be too dynamic, profit margins promise to be significantly wider owing to improved plant utilization, effective inventory control and reduced interest expense."

- Morton Corp. (Subsidiary of Acton Corp.) (3/9/1979, p. 1453):

> "Through improvement in commodities, purchasing, production methods, distribution and packaging, combined with aggressive advertising and the introduction of new products. Morton is expected to become profitable this year."

6. Issuing preferred stocks to reduce long term debt: The Value Line Survey, in its comment on IC Industries (1/26/1979, p. 644), states:

> "IC is reducing its long-term debt. The company is using funds from a $100 million placement of preferred stock and the sale of five financial subsidiaries for $95 million to reduce the $390 million in long-term debt.....................................
> ....IC hopes to reduce its debt/equity ratio, which exceeded 50% after the Pet purchase, to about 43% by the end of 1979. A lower debt/equity ratio will probably make it easier for the company to obtain additional funds for future projects.

7. Closing out certain plants: The Value Line Investment Survey comment on Chrysler Corporation (10/1/1982, p. 104) reads

as follows:

> "Cost-cutting has helped, too. Plant closings and consolidations and overhead reductions have sharply reduced Chrysler's breakeven point. And the restructuring of its debt together with proceeds of the sales of non-auto operations have substantially reduced financing costs."

Implications

The results obtained from the exploratory survey indicate that nearly all financially troubled firms engage in certain corrective actions, the effects of which have the potential to help the firm avoid bankruptcy. In other words, upon becoming financially distressed, the firm changes its behavior to reduce the likelihood of bankruptcy.

The implication of these findings is that business failure predictions might not materialize because of the corrective actions taken by financially distressed firms. This explains why, whenever a business failure prediction model is used to make ex ante predictions, Type II prediction error tends to be very high.

CHAPTER V

Conclusions and Implications

Summary of the Research Project

It has been found that when business failure prediction models are used to make predictions, on an ex ante basis, the rate of Type II prediction errors (i.e., firms predicted as going to fail that do not actually fail) is very high (about 97%). Although the above phenomenon does have direct implications on the decisions made by users of business failure prediction models, it has received little attention in the financial literature. The objective of this research project has been to advance our understanding of the reasons behind the observed high rate of Type II prediction errors. Understanding such reasons might help us to appreciate the actual predictive ability of business failure prediction models in decision-making contexts, where one knows neither which firms will fail nor the date on which they will fail.

It has been proposed, in chapter three of this research project, that the observed high rate of Type II prediction errors could be attributable to the inadequacy of business failure prediction models. Business failure prediction models are based on past experience. The assumption behind business failure prediction models is that observations of certain independent variables associated with firms that have failed can be formulated into a rule. This rule will then determine which firms will fail in the future. However, the mere possession of similar characteristics does not necessarily indicate that failure is pending. If all variables and circumstances are considered, certain similar characteristics may have different implications regarding solvency. For example, in the following comment on the Casey and Bartczak (1984) study, Bernstein (1984) pointed out a situation where negative cash flow from operations can lead to different conclusions regarding solvency.

> "While I can sympathize with the authors' desire to subject the usefulness of OCF (operating cash flow) data to a statistical test, such tests do not reflect the way in which these data are used in actual lending decisions.
>
> Negative operating cash flows cannot be interpreted mechanically. They are far less ominous a sign in a growing profitable enterprise subject to a "prosperity squeeze" than they are in an enterprise displaying a trend toward declining profitability and market share. Thus, the same manifestations can have vastly different implications. Such variables cannot be captured in statistical tabulations." [Bernstein, (1984) p.].

In addition, as discussed in Chapter III, human factors might also intervene to save certain financially troubled firms from bankruptcy. This in turn will contribute to the observed high rate of Type II prediction errors.

To investigate the above issue, Altman's (1968) Z-score model was chosen as a representative business failure prediction model, and was used to predict which firms, among those included in the COMPUSTAT file of fiscal year ended 1979, were going to fail. A total of 132 firms were predicted as going to fail. However, upon following-up the financial performance of those 132 firms over the 5-year period from 1979 to 1983, it was found that only two firms went bankrupt, three firms were liquidated, eleven firms were merged, four firms became private and 112 firms still survive. Further investigation of the three liquidated firms revealed that one firm was financially healthy at the time the liquidation decision was made. The other two firms, however, were apparently financially troubled when the liquidation decision was made. Classifying these two liquidated firms as business failures, the Type II prediction error rate is 97% (of the 132 firms predicted to fail, 128 firms have not gone bankrupt or been liquidated due to financial problems).

To investigate the reasons for such a high level of Type II prediction error, the following two aspects were examined:

1. The adequacy of the model to identify financially distressed firms, and

2. Type of actions taken by interested parties to bail out financially distressed firms.

The adequacy of the model was examined through the following:

First: The financial conditions of the firms identified by the model as going to fail were examined, using bond ratings, Value Line Financial Strength ratings, solvency ratios, and financial press news. Of the 112 firms investigated, 45 firms (40%) were found to be apparently financially healthy [they have investment-grade bond ratings (i.e., "BBB" or better), Value Line

Financial Strength ratings of "B" or better, and/or solvency ratios that are comparable to industry norms]. Only 36 firms (32%) were found to be apparently financially distressed [they have speculative-grade bond ratings, (i.e., less than "BBB"), Value Line Financial Strength ratings of "C+" or less, and/or solvency ratios that deviate significantly from industry norms]. The remaining 31 firms were classified in the "gray area" because it was difficult to classify such firms as financially healthy or financially distressed.

