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**Corporate failure prediction models for the U.S. manufacturing
and retailing sectors**

Theodossiou, Panayiotis Theofanis, Ph.D.

City University of New York, 1987

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**CORPORATE FAILURE PREDICTION MODELS FOR THE U.S. MANUFACTURING
AND RETAILING SECTORS**

by

PANAYIOTIS THEODOSSIOU

**A dissertation submitted to the Graduate Faculty in
Economics in partial fulfillment of the requirements
for the Doctor of Philosophy, The City University of
New York**

1987

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This manuscript has been read and accepted for the Graduate Faculty in Economics in satisfaction of the dissertation requirement for the Doctor of Philosophy.

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Abstract**CORPORATE FAILURE PREDICTION MODELS FOR THE U.S. MANUFACTURING AND
RETAILING SECTORS****by****Panayiotis Theodossiou****Advisor: Professor Salih Neftci**

The objective of this study has been the development and testing of more efficient corporate failure prediction models. Many researchers have identified their models using stepwise techniques or a priori information implied by finance theory. Unlike their approach we have selected the variables in our models by combining statistical criteria and a priori information.

An innovation in this study is the development of models incorporating industry effects and time trends. For this purpose we have used variables standardized by their industry means and standard deviations. Surprisingly, although such models are expected to outperform models including non-standardized variables, their performance over the latter has been found marginal.

The nature of corporate failure studies necessitates the use of non-random samples. Most studies have treated such samples as random thereby resulting in biased probabilities of failure. This issue is further explored and an estimation technique based on Bayes' formula has been used in order to avoid this problem. It is evident from our results

that correcting the bias results in lost of efficiency in the sense of mean square error.

Another innovation is the association of the cutoff probability used in the evaluation of the models with the different types of misclassification costs. Using different cutoff points to assess the performance of different statistical models we have found logit and probit to have the same classification accuracy and perform slightly better than linear probability model and discriminant analysis.

To my son Theofanis and my lovely wife Alexandra. Theofanis spent the last three years with his grandparents so that his father could finish his studies. Alexandra typed most of the tables of this study with great efficiency, saving me both valuable time and energy.

Acknowledgements

Many people have contributed both directly and indirectly in completing this study. Specifically, I would like to express my sincere gratitude to Professor Salih Neftci for teaching me Econometrics and providing valuable guidance and support. Also, thanks to Professor Michael Grossman for his support and provision of a pleasant work environment and to Professors Ronald Anderson and Steve Lustgarten for their useful comments and support.

I am also grateful to Marc Jacobs for his assistance in manipulating large amounts of data. Special thanks to my office-mate Stephanie Dieringer who made available to me her micro computer. Frankly, without their help this study would not have been completed on time. I also thank Professor Howard Ross for allowing me to use his computer accounts. Special thanks go to the technicians at COMPUSTAT, and SAS institutes for their advice.

Finally I would like to thank my mother Aristoniki and my father Theofanis for their support in both my undergraduate studies in Greece and the postgraduate studies in the U.S.A. Also I thank my father- and mother-in-law for taking care of my son all these years.

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CHAPTER 1

LITERATURE REVIEW, CRITIQUE, AND SUGGESTIONS

1. Introduction

In recent years, the number of corporate failures has reached a serious level for the economies of many countries. In the past mainly small firms failed while today large corporations are also vulnerable. Thus, the need to construct and test forecasting models as early warning systems for business has increased. The estimates of such models, along with current financial data, can be used to construct indices and calculate probabilities of failure to be used for decision making.

Predicting the probability of failure for individual firms is a topic of great importance to researchers in finance, investors buying publicly traded stocks and bonds of risky firms, and potential lenders to such firms. Regulatory agencies and state insurance commissioners need to know if a regulated company is in danger of failing. A potentially failing firm can be exempted from some antitrust prohibitions and allowed to merge under the failing company doctrine. Furthermore, estimated probabilities of failure can be used as parameters in valuation formulas for the value of the firm or bankruptcy cost.

Corporate failures, especially among large corporations, have always been a serious issue. In many countries, business failures, besides the obvious costs to shareholders, corporate creditors and employees, are associated with political costs. Often, governments provide financial

assistance in order to avoid such costs. However, early diagnosis of a firm's tendency toward failure is very valuable, because corrective actions can be taken early enough in order to be successful.

Generally, the use of corporate failure prediction models is characterized as Pareto optimal, in the sense that all types of bankruptcy costs can be avoided, thus the welfare of the society as a whole improves. In this respect different multivariate statistical techniques can play a significant role. This is a study of such techniques.

2. Research Survey

The development of corporate failure prediction models has been of great interest to researchers during the last twenty years. Numerous domestic and international studies have been published dealing with this topic. This section presents a brief review of the most representative studies. Other studies in related areas are also discussed.

2.1 Univariate studies

Beaver (1966) examined the sampling characteristics of failed and non-failed firms and identified those variables which were able to differentiate a failed from a non-failed firm. He used a sample of 79 firms that failed, and matched it with a sample of 79 firms that did not fail. He compared the financial ratios of the two groups and he found out that on the average the failed firms had more debt, lower return on sales and assets, less cash, and more receivables than the surviving

firms. Also, contrary to the popular belief, the failed firms had less rather than more inventory.

Beaver's work was a type of univariate analysis whereby each ratio was analyzed separately and an optimal cutoff point was used, so that the number of accurate classifications was maximized. He tested 14 ratios and found that the best classifiers of corporate failure were the ratios of cash flow to total debt, net income to total assets, total debt to total assets, working capital to total assets, and the current ratio.

Interestingly, the group of failed firms appeared to be consistently less healthy even five years prior to failure. The divergence between the two groups became even more marked as they moved closer to the date of collapse. An implication of Beaver's work is the establishment of financial ratios as corporate failure predictors.

2.2 Studies using discriminant analysis

Altman (1968) was the first to apply the multivariate technique known as linear discriminant analysis to the failure classification problem. He used a sample of thirty-three bankrupt firms from the manufacturing industry, and he matched each of them with a non-bankrupt firm collected randomly from a group of firms with similar characteristics as the bankrupt. The mean asset size of his sample was \$ 6.4 million ranging between \$.7 and \$25.9 million.

Based on past studies, he evaluated twenty-two financial ratios, falling into the standard categories of liquidity, profitability, leverage, solvency, and activity. From this list, a set of five ratios

was selected as doing the best overall job. The final discriminant function was as follows:

$$Z = .012 X_1 + .014 X_2 + .033 X_3 + .066 X_4 + .999 X_5$$

Where:

- X_1 = Working capital/ total assets
- X_2 = Retained earnings/ total assets
- X_3 = Earnings before interest and taxes/ total assets
- X_4 = Market value of equity/ book value of total debt
- X_5 = Sales/ total asset

Altman, based his selection methodology on the statistical significance and predictive ability of various discriminant functions, on correlation coefficients between the variables and on his judgement.

The above model was evaluated on the initial sample (sample used to estimate the model) using data collected one year prior to bankruptcy. The function was extremely accurate in classifying ninety-five percent of the firms correctly. Specifically one non-bankrupt and two bankrupt were misclassified. A second test was made to observe the discriminating ability of the model using data from two years prior to bankruptcy. In this case the percent of correct classification was seventy-two percent. Two bankrupt and nine non-bankrupt firms were misclassified.

In order to test the model more rigorously, he used two secondary samples consisting of twenty-five bankrupt and sixty-six non-bankrupt firms. The percent of correct classification for these new samples was ninety-six and seventy-nine respectively.

In 1973, Altman used the same sampling methodology with discriminant analysis in a railroad study. The sample contained twenty-one railroads that went bankrupt between the years 1939-1970 paired matched with a

sample of twenty-one non-bankrupt railroads. He examined fourteen financial variables falling into the groups liquidity, solvency, efficiency, profitability, and leverage. Using the same variables selection procedure as that of his 1968 article he estimated a seven variable discriminant function which had 97.7 percent correct classification at one and two years prior to bankruptcy.

A few years later, a modification of his 1968 model, adjusting for the changes that took place since the 60's, appeared as ZETA-analysis [Altman et al. (1977)]. For the estimation of the ZETA model, they used a sample of 53 bankrupt firms which failed between 1969-75, paired matched with 58 non-bankrupt. All bankrupt firms were publicly held corporations.

Unlike the 1968 model ZETA analysis utilized large corporations. Their mean asset size was \$ 100 million, and in no case were the total assets of a firm less than \$ 25 million. Also, retailing companies were included in the samples and they were analyzed on an equivalent basis with manufacturers.

From the 27 variables analyzed, seven variables were chosen which classified the test sample well and also proved the most reliable in various validation procedures. These were the ratios of EBIT to total assets, EBIT to total interest payment, retained earnings to total assets, working capital to total assets, common equity to total capital, a variable measuring the stability of earnings across time, and the logarithm of total assets as a proxy for size.

The authors tested for equality of the variance-covariance matrices and they rejected this hypothesis. Then, they estimated a linear and a

quadratic discriminant model and they compared their performance on the initial and a holdout sample. Both models had the same performance on the initial sample, but on the holdout sample the linear model had better performance. The linear model was also compared to the 1968 model and it was found to be superior.

Other studies which utilized linear discriminant analysis for the United States, were those in Deakin (1972) and (1977), Edmister (1972), Stuhr and Wicklen (1974).

Deakin (1972) used a sample of thirty-two firms that failed between 1964-70, and a random sample of 32 non-failed firms drawn from Moody's industrial manual for the years 1962-66. He estimated a discriminant function for each of the five years prior to bankruptcy by linearly combining the fourteen financial ratios used by Beaver. The most important variable utilized by Deakin is the ratio of cash flow to total debt.

In 1977, Deakin extended his study using a sample of 63 failed firms and a random sample of 80 non-failed firms. He estimated both linear and quadratic discriminant analysis and adopted the following classification rules: "Classify a firm to either failing or not failing if both the linear and the quadratic functions agreed. Investigate more if they produce contradictory results". The variables found significant in this study were the ratios of net income to total assets, current assets to total assets, cash to total assets, current assets to current liabilities and sales to current assets.

Edmister (1972) tested the usefulness of financial ratios in predicting small business failures. He worked with two different data

sets, each containing the same number of failed and non-failed firms. The first data set contained 84 firms for which data were available for up to three years prior to failure, whereas the second data set contained 1004 firms for which data were available a year prior to failure.

He examined 19 common ratios which were found to be significant predictors of business failure in other empirical studies. These ratios were transformed to zero-one form. Using stepwise linear discriminant analysis he developed a seven-variable discriminant function which classified 93% of the sample correctly. It is worth noting that the transformation of the independent variables into zero-one form is arbitrary and results in losing information.

Stuhr and Wicklen (1974), used linear discriminant as a scoring technique for rating the financial condition of banks. In their case the sample was composed of high-rated and low-rated banks.

Linear discriminant analysis and Altman's sampling methodology, with a few modification mainly on the variables used, or the industries applied, were used by many researchers outside the United States, United Kingdom, Japan, Australia, Canada, and France. A brief discussion of these studies can be found in Altman (1984), Taffler (1984), and Takawashi (1984). Other relevant studies can be found in the 1984 special issue on the subject of the Journal of Banking and Finance.

2.3 Studies using linear regression

The linear probability model (LPM) was rarely used for forecasting corporate failures, even though it is easier to apply than linear discriminant analysis and gives identical results. This model was used by Meyer and Pifer (1971), by Edmister (1971), by Collins (1980).

Meyer and Pifer used a sample of 39 banks that failed between 1948 and 1965 and paired each of them with a non-failed bank with similar characteristics. Using stepwise regression they searched a data set of 160 variables to find the best model. The final result was a regression of nine variables, which classified correctly 80 percent of the sample. The model had a lack of predictive ability beyond two years prior to failure. Eight of the nine variables used were time trends, coefficient of variations, and lagged values generated by regressing financial variables on time.

Collins (1980), used a sample of 162 failed credit unions matched with non-failed unions. He compared an Altman type model to that of Meyer and Pifer. Both models were found to provide good results. The author concluded that Altman's model was more appropriate because of its simplicity.

2.4 Studies using logit or probit analysis

By the end of seventies, a second generation of corporate failure prediction models had been developed by a number of researchers, using advanced statistical models such as logit and probit. Logit was used by Martin (1977) in a bank failure study, by Ohlson (1980) in a corporate failure study, by Collins and Green (1982), by Schmidt (1984) in a debt

rescheduling for developing countries study, by Hong (1984) and McGee et. al. (1986) in reorganization liquidation studies, and by Palepu (1986) in an acquisition study. Probit was used by Grablowsky and Talley (1981) in a credit applicant evaluation study and by Pastena and Ruland (1986) in a merger bankruptcy study.

Martin (1977) was the first to apply logit in developing an early warning system for banks. His data consisted of a population of 5598 Federal Reserve banks, which included 23 banks that failed as of 1974. Failed banks were defined as those which went bankrupt, or merged because of financial problems, or suffer a drastic decline of their net worth over a year or less. The author tested twenty-five financial variables, and chose a set of eight variables as being the best.

Combining these variables, he estimated different logistic functions and compared their predictive ability to those of linear and quadratic discriminant analysis. Martin concluded that the classification ability of logit and quadratic discriminant analysis was virtually the same, but he favored logit arguing that a probabilistic measure was of greater interest than a discriminant score. The performance of linear discriminant analysis was not as good as that of logit and quadratic discriminant analysis.

Ohlson (1980) presented some empirical results of a study predicting corporate failures. This study relied on a sample of 105 bankrupt firms and 2058 non-bankrupt firms collected from the industrial sector over the period 1970-76. The bankrupt firms were defined as those which filed for Chapter X or chapter XI. All firms were publicly traded corporations.

Logit analysis was then used to test the predictive ability of nine variables. The major finding was the identification of four basic factors as being statistically significant in affecting the probability of failure. These were (1) the size of the company measured by the logarithm of total assets deflated by the GNP deflator, (2) a financial structure factor measured by the ratio of total liabilities to total assets, (3) a performance factor measured by the combination of the ratio of net income to total assets and the ratio of funds provided by operation to total liabilities, and finally (4) a liquidity factor measured by the working capital ratio.

Collins and Green (1982), used a sample of failed and non-failed credit unions to compare the predictive ability of linear discriminant analysis, linear probability model, and logistic regression. They found the discriminating ability of logistic regression to be lower than that of discriminant or regression analysis. It is worth noting that the authors fitted a logistic model using the non-linear least squares method rather than maximum likelihood.

Schmidt (1984) compared the ability of logit, linear discriminant analysis, cluster analysis and univariate methods in a debt rescheduling for developing countries study. His sample consisted of a "bad" group of nine countries which at least once rescheduled their debt for the years 1979 to 1981 but never did so for the years 1974 to 1978, and a "good" group of forty-three countries with no debt rescheduling for the period 1974-81.

An innovation of this study is the use of standardized measures. Each variable was normalized by subtracting its mean and dividing by its

standard deviation. This made the variables stationary across time. The author then estimated different discriminant and logit functions for the years 1974-78 and compared their coefficients over time. Logit was found to be more efficient to the other three methods. Interestingly, both the discriminant and logit coefficients were stable across time.

Hong (1984), collected a sample of firms which filed for bankruptcy between the years of 1976 to 1979, to study two different outcomes of bankruptcy; those of reorganization and liquidation. Using a theoretical model he identified five variables as being important in predicting whether a bankrupt firm will reorganize or liquidate. Logit analysis was used to test the ability of these variables in predicting the course of a bankrupt firm between the two events.

Out of the five variables examined, three of them were found statistically significant. These were the ratios of current assets to total tangible assets, free assets (total assets minus secured loans one year prior to bankruptcy) to total tangible assets and a dummy variable taking the value of one for the retailing industry and the value of zero otherwise. The dummy variable was introduced as a proxy for risk. At this point we would like to indicate that the statistical significance of the dummy variable does not necessarily imply different risk levels in the two industries. Its significance might be due to other factors specific to each industry and not represented in the model.

Hong's work can be viewed as an extension of bankruptcy prediction studies. The estimated logistic distribution can be interpreted as a probability function for the reorganization, conditional on the event of bankruptcy. The conditional probability for liquidation is equal to one

minus the probability of reorganization. The unconditional probability of reorganization is the product of the conditional probability of reorganization and the unconditional probability of bankruptcy.

Grablowsky and Talley (1981) evaluated probit and linear discriminant analysis as techniques for classifying credit applicants. Their data included a sample of one hundred applicants with long histories of good credit ("good" risk) and a sample of one hundred applicants with histories of delinquent credit or defaults ("bad" risk).

A probit and a discriminant function were specified using a stepwise technique and evaluated on a new sample of 100 "good" credit applicants and 100 "bad" credit applicants. Both models were found to perform equally well on the sample of "good" credit applicants, but, probit performed better on the other sample. The authors, concluded that probit was a viable alternative to discriminant analysis for classifying credit applicants.

Their results appear reasonable; however, one might question them because, to derive the maximum likelihood estimators for probit they did not solve the first order conditions iteratively, but they rather approximated them by Taylor series expansions. Also, for the specification of the likelihood function, they gave a value of one to an individual if he was a "good" risk and the value of two to an individual if he was a "bad" risk, instead of one and zero which was the usual procedure.

The above shortcomings might lead to biased results. A point to support our comments is the following. The reported log-likelihood value was -1603.63. For their sample this should range between zero and

-138.63 where these thresholds are the likelihood values under perfect fit and under the null hypothesis respectively.

Palepu (1986), discussed some methodological problems associated with the application of binary choice models into predicting takeover targets and adopted some modifications to avoid these problems. He also pointed out that these problems made the reported accuracies of earlier acquisition studies unreliable.

The problems indicated by Palepu focus on the use of non-random samples in the estimation and testing of the models and use of arbitrary cutoff points. Specifically, the treatment of non-random samples in the estimation as random, without the appropriate modifications leads to inconsistent and biased estimates of the acquisition probabilities. Also the use of non-random test samples yields erroneous results that fail to represent the model's predictive ability. Finally, the use of arbitrary cutoff probabilities in the evaluation tests, makes the predictive ability of the models difficult to interpret.

The question Palepu examined was whether acquisition targets can be accurately predicted by models using public data. He used a sample of 163 firms that were acquired during the period of 1971 to 1979 and a random sample of 256 firms that were not acquired as of 1979. He selected variables on the basis of six hypotheses suggested in the financial literature on the types of firms that are likely to become acquisition targets. Specifically, firms with inefficient management, or a mismatch between their growth and their financial resources at their disposal, or firms that are in industries sensitive to economic disturbances, or small sized firms, or firms with lower market values

lower compared to their book values, or firms with low price earning ratios are likely to become acquisition targets.

Based on the above six hypotheses he identified ten variables, and, after adopting some modifications to avoid the above problems, he estimated two different versions of logit model. He then tested the model on two samples consisting of 30 target and 1087 non-target firms. Using a cutoff probability derived under some theoretical conditions, he found that the model's correct classification rates were 45 percent for the sample of non-target firms and 80 percent for the sample of target firms. He then concluded that investing in the firms that classified as potential acquisition targets will result in insignificant excess returns. Thus the model's ability to predict targets is not superior to that of the stock market.

The conclusion that the model's predictive ability cannot result in earning positive excess returns is based on the assumption that an investment is made on all firms classified as acquisition targets. However, if someone invests on the most likely targets, positive excess returns may result. Moreover, the author made use of the capital asset pricing model which he estimated using linear regression. If one questions the validity of the CAPM and particularly its OLS estimation, Palepu's conclusions become very weak. A model with predictive ability higher than 50 percent in each group may be justified useful in predicting acquisition targets since investing in the identified as potential target firms, after the announcement is made for some of them the arbitrageur will make excess returns for those not announced the returns might be regular.

Pastena and Ruland (1986), studied the alternative of merger/bankruptcy as a joint function of the characteristics of a distressed firm's ownership and of the distressed firm itself. Based on the literature, they considered variables related to the firm ownership concentration, financial leverage, tax carryover, firm size and financial distress. Specifically the variables used were the total percentage of voting stocks owned by managers, directors, and other parties, the ratio of total debt to total assets, the ratio of tax carryforwards to total revenues, the logarithm of total revenue adjusted for changes in the consumer price index as a proxy for size, and Altman's Z-score measuring the severity of financial distress.

Their sample was obtained from the 1983 Compustat Annual Industrial Research Tapes and included 68 distressed manufacturing firms that merged and 42 manufacturing firms that entered bankruptcy. Using the above sample and probit analysis they tested the significance of the five variables and found size, leverage, and ownership to be statistically significant. Tax carryforwards were not important in the model.

Their findings revealed that distressed firms with high ownership control show an increased tendency to merge rather than to declare bankruptcy. Moreover high leveraged firms are expected to enter bankruptcy rather than merge. Tax carryforward, although it had a positive sign (i.e favoring merger) was found insignificant. On the contrary size showed highly statistically positive sign also favoring merger. This result appears counter intuitive because smaller firms are more easily acquired.

3. Criticism of Corporate Failure Prediction Models

Research in the area of predicting corporate failures involves different types of estimation and methodological problems. This section focuses on shortcomings related to predicting corporate failures and suggests ways to correcting them.

3.1 Ratio fallacy

Accounting principles often permit more than one approach to treating a financial event. Alternative depreciation or inventory valuation methods or financial policies, may result in different values for the firm's current earnings or other financial variables. This may result in biased and sometimes questionable figures on the balance sheets and income statements of the firms, which do not reflect their actual values.

For example, during inflationary periods LIFO (last in first out) produces higher values for the cost of products sold and lower earnings than FIFO (first in first out). The opposite occurs in deflationary periods. Also accelerated depreciation may be used to reduce current earnings. Research and development cost, if expensed during the period incurred, may again reduce current earnings or, if not expensed, may increase current earnings. The liquidity position of a firm can be improved by increasing long term debt and using the proceeds to pay off short term debt or by selling fixed assets and using the funds to reduce current liabilities.

All the above problems exist and they are well known, but still accounting data are important tools which give answers to many questions concerning the financial condition of a firm. Bank managers, creditors, security analysts, and the management of the firm often use financial ratios, to measure the performance of a firm.

Univariate ratio analysis often leads to biased results because it is not able to capture the complex relationships between the variables. This is probably the main reason why ratio analysis has been questioned. However, analysis based on multivariate models containing the appropriate variables is able to provide adequate measures of performance.

The present study does not intend to discuss new solutions to the above problems although such issues are very important and are of interest to accounting researchers. Its objective is to develop and test more efficient corporate failure prediction models.

3.2 Sampling bias

The annual rate of firms which fail in the U.S.A. ranges between three and eight percent of one percent. For publicly traded corporations this rate is even smaller. As a result of this, a random sample will generally contain few failed firms. Researchers have responded to this problem by using non-random sampling methods.

The use of non-random samples result in an overall sample with a much higher representation of bankrupt firms than actually occurs in the real world. Throughout the years this sampling bias has been ignored and non-random samples have been treated as random. This results in

inefficient estimates and estimated probabilities of failure which are upwardly biased.

In chapter four we discuss the effect of the sampling bias on the coefficients and estimated probabilities of failure when these samples are treated as random. Then we present a stratified estimation technique based on Bayes' formula which corrects for these problems.

3.3 Random Stratified v.s Matched stratified Samples

The great majority of corporate failure prediction studies have used matched stratified sampling techniques. A serious problem with this type sampling may be the rejection of variables which are significant. For example, if size or activity and the ratio of sales to total assets are perfectly correlated and failed firms were matched with non-failed firms according to activity or size, then this ratio will be rejected as insignificant. In this respect random stratified sampling may be more adequate than matched stratified sampling.

3.4 Stability of the Variables Over Time

Most of the bankruptcy studies utilized samples consisting of firms that failed during different years. Firms' data for these years were used to develop corporate failure prediction models which are still used for decision making. Such treatment implicitly assumes that different coefficients are stable across time.

Industry ratio averages vary over time due to changes in the economic conditions, or accounting standards, or tax laws, or other changes as well. An acceptable ratio a few years ago might be

unacceptable in the current year. For example a low profitability ratio may be acceptable during periods characterized by low interest rates, but unacceptable during periods of high interest rates. The reverse might be true for a leverage ratio. Industry trends are expected to have an effect on the coefficients. If this is true then models adjusting for such changes are more appropriate.

Researchers in the field have ignored this problem. Ignoring it may result in dropping important variables if their values change easily over time. In this study we develop and test corporate failure prediction models which are based on measures which are stationary over time. To avoid a similar problem, Shmidt (1984) in his debt rescheduling for countries study used standardized measures.

3.5 Dynamic Models

All the bankruptcy studies used statistical models which were static in nature. These models evaluate the performance of a firm, taking into account the financial profile of a firm at a given point in time and ignoring the path of its profile over time. In this respect, two firms with the same financial profile will be assigned the same performance score.

However, if the profile of one firm is improving and on the contrary, the profile of another firm is getting worse, a static model will be unable to contemplate this valuable information. Some researchers became aware of this problem and tried to capture dynamic changes by using trend coefficients and coefficient of variation, see

Mayer and Pifer (1971), or variability of earnings measures, see Altman (1977).

3.5 Linear v.s Non-linear index

So far the models applied utilized linear indices (LPM or LDA). Linear models imply that the marginal impact of a given variable on the index is equal for all firms regardless of the values of other variables. To understand the magnitude of this assumption, consider two firms, one which is financially sound and one which is financially unsound. It is intuitively clear that a decrease in the current ratio of the two firms by one unit will have a greater impact on the probability of failure for the unsound rather than the sound one.

The above argument suggests that a non-linear index may be more appropriate than a linear index. A quadratic approximation of a non-linear index is shown to produce better results than the linear.

CHAPTER 2

DATA AND BASIC RESULTS

1. Introduction

This is an industry wide study covering the manufacturing and retailing sectors. The manufacturing division includes establishments engaged in the mechanical or chemical transformation of materials or substances into new products. It also includes establishments engaged in assembling component parts of manufactured products, blending materials such as lubricating oils, plastics, and liquors. The material processed by the manufacturing establishments include products of agriculture, forestry, fishing, and mining, as well as products of other manufacturing firms.

Some borderline activities which lie between the manufacturing and other divisions of the classification system and are not always considered as manufacturing, such as milk bottling and pasteurizing, fresh milk packaging, publishing, ready-mixed concrete production, leather converting, wood preserving, electroplating, and metal heat treating are classified as manufacturing.

The retailing industry includes establishments engaged in selling merchandise for personal or household consumption and rendering services incidental to the sale of goods. These firms are classified according to the principal lines of commodities sold or the usual trade designation.

Every firm is characterized by a four-digit number called the standard industrial classification code (SIC). In the manufacturing

sector the SIC codes range between 2000 and 3999; in the retailing industry these range between 5000 and 5999. The SIC codes are assigned to firms according to their activities. Moreover, the first two digits of the SIC code can be used to classify similar industries into broader groups. For example, major group 20 includes manufacturing firms primarily engaged in processing foods such as meat packing, making sausages and other prepared meats, poultry dressing, baby food, frozen fruits and vegetables, confectionery products, chocolate and cocoa products, chewing gum, different vegetable or cooking oils, canned and cured seafood. Major group 52 includes retailing establishments primarily engaged in selling lumber and other building materials such as paint, glass, wallpaper, hardware, nursery stock, lawn and garden supplies, and mobile homes. For complete and more detailed information refer to the Standard Industrial Classification Manual.

Appendix 1 provides the short titles of the major manufacturing and retailing groups and also gives the total number of COMPUSTAT firms in each major group. The COMPUSTAT library includes about 7000 firms, from which approximately 2000 are manufacturing and retailing firms. It is composed of the Primary industrial file, the Supplementary industrial file, the Tertiary file, the Over-the-counter file, the Canadian file, and the Industrial annual research file. The first five are active files and contain approximately 5000 companies. The research file includes approximately 1900 companies which have been deleted from the COMPUSTAT active files because of reorganization, liquidation, acquisition or merger, privatization, and other reasons. Data for all companies are available for as many as twenty years.

Firms on COMPUSTAT are generally the largest and most significant companies listed and traded in the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), other regional stock exchanges, as well as in Canada. The general criteria for trading on these exchanges are different for each exchange, but any company trading on them should generally meet the State or Securities Exchange Commission requirements.

2. Data Collection

The data is composed of two groups of 101 failed and 2008 non-failed manufacturing and retailing firms. The failed group includes companies which filed for bankruptcy liquidation and have been listed in the COMPUSTAT files. In forming this group we have searched the research file and collected those firms which have been assigned a deletion code of 02. Canadian firms have been excluded from the sample. We have also excluded firms which filed for reorganization because their characteristics have been quite different.

The final result of this search has been a sample of 101 companies which filed for bankruptcy liquidation between the years of 1969 to 1980. For simplicity we will refer to these firms as failed although this definition is broad and it also includes firms which filed for bankruptcy reorganization and in some cases merged firms.

Table 1 shows the number of failed firms in every major group. Almost all 30 manufacturing and retailing groups include a bankruptcy liquidation case. Specifically, 79 of our failed firms belong to the manufacturing sector and 22 to the retailing sector. Forty-nine of the

failed manufacturing firms were in heavier industries, such as those with SIC codes between 3000 and 3999.

Table 2 presents the number of failed firms by year of failure. As one would suspect, relatively more firms failed during the period 1969-75 compared to the period 1975-80, where more firms chose to reorganize rather than liquidate. This is probably a reflection of the changes in the bankruptcy law that took place in 1977. The latter might cause a bias to our study; however, we believe that this will not create any serious problems.

Our non-failed group includes 2008 manufacturing and retailing firms listed and traded as of 1983, and almost spans the entire population of firms in the COMPUSTAT active file. The great majority of these firms (1070) belong to the heavier manufacturing sector. The lighter manufacturing sector, and the retailing sector include 578 and 360 firms respectively. Interestingly, the percentages of healthy firms in these three major sectors do not differ much from those in the failed group. This is an indication that all three industries are associated with the same amount of risk.

Appendix 2 presents the names, the filing date for bankruptcy liquidation, the total assets, total liabilities and long term debt of the failed firms. Data on these variables were extracted from the firms' last financial statement. The length of time between the filing date and the date of the data was on the average two years and in no case less than a year. The filing date was extracted from the Commerce Clearing House/and Capital Changes Reporter, because the COMPUSTAT did not provide this information. However, we would like to note that the

year of deletion, information provided by COMPUSTAT, in most cases coincided with the bankruptcy filing year.

The total assets of the failed firms, are distributed between 2 million dollars and 1 billion dollars, with a mean of 45.39 million dollars and a standard deviation of 119.76 million dollars. Their mean total liabilities is 36.6 million dollars and on the average constitutes 78 percent of the total assets of the failed firms. Total liabilities are distributed between .5 million and 967.54 million dollars with a standard deviation of 104.64 million dollars.

The mean total assets of the healthy group is 885.83 million dollars distributed between .67 million and 62.96 billion dollars with standard deviation of 3.35 billion dollars. Obviously the mean total assets of the failed group is lower than that of the healthy group; thus, it is reasonable to assume that on the average smaller firms are more vulnerable. However, one might argue that the above results are biased in favor of larger corporations because of government intervention to rescue large firms from failing. A counter argument to this is that larger firms are often associated with greater market power. Thus they are less vulnerable to economics shocks. On the contrary smaller firms are more sensitive to adverse economic condition and thus comparatively more smaller firms fail.

Another interesting finding is the relationship between long term debt and total liabilities of the failed firms. Long term debt is distributed between 0 and 216 million dollars with mean of 12.2 million dollars. Clearly the largest component of total debt (liabilities) is based on short term liabilities. Specifically, long term constitutes 33

percent of the total liabilities and this is approximately 26 percent of the total assets.

The above image is repeated for two, three, and four financial statements prior to failure. However, as we move backwards the mean total liabilities and long term debt of the failed firms decrease at an annual rate of two to three million dollars and at ten years prior to bankruptcy the firms' figures appear to be the same to those of the healthy firms.

3. Variables and Basic Results

In this study we choose to examine twenty-nine financial ratios, falling into five standard categories including liquidity, profitability, leverage, activity and solvency. The criteria have been their potential ability to differentiate healthy from failing firms, their popularity in the literature and simplicity. Appendix 3 refers to studies which have found these variables significant and also provides a concise description of them. We choose not to review the definition of the variables; however, we refer to the corresponding pages of the COMPUSTAT manual for a detailed discussion.

3.1 Unstandardized Variables

Table 3 presents the means of the unstandardized variables in the two groups at two years prior to failure. It also provides the t-statistics for testing the difference of the means in the two groups. The data show that on the average the failed firms have less cash and

working capital, are more leveraged, have lower returns on sales and assets, less fixed assets, and more inventory than healthy firms.

The ratios of cash to total assets (L3) and cash to total liabilities (L5) provide strong evidence that failed firms have relatively less cash than healthy firms. Their mean values are 3.9 percent and 5.7 percent in the failed group, and 12.0 percent and 45.9 percent in the healthy group respectively. Healthy firms have on the average three times more cash than failed firms.

Another important liquidity measure is the working capital ratio (L2) with means of 15.4 percent in the failed group, and 32.9 percent in the healthy group. Healthy firms have on the average twice as much working capital as failed firms. Low liquidity for the failed firms is also revealed by the ratios of current assets to current liabilities (L1) and the quick ratio (L4). The ratio of current assets to total assets (L6) is statistically insignificant.

The second best univariate measure is a variable for size (LTA) measured by the natural logarithm of total assets. The logarithmic transformation of this variable is a common practice followed in many studies and helps to smooth the distribution from outlier observations. Healthy firms are on the average larger thus this variables appear to be greater for these firms. Studies which found this variable significant are those of Horrigan (1968), Altman et.al. (1977), and Ohlson (1980). We expect this variable to be an important predictor in our models.

Two other highly significant variables are the ratios of total liabilities to total assets (LV5) and that of total liabilities to market value of the firm (LV6). Total liabilities constitute 78 percent

of the total assets of the failed group and 49.1 percent of the total assets of the healthy group. The ratio of total liabilities to market value of the firm displays the same image as LV5. A reason for this is that the total assets and the market value of the firms are close to each other, especially for failed firms. Specifically, total liabilities constitute 74.4 percent and 40.0 percent of the market value of the firm for the failed and healthy group respectively. The market value of the firm is approximated by the sum of total liabilities and market value of shares outstanding at the closing date.

The ratio of market value of equity to total assets (LV7) also appears to be significant. In the failed group this is 38.8 percent while in the healthy group it approaches unity. The ratio of long term debt to market value of equity (LV1) is also statistically significant and in the failed group it reaches the high level of 234.1 percent while for the healthy group it is equal to 41.5 percent.

Another leverage measure of great importance is the ratio of total interest expense to total assets (LV3). This makes up 4.8 percent of the total assets of the failed firms and 2.6 percent of the non-failed firms. The interest expense to total liabilities ratio (LV4) is significantly higher in the failed group implying higher cost on borrowing for these firms. Possible reasons might be their urgent demand for borrowing and probably their riskiness. The long term debt to total assets (LV1) ratio shows that failed firms have more long term debt (26.8%) than healthy firms (16.9%).

Profitability measures of univariate importance are the ratio of EBIT to total assets (P1), net income to total assets (P2), and

operating income to total assets (P3). As expected, failed firms have significantly lower rates of returns on total assets than healthy firms. Earnings before interest and tax (EBIT), net income, and operating profit constitute 8.2 percent, 3.3 percent, and 12.3 percent and of the total assets of the non-failed firms respectively, while for the failed group these are all negative at 6.8 percent, 10.2 percent and 3.6 percent respectively.

Two profitability measures, the ratio of gross profit to sales (P4) and operating income to sales (P6) give counter intuitive results because the healthy group appears with relatively lower profitability. However a closer examination of the data revealed an outlier firm with values of -482200 and -482100 percent for P4 and P6 respectively. This problem could have been avoided if we had used standardized measures.

Other profitability measures of importance are the ratios of retained earnings to total assets (P5), the earnings price ratio (P7), and the dividend payout ratio (P8). Retained earnings of the failed firms are negative due to losses incurred by the firms for a series of years prior to failure. The mean value of the retained earnings ratio in the failed and non-failed group are -12.7 percent and 25.2 percent respectively. Surprisingly, the earnings per share ratio is -100 percent in the failed group and close to zero for the healthy group. On the contrary dividend payout ratio is positive and it is on the average 5 tenths of a percent of the stock price of the failed firms and 2 percent of the stock price of the healthy firms.

Statistically significant activity ratios are those of inventories to current assets (A6), inventories to total assets (A8), fixed assets

to total assets (A7), and sales to fixed assets (A4). Specifically, inventories make up 34.0 percent of the total assets and 52.9 percent of the current assets of the failed firms. For the healthy group these are 29.1 percent and 41.1 percent respectively. This is evident that on the average failed firms have more inventories probably due to their inability to sell their final product.

Fixed assets appear to be lower for the failed firms because on many occasions firms in financial distress sell productive assets in order meet their short term obligations. The sales ratio to total assets (A1) appear higher in the failed group while the ratio of sales to current assets (A2) appear to be equal in both groups. These ratios are both insignificant. Other insignificant ratios are those of inventories to cost of goods sold (A3) and accounts receivables to current assets (A5). The ratio sales to fixed assets (A4) is higher in the failed group basically because the failed firms have relatively lower fixed assets.

At this point we would like to note that although some variables have high univariate forecasting ability this never the less imply that when examined in a multivariate framework they would be more important than other variables with lower univariate discriminating ability. Their forecasting ability will also depends on the correlation coefficients with other variables in the models. Another point we would like to note is that standardization of the variables provides at least the same amount of information as unstandardized variables, thus models with standardized variables are expected to produce better results. This issue is discussed further in the next two sections and it is also tested in chapters 3, 4 and 5.

3.2 Standardized Variables

Comparing ratios for the current period with similar computations for prior years affords some basis for judging whether the position of a business is improving or worsening. Another yardstick against which to evaluate the performance of any particular firm is the average performance of other comparable firms in the same industry. These two types of analyses are clearly very useful.

The acceptance levels of different financial ratios differ from industry to industry and might vary over time due to changes in economic conditions. To emphasize this point consider the following evidence taken from major groups which include a considerable number of firms.

In the Food and Kindred Products major group (group 20) the fixed assets make up on the average 39.6 percent of total assets (ratio A7). The mean value of the same ratio in the Textile and Mill Products major group (group 22) is 31.9 percent, in the Paper and Allied Products major group (group 26) is 55.9, while in the Wholesale Trade- Durable goods major group (group 50) is 17.7 percent. Obviously capital intensive industries will have higher fixed assets to total assets ratios. The opposite is true for the ratio of sales to fixed assets ratio (A4), whose mean values in the above four groups are 6.97 percent, 6.30 percent, 257 percent, and 1810 percent respectively.

Another measure which significantly deviates in different industries is the working capital ratio (L2). Specifically in the Apparel and Other Finished Products major group (group 23) the working capital ratio has a mean value of 41.4 percent. However, its mean value in the Food and Kindred Product major group is 23.5 percent, in the Paper and Allied

Product major group is 18.1 percent, in the Petroleum and Refining and related Industries major group is 9.7 percent, in the Machinery (Except Electrical) major group (group 35) is 36.1 percent, while for the major groups 37 and 51 this is approximately 27 percent. Other ratios also behave in the same manner.

Most of the ratios have shown remarkable stability over time. However some of the activity and most of the profitability ratios have been found quite unstable over time. The most unstable of them is the earnings price ratio. On the contrary the dividend price ratio has been found quite stable over time. This is hardly surprising because the decision to pay dividends is more of a managerial decision and it is not so much affected by the economic conditions.

Previous discussion suggests that an appropriate evaluation of a firm's financial position should not ignore industry and time trends. Existing corporate failure prediction studies seem to ignore this problem. Ratios for firms belonging to different industries and time periods have been treated on equivalent basis and equal weights have been attached to each of them regardless of time or industry.

The development of corporate failure prediction models directly incorporating industry or time effects involves serious estimation difficulties. Many industries include a few failed firms and moreover these are from different years. Therefore such models will not allow enough degrees of freedom in order to estimate them. The simplest and perhaps the most efficient way to incorporate industry and time effects in the models is to use standardized measures. These can be easily

calculated by subtracting from the variables their industry means and dividing by their standard deviation.

For this purpose we use all the manufacturing and retailing firms that are included in the COMPUSTAT files. Specifically, for every year and major group we have computed the means and the standard deviations of all 29 variables. This amounts to 1740 means and 1740 standard deviations (29 variables x 30 major groups x 20 years). Then we have used these means and standard deviations to standardize all the variables. We expect the standardized variables of the healthy firms in every major industry and year to be distributed with zero mean and variance one.

However, this is not necessarily true for the failed group, where significant deviations from zero will be a sign that the variables are potential predictors of failure. Specifically, negative means would be an evident that failed firms have values which are below the industry's means. Their absolute mean value signifies their importance in discriminating a failing from non-failing firms.

Tables 4 to 13 show the means, the t-values, and the level of significance of the standardized variables for 1 to 10 periods prior to filing for bankruptcy liquidation. The average length of time between the last report (FSN=1) and the filing time is approximately 2 years deviating between 1 year and five years. In no case this is less than a year. The results are hardly surprising. Many ratios deteriorate as one moves closer to the time of bankruptcy.

All the profitability measures (P1-P8) are consistently negative even more than ten years prior to failure. As we move closer to the time

of collapse the absolute mean values of these ratios increase indicating remarkable differences from the healthy firms in the industry. These differences are statistically significant for almost the entire period, indicating that the failing firms earn returns which are below the industry's means for a series of years before failure. These findings imply that bankruptcy is not an instant event but rather a process which evolves over time.

Table 14 presents the correlation coefficients of all 29 variables. Seven of the eight profitability ratios appear to be highly correlated with each other. In most cases their correlation coefficients are well above .40. Thus their informational context is expected to be able to be summarized by a few of them.

All liquidity variables deteriorate as we move closer to the year of collapse. The only exception is the ratio of current assets to total assets (L6). It appears that on the average failed firms maintain a higher fraction of their total assets as current assets. An explanation can be given in conjunction with the ratio of inventories to current assets (A6) which is also higher for failed firms. It appears that failed firms have larger inventory levels than healthy firms probably due to their inability to sell their product.

All leverage ratios display significant differences from their industry means for the whole period under examination. Their highly significant positive values indicate that failed firms are more leveraged. Leverage measures of interest are the ratios of long term debt to market value of equity (LV2) and interest expense to total assets (LV3).

An interesting aspect of this analysis is the ratio of sales to total assets (A1). Approximately from one to five years prior to bankruptcy its value is mildly negative, after the fifth year it becomes positive and as we move backwards it becomes significantly positive. For all periods the ratio of sales to total assets is accompanied by low profitability and low liquidity ratios. A possible explanation is that low profitability, years before filing for bankruptcy, forced the firms to cut their prices in order to increase sales and thus their profits. However, the result of this policy was higher sales but lower profits and as a consequence the profitability ratios decreased more.

After the realization that cutting prices was not the appropriate policy to improve their financial position, they start behaving normally. As a result of this their sales drop, their liquidity position deteriorates further, their profitability becomes poorer, and their debt obligations increase. This irreversible state leads the firms a few years later to file for bankruptcy liquidation.

An activity measure which provides very useful information with regards to firms behavior prior to failure is the ratio of fixed assets to total assets. This appears to be negative for many years prior to bankruptcy. The above event in conjunction with poor liquidity indicates that firms sell productive assets in order to meet their liquidity needs.

4. Standardized v.s Unstandardized Measures

Standardized measures are the basic tools of our analysis. This section provides a rationale for the use of standardized variables in

corporate failure prediction models instead of unstandardized variables. Let I_{ijt} be a performance index for firm i in industry j at time t , such that the lower its value the better off the firm and the lower the probability of failure. Furthermore, suppose that the index is linear and it is written as,

$$I_{ijt} = b_0 + \sum_{k=1}^K b_k Z_{ikjt}$$

where Z_{ikjt} are explanatory variables standardized by their means and standard deviations. For simplicity and without any loss of generality assume that all b_k 's are negative indicating negative marginal effects of the variables on the probability of failure. This assumption does not restrict the model because the signs of the coefficients can always be reversed by alternating the signs of the variables.

Expressing the variables in terms of their means and standard deviations and manipulating gives,

$$\begin{aligned} I_{ijt} &= b_0 - \sum_{k=1}^K b_k \frac{(X_{ikjt} - \bar{X}_{kjt})}{S_{ikjt}} \\ &= b_0 - \sum_{k=1}^K \frac{b_k}{S_{kjt}} \bar{X}_{kjt} + \sum_{k=1}^K \frac{b_k}{S_{kjt}} X_{ikjt} \\ &= b_{0jt} + \sum_{k=1}^K b_{kjt} X_{ikjt} \end{aligned}$$

where,

$$b_{0jt} = b_0 - \sum_{k=1}^K b_{kjt} \bar{X}_{kjt}, \quad \text{and} \quad b_{kjt} = b_k / S_{kjt} \quad \text{for } k=1,2,\dots,K.$$

are the intercept and slopes of the index I_{ijt} respectively. Obviously the index depends on both the industry and time.

There are interesting implications in the assumption that standardized variables are more informative than unstandardized variables. To show this point consider the following argument:

Suppose that the means of the variables in a given industry increase but the standard deviations do not change. Larger means will have a positive effect on firm's i performance index I_{ijt} (note that all b_k 's are assumed to be negative). If the variables of firm j do not change, its index will increase indicating that its performance is worsening. However, if the firm's variables change in such a way that its standardized variables stay constant, the firm's condition will neither improve or worsen.

A shortcoming of this formulation is that the industry's means do not affect the slopes of the index, only the standard deviations of the variables affect them. This is a consequence of the assumption that the index is linear. In case a non-linear index is introduced the slopes will also be dependent on the industry's means. A non-linear index might be more appropriate in case the data imply a quadratic structure.

Next suppose that the standard deviations of the variables increase while the means stay constant. Larger standard deviations imply higher variations of the variables from the industry means. This reduces the

discriminating ability of the variables. In this case it is reasonable to assume that the marginal impact of the unstandardized variables on the index will reduce. This intuitive argument is evidenced in the slopes whose size is inversely related to the size of the standard deviations.

Similarly it can be argued that as the standard deviations increase the impact of the means on the intercept decreases in absolute value. Whether the index will increase or not it will be dependent on the sign of the mean. If the industry mean of a variable has a positive sign and its standard deviation increases then the intercept and subsequently the index will decrease.

In the next section we estimate and compare the predictive ability of our models using standardized as well as absolute measures. At this point we would like to note that models including standardized variables (standardized models) are expected to perform at least as well as models with unstandardized variables. However, if variables are not stationary we expect standardized models to produce better results.

CHAPTER 3

IDENTIFICATION AND ESTIMATION OF THE MODELS

1. Introduction

The objective of this chapter is to develop models for forecasting corporate failures in the manufacturing and retailing sectors. For this purpose we use multivariate statistical techniques of linear probability model (LPM), Bayesian discriminant analysis (BDA), logit, and probit.

2. Linear Probability Model

This is a term used to denote a regression model in which the dependent variable Y_i is a dichotomous random variable which takes the value of one for failed firms and the value of zero otherwise. The model is written in the usual regression framework as,

$$Y_i = X_i b + e_i \quad \text{for } i=1,2,\dots,n$$

where, $X_i = (1, X_{1i}, \dots, X_{ki})$ is a $1 \times (k+1)$ non-stochastic vector of financial characteristics for firm i . The disturbance term has an expected value of zero and is uncorrelated across firms.

It can be easily shown that the expected value and variance of Y_i are equal to:

$$EY_i = X_i b = P_i$$

$$\text{Var}(Y_i) = \text{Var}(e_i) = X_i b (1 - X_i b) = P_i (1 - P_i)$$

where, P_i is the probability of failure conditional on the vector X_i .

Ordinary least squares is usually the method used to estimate the model. It is well known that the OLS estimators are unbiased but inefficient, because the model has a heteroscedastic disturbance term. Thus generalized least square method can be used to estimate the model. An easy way to estimate the variance covariance matrix is to use the ordinary least squares estimated probabilities. Although this method appears to be simple, it is associated with a few weak points. In practice some of the predicted probabilities lie outside the unit interval and this generates negative variances. The above technique has been proposed by Goldberger (1964).

Moreover, the disturbance term is not normally distributed and as a result classical statistical tests on the estimated parameters are not appropriate. Warner (1967) discusses some special statistical tests, which we will not present here.

2. Linear Discriminant Analysis

Interestingly, almost all corporate failure prediction studies have made use of Fisher's traditional discriminant analysis, proposed originally in 1936. In this section we provide a brief review of Fisher's technique, and in a latter section we present its Bayesian extension.

The objective of discriminant analysis is to derive the linear function of financial variables which has the "best" discriminating ability. Fisher's basic idea was that the weights attached to the variables -called the discriminant coefficients- should maximize the

variance between the two groups, relative to the variance within the groups. That is,

$$\max D = \frac{d'(\bar{X}_1 - \bar{X}_2)'(\bar{X}_1 - \bar{X}_2)d}{d'Sd}$$

where, \bar{X}_1 and \bar{X}_2 are the mean vectors of the variables in the two groups and S is the pooled variance-covariance matrix, and d are the discriminant coefficients.

Note that the above function is homogeneous of degree zero in d . Thus, if d^* is a vector that maximizes D , then any multiple of it will also maximize the above function. In practice these coefficients are standardized to a given constant to give,

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

For a discussion on the derivation of the discriminant coefficients using the above technique see, Dhrymes (1970) pp. 65-71 or Maddala (1983) pp. 79-80.

The application of discriminant analysis in business and economics involves different types of problems related to: (1) the probability distribution and variability of variables in the groups; and (2) the interpretation and statistical significance of the discriminant coefficients.

Specifically, linear discriminant analysis assumes that the variables in the groups follow multivariate normal distribution with different means but the same variance. In practice, especially in the

area of predicting corporate failures this assumption is usually violated because many financial variables do not take negative values and their distributions are not symmetric.

Furthermore, the normality assumption excludes the use of discrete variables. A simple way to resolve this problem is to form new groups by splitting the original groups in accordance to the values of the discrete variables and then apply discriminant analysis. However, although this procedure appears to be simple, it results in increasing the number of estimators and efficiency is lost.

A second shortcoming of linear discriminant analysis is the assumption of equal variance-covariance matrices in the two groups. In the bankruptcy context the variability of financial variables in the failed and non-failed firms is more likely to be different. Altman et al. (1977), Collins and Green (1982), and others, tested the hypothesis of equal variances and they rejected it.

Unequal dispersions imply that a quadratic discriminant analysis should be used. Deakin (1977), Altman (1977), Martin (1977) applied quadratic discriminant analysis and compared its performance to that of linear discriminant analysis, using a sample of failed and non-failed firms. They found that both the linear and the quadratic discriminant analysis produce similar results. Studies in areas other than economics and business concluded that for large samples quadratic discriminant analysis performed better than linear discriminant analysis.

As we have seen the discriminant coefficients are not unique and any multiple of them meets the criterion used to derive them. Therefore it is not possible nor does it make sense to test whether a coefficient is

equal to zero or any other value. Several methods have been proposed for testing the relative importance of different variables in the discriminant function. However, a problem with them is that they assume equal variance-covariance matrices within the groups.

A more extensive discussion of the pitfall associated with the application of discriminant analysis in business and economics can be found in Eisenbeis (1977) and Pinches (1980).

At this point we would like to note that the discriminant and the regression coefficients are proportional to each other, the constant of proportionality being the same for every coefficient. As a consequence of this, the estimated linear probability and the discriminant score are linearly related, thus the two models classify firms identically. A proof of the above result can be found in Ladd (1966) and also in Maddala (1983) pp. 18-21.

3. Bayesian Discriminant Analysis

Suppose that a stochastic vector X arise from two multivariate normal distributions differing in mean, but, having the same covariance matrix. Define $Y_i=1$ if an observation X_i arises from population 1, and $Y_i=0$ if it arises from population 2. Let q_1 and q_0 be the prior probabilities for $Y_i=1$ and $Y_i=0$ respectively. The above are formally stated as:

$$X_i \sim N(\mu_1, \Sigma) \text{ with } P(Y_i=1) = q_1$$

$$X_i \sim N(\mu_0, \Sigma) \text{ with } P(Y_i=0) = q_0$$

The posterior probability of Y_i given X_i is,

$$P(Y_i=1 | X_i) = \frac{f_1(X_i) q_1}{f(X_i) q_1 + f(X_i) q_0}$$

where f_1 and f_0 denote the multivariate normal densities for the two populations. This can be simplified to:

$$P(Y_i = 1 | X_i) = \frac{1}{[1 + \exp (-b_0 - X_i b_1)]}$$

where, $b_0 = \ln(q_1/q_0) + \frac{1}{2} (\mu_0 - \mu_1) \Sigma^{-1} (\mu_1 + \mu_0)'$

$$b_1 = \Sigma^{-1} (\mu_1 - \mu_0)'$$

The unknown parameters μ_1 , μ_0 , q_1 , q_0 , and Σ are usually estimated using maximum likelihood, see Efron (1975). These estimates are:

$$\bar{X}_1 = \frac{1}{n_1} \sum_{i=1}^n Y_i X_i, \quad \bar{X}_0 = \frac{1}{n_0} \sum_{i=1}^n (1 - Y_i) X_i,$$

$$\hat{q}_1 = n_1/n, \quad \hat{q}_2 = n_2/n$$

$$S = \frac{1}{n} \sum_{i=1}^n (Y_i (X_i - \bar{X}_1)' (X_i - \bar{X}_1) + (1 - Y_i) (X_i - \bar{X}_2)' (X_i - \bar{X}_2))$$

The maximum likelihood estimators for b_0 and b_1 are obtained by substituting the above estimates into the respective formulas. The discriminant function is given by $Z_i = b_0 + X_i b_1$. Note that the maximization of the sample likelihood function formed by the posterior probabilities yields the logit estimates for b_0 and b_1 .

The Bayesian approach presents certain advantages over regression analysis and traditional discriminant analysis. Unlike regression analysis, it does not suffer from heteroscedasticity and always yields probabilities which range between zero and one. In contrast to traditional discriminant analysis, the discriminant score produced by the Bayesian approach is invariant to the sample size and the nature of the data. Also, the probabilistic nature of the technique makes the comparison with logit and probit more feasible.

4. Logit and Probit

Given the firm's attribute vector X_i , suppose that there exists a random index $I_i = Z(X_i, b) - u_i$, such that the larger this index is the greater the probability that firm i fails. This index is composed of a deterministic component $Z(X_i, b)$ which is usually specified as a linear function of X_i , and a random component u_i distributed with zero mean and unit variance, and probability density function $f(u_i)$. Note that the latter assumption does not restrict the model. The unobservable index I_i can be scaled in such a way that u_i meets the specification of zero mean and unit variance.

Furthermore, if the value of $I_i > 0$, or $u_i < X_i b$ we assume that the

firm fails, otherwise the firm remains solvent. The probability that firm i fails is equal to:

$$P(u_i < X_i b) = F(X_i b) = F_i$$

where in the opposite case is $1 - F(X_i b)$. The dichotomous variable Y_i is modeled as a Bernouli random variable with a probability distribution given by:

$$P(Y_i) = F_i^{Y_i} (1 - F_i)^{1 - Y_i} \quad \text{for } Y_i = 0, 1$$

The log-likelihood function of a random sample of n firms is written as:

$$L = \sum_{i=1}^n \{ Y_i \log F(X_i b) + (1 - Y_i) \log [1 - F(X_i b)] \}$$

Differentiating this with respect to the parameter vector b gives,

$$S(b) = \sum_{i=1}^n \frac{[Y_i - F(X_i b)]}{F(X_i b) [1 - F(X_i b)]} f(X_i b) X_i$$

The solution of the system of equation $S(b) = 0$ gives the maximum likelihood estimators (MLE) for the parameter vector b . These are asymptotically minimum variance unbiased estimator (AMVUE) and follow multivariate normal distribution with mean b and variance the inverse of

the information matrix $I(b)^{-1}$. This evaluated at the maximum likelihood estimates gives the estimated asymptotic variances of the estimators.

The information matrix is equal to:

$$I(b) = \sum_{i=1}^n \frac{f(X_i b)^2}{F(X_i b) [1-F(X_i b)]} X_i' X_i$$

For logit the function $F(\cdot)$ is the cumulative standardized logistic distribution, while for probit this is equal to the cumulative standard normal distribution.

The system of equations $S(b)=0$ is highly non-linear for either logit or probit. Its solution requires the use of a non-linear iterative procedure. In this study we use the Newton-Rapson iterative method, programmed in SAS matrix. We find this necessary for two basic reasons. First, some statistical packages approximate the second order conditions and the information matrix resulting in inaccurate variances for the estimators. Second, for the type of estimation (stratified estimation) which follows in the next chapter, they are no readily available packages.

To test different hypotheses concerning more than one parameter we use the log-likelihood ratio test, defined as:

$$LR = 2(\log L_1 - \log L_0)$$

where, L_0 is the maximum of the log-likelihood under the null hypothesis and L_1 the maximum value of the log-likelihood function under the alternative hypothesis. For large samples, this follows Chi-square

distribution with k degrees of freedom, where k is the number of parameters specified a value.

As a measure of the accuracy with which the models approximate the observed data, an indirect pseudo R-square is used. This is based on the likelihood ratio test and is defined as:

$$\text{Pseudo } R^2 = 1 - (L_1/L_0)$$

McFadden (1974) was the first to propose this measure. In practice this has similar interpretation as the regression analysis R-square.

Efron, suggested an analogue of regression R-square defined by

$$\text{Efron's } R^2 = 1 - \frac{\text{MSE}}{n_1 n_2}$$

where MSE is the mean squared error. Specifically,

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (Y_i - P_i)^2$$

A review of Efron's R-square and other criteria for comparing the predictive accuracy of binary models can be found in Amemiya (1981).

5. Sampling and Estimation

5.1 Sampling

The initial data set includes a population of 101 failed and 2008 non-failed manufacturing and retailing entities. From this set we collect a random stratified sample of 74 failed and 1050 healthy firms.

We do not use the entire population of firms for two basic reasons. First we reserve some firms for the validation of our models and secondly using the entire population of firms will be computationally costly.

We would like to note that most corporate failure prediction studies have used matched stratified samples, where failed and healthy firms were matched by year of failure, industry, and sometimes by size. We have not adopted this sampling method because it may result in dropping variables from the models which are important, or produce inconsistent estimators. Further discussion of this issues is provided in White (1983) pp. 77-79.

Financial data for the failed firms were collected from their last financial statement prior to failure at approximately two years prior to filing for bankruptcy. In no case was the length of time between the year of data and the year of bankruptcy less than a year. Specifically, the average lag time is 1.986 years, ranging between one and four years with standard deviation of 1.088 years. Firms with a length of time more than four years have been dropped from the sample.

Many studies used data from one year prior to failure. The COMPUSTAT database did not, however, have data one year prior for all failed firms. Data for a few failed and non-failed firms were incomplete thus the final sample used in the estimation has been reduced. The exact numbers are given along with the estimates of the models.

5.2 Selection of the Variables

A very important procedure in any corporate failure prediction study is the identification of those sets of variables (model specification) which best differentiate a healthy from a failing firm. Finance theory does not help much. Thus model identification becomes a difficult task, particularly for non-linear models such as logit or probit. To our knowledge, no convenient program exists for selecting the regressors in logit or probit models. For discriminant analysis, the selection is done by using different stepwise techniques. A pitfall with these techniques is that they often lead to model misspecification.

In this study we use regression analysis as the basic tool in order to select the variables. This is because regression analysis is well developed and understood; it is faster; and it is computationally more efficient. It also provides a variety of statistics which are very helpful in selecting the models. For this purpose we have used the SAS statistical procedure called RSQUARE. This is a very powerful, economical, and time efficient procedure, and traces out all possible models of variables. Moreover, for every model it prints the coefficients, the corrected and uncorrected R-squares, and different statistics like the C_p (conditional mean square error prediction), Amemiya criterion etc. The above enables the researcher to combine statistical as well as subjective criteria in modeling.

To identify the models and select the best sets of variables we have used the following steps:

- (1) For every size we estimate those 200 hundred models with the

largest R-square. For every estimated model we request the coefficients, the R-square, and the C_p statistics.

(2) From these models we consider those profiles of variables with C_p statistics approximately equal to the number of variables in the models. A detailed discussion of the theoretical foundation and application of the C_p criterion can be found in Judge et.al (1985) p. 865.

(3) In order to keep our analysis simple and avoid data complexities we eliminate those models with counter intuitive coefficients. Often, the estimated coefficients have signs which are not expected by finance theory. Reasons for this are unknown, but one possible explanation might be the over-identification of the models by including variables which are highly correlated. Another explanation might be that the different sets of variables imply non-linear indices. However, the identification of a non-linear structure is a very difficult task and we do not intend to explore this issue in the present study.

(4) Next we eliminate all profiles of variables which are subsets of other profiles already kept for further examination.

(5) All sets of variables considered in step 4 are estimated using regression analysis. Insignificant coefficients are dropped from the models.

(5) Estimation of logit and probit models and elimination of those profiles with insignificant coefficients.

(6) Estimation of the discriminant models.

The final product of the above selection methodology has been the identification of two models, each including eight explanatory

variables. The first model includes the ratios of sales to total assets (A1), fixed assets to total assets (A7), inventories to total assets (A8), working capital to total assets (L2), long term debt to total assets (LV2), operating income to sales (P6), earnings per share to price of share (P7) and the logarithm of total assets (LTA) as a proxy for size. The second profile includes basically the same variables, however the ratio of long term debt to total assets is replaced by the ratio of interest expense to total assets (LV3).

In our effort to identify the best theoretically appealing models, we have repeatedly tested several variables found significant in other studies by combining them with the above sets of variables. In all cases this attempt failed to produce any significant results. Some of the variables tested were the ratio of EBIT to total assets, sales to total assets, retained earnings to total assets, and market value of equity to total assets.

5.3 Models

We estimate each of the four statistical models using the above profiles with standardized and unstandardized variables. Tables 15-18 present the estimates for the linear probability, the linear discriminant, the probit, and the logit models respectively. Note that all coefficients have the expected signs.

Positive signs imply that an increase in the values of these variables, other things being equal, will increase the probability of failure. Negative signs imply the opposite. The coefficients measure the impact of each variable on the estimated probability of failure. Besides

that, the coefficients of the standardized models are independent of units, therefore they can be treated as elasticities. Generally the higher their values the greater the relative importance of the variables in the models. However this is not true for the coefficients of the unstandardized variables because they are not independent of the measurement units.

The most important predictor of corporate failure is the working capital ratio. Its negative coefficient is highly statistically significant and appears to have the greatest value in all four standardized models. Generally, an increase in the value of this ratio decreases the probability of failure.

Size (LTA), also appears highly significant. Its negative sign implies that smaller firms are more vulnerable than larger firms. Other variables which are statistically significant in all models, are the ratios of fixed assets to total assets (A7), operating income to sales (P6) and long term debt to total assets (LV2). Their coefficients imply that firms with a higher level of fixed assets, or higher return on sales, or lower long term debt are less likely to fail.

The ratio of interest expense to total assets (LV3) provides a very good substitute for the long term debt ratio (LV2). Its coefficients have positive signs and they are statistically significant in all standardized models. However, they appear insignificant in the unstandardized LPM and logit model. A possible reason might be high deviations of the variable from the industry's means.

The ratios of sales to total assets (A1), inventories to total assets (A8) and the earnings price ratio (P7) are statistically

significant in the linear probability and probit models, however their t-statistics in the logit models are very low. Their signs are as expected indicating that firms with higher sales, or higher profitability, or lower inventories are generally healthier.

As it is evident from the above tables, logit usually produces t-statistics which are lower than those of probit. A possible explanation can be found in the shape of the standard logistic distribution whose tails are flatter than those of the standard normal distribution. Because of this the diagonal elements of the Hessian matrix are generally lower, generating higher variances and lower t-values for the estimators than probit. This incidence creates some problems as to which model's t-values to base our inference on about the significance of the coefficients. To resolve this problem we have applied a dual criterion. If both probit and LPM agree on the significance of a coefficient we favor probit, otherwise we favor logit.

Along with the t-values of the estimates we also supply measures of how well the models fit the data. For the linear probability models we provide the corrected and uncorrected R-square, the F-value, and the mean square forecasting error (MSE). The first three measures do not allow a direct comparison of the LPM with logit, probit, or linear discriminant analysis because their computational basis is different. However, the mean square error enables comparison of the models. For linear discriminant analysis, logit and probit we provide the log-likelihood ratio, Efron's R-square (see Amemiya 1981), McFadden's pseudo R-square and the mean square forecasting error.

Model 1 has a slightly better fit than model 2 in all four statistical models either when used with standardized or unstandardized variables. Using the MSE as a criterion, we conclude that Probit has a better fit than logit in the standardized models, but logit appears slightly better in the unstandardized models. When logit and probit are compared to LPM or discriminant analysis they obviously out performed them in terms of MSE.

The fact that logit out performs the linear discriminant analysis is not surprising. The a posteriori likelihood function for linear discriminant analysis is identical to that of logit. In logit the estimated coefficients are taken as those which maximize the likelihood function, however for discriminant analysis these are estimated using the functions presented in section 3. Obviously the value of the log-likelihood function for discriminant analysis will be at least as equal to that of logit, implying worse fit and higher MSE.

In chapter 5 we intend to evaluate the performance of the models using more sophisticated tools. Also note that the LPM coefficients excluding the intercept are proportional to discriminant coefficients.

CHAPTER 4

STRATIFIED ESTIMATION

1. Introduction

The application of different statistical models to predicting corporate failures necessitates the use of non-random sampling methods. Previous studies have treated such samples as random thereby resulting in inconsistent estimates, and upwardly biased probabilities of failure. The purpose of this chapter is to discuss and apply an estimation technique based on Bayes' formula which corrects for these problems.

These findings are of interest to creditors and potential investors who like to have unbiased and more efficient measures in evaluating a firm' performance. Further more under risk neutrality unbiased probabilities of failure are the appropriate parameters to be used in formula's for the value of a firm or bankruptcy cost.

2. Sampling Bias

The annual rate of firms that fail in the U.S.A. ranges between .01 and .08 percent. For publicly traded corporations this rate is smaller. As a result of this, a random sample will generally contain a few of these. In a corporate failure study, it is necessary to have many failed firms in the sample. Collecting the whole population is time consuming, costly, and often impossible. Most researchers have responded to this problem by using non-random sampling methods like those of matched stratified sampling or stratified random sampling.

The use of non-random sampling methods results in an overall sample with a much higher representation of failed firms than actually occurs in the real world. Estimation of models using such samples without correcting for the "sampling bias", produce estimated probabilities of failure which are upwardly biased. To see the latter, consider the following heuristic argument.

Let a random sample of n firms. Define n_1 and $n_2=n-n_1$ as the number of failed and non-failed firms respectively. The first normal equation, of either LPM or logit states that $\sum P_i = n_1$, where P_i is equal to $X_i b$ for the LPM and $F(X_i b)$ for logit. Divide this equation by the sample size to get:

$$\sum_{i=1}^n P_i / n = n_1/n$$

For a random sample, either n_1/n or $\sum P_i/n$ are unbiased and consistent estimators for the proportion of failed firms in the population. However, when non-random samples are treated as random, these measures overestimate the proportion of failed firms in the population, resulting in estimated probabilities which are upwardly biased. The bias for the logistic model or discriminant analysis is incorporated in the intercept. However, for probit this is not the case. The resulting bias affects all coefficients in a non-systematic fashion. These are further discussed in later sections.

3. Models

3.1. Probit and Logit

The stratified estimation of logit and probit presents certain similarities with random estimation. Particularly random stratified sampling with equal proportions sampled from each group, is equivalent to pure random sampling in the sense that each observation has the same probability of being in the sample. Thus, the two sampling schemes should give the same estimators. We intend to further explore this issue in this section.

Let again the random index $I_i = X_i b + u_i$ such that the larger its value the greater the probability of failure. Furthermore assume that failure occurs when the value of the index I_i passes the threshold level of zero otherwise the firm remains solvent. The probability that firm i fails is then equal to

$$P(u_i < X_i b) = F(X_i b)$$

where in the opposite case this is equal to $1 - F(X_i b)$.

Let B and N be the sets of all failed and non-failed firms respectively. These sets are mutually exclusive. Let q_1 and q_2 be the proportions sampled from B and N respectively, and let S be the set of all firms in the sample. The probability that firm i belongs to the population of failed firms while in the sample