These findings indicate that the Z-score model is not only a poor predictor of bankruptcy, but also fails to adequately identify firms in financial distress. Thus, the poor predictive ability of the model represents a major source of the observed high rate of Type II prediction error.

Second: The adequacy of the cutoff point was examined. The 132 firms having Z-scores below the cutoff point of 2.675 were ranked from the lowest to the highest Z-score. The bankrupt firms, as well as most of the financially distressed firms, ranked low. A cutoff point of 2.575 classified correctly all the bankrupt firms, as well as the financially distressed firms. If that cutoff point had been used, 20 healthy firms would not have been classified as going bankrupt.

Thus, the location of the cutoff point caused about 15% of the observed Type II prediction error.

Third: The stability of the Z-score over time was examined. Serial correlation analysis was used to examine the time series behavior of the Z-score. The time series analysis showed that the Z-score tends to alternate above and below its mean. Such fluctuation causes healthy firms to have a Z-score below the cutoff point in some years, and consequently, they are incorrectly predicted as going to fail. This explains, in part, the observed rate of Type II prediction error.

Fourth: The association between the changes in Z-score and the changes in independent variables was examined. Correlation coefficients were computed to see which independent variable changes have the highest (lowest) correlation with changes in Z-score. The analysis showed that X_4, market value of equity to the book value of total debt, has the highest correlation coefficient in most cases, followed by X_5, sales to total assets. The results suggest that the fluctuation in Z-score is caused, in most cases, by fluctuation in the market value of equity and the fluctuation in sales. Therefore, the overall stock market condition and short-term changes in sales cause the Z-score to fall below the cutoff point.

Finally, possible actions by interested parties were examined. An exploratory survey of 45 firms (15 financially troubled, 15 financially healthy, and 15 from the "gray area") was used to see what actions might have been taken to keep financially troubled firms from bankruptcy.

The results of the survey showed that financially troubled firms tend to take the following corrective actions to avoid bankruptcy:

1. Sell off assets and/or entire divisions or subsidiaries,
2. Restructure debt,
3. Obtain government guaranteed loans,
4. Request relief from labor unions,
5. Change the production and/or market strategies,
6. Sale-leaseback of property,
7. Cut dividends, and
8. Follow cost reduction and or strict cash policies.

These actions may enable financially troubled firms to avoid bankruptcy. As a result, so many business failure predictions do not materialize. This could explain why when business failure prediction models are used to predict the failure of firms currently nonfailed, Type II prediction error rate tends to be very high.

Contribution of the Study:

This study contributes to our understanding of the extent to which business failure prediction models can be used, on an ex ante basis, in a decision-making context. In fact, the empirical findings of this study could have important implications for the users of business failure prediction models with respect to the following:

1. A cutoff point that assumes equal costs of incorrectly classifying bankrupt/nonbankrupt firms can be used only as a benchmark. Both Type I and Type II prediction error rates must be considered if asymmetric costs of incorrectly classifying bankrupt/ nonbankrupt firms exist.

2. Business failure prediction scores (e.g., Z-score) fluctuate from one period to another due to similar fluctuations in non-firm-specific variables (e.g., macroeconomic variables). Such fluctuation could cause the scores of healthy firms to fall below the cutoff point, although these firm are not actually distressed.

3. Ex ante business failure predictions do not materialize, in many cases, because interested constituents may intervene and thereby prevent ailing firms from going bankrupt.

Limitations of the Study

This study is subject to some limitations that are evident in its scope and others that arise from the methodology employed. These limitations can be summarized in the following:

1. In order to have at least a five-year period to follow-up the financial performance of companies predicted as going to fail, it was necessary to use a version of the COMPUSTAT tape from 1979 or earlier to avoid the effect of an updated COMPUSTAT tape. In this updating process, firms that were bankrupt, liquidated, merged, went private, or no longer file with the S.E.C. are deleted from the tape. Unfortunately, only the 1979 version of that tape was available. Because of this, the number of firms included in this study was limited to the 132 firms predicted by the Z-score model as going to fail. Other time periods might provide other results. However, there is no reason to expect that the results reported in this study are dependent upon tne particular study year or that the results would differ if a different study year were selected.

2. Because it was difficult to use more than one model in this study, a representative model, Altman's (1968) Z-score model, was chosen for the purpose of this study. This specific model was chosen because it is well-known among both academicians as well as practitioners. Although, it has been shown empirically that all

business failure models produce similar predictions, there are differences in their accuracy with respect to Type I vs. Type II prediction errors. To the extent that such differences could produce different rates of Type II prediction errors, the results obtained by using only one model, the Altman (1968) model, are not generalizable.

3. Altman's Z-score model was developed using firms whose asset sizes are relatively smaller than those of the COMPUSTAT's firms. Altman (1968) intended to control for a possible size effect by dividing his financial variables by total assets. Lev and Sunder (1979) indicated that this will not control completely for a possible size bias effect. That is, to the extent that smaller firms are more vulnerable to failure than larger firms, and to the extent that the sizes of the COMPUSTAT firms differ from those used in developing the Z-score model, there is a possible size bias effect.

Direction of Possible Future Research

It has been shown in this research project that among the financially distressed firms predicted as going to fail, some are bailed out while others ultimately fail. The unanswered research question is, which firms are more likely to be bailed out and which firms are more likely to fail? In other words, do preconditions (e.g., size of organization, internal management, financial ratios, etc.) exist that can help to distinguish between firms that will be bailed out versus those that will ultimately fail? Exploring this issue might aid investors in their investment or lending decisions.

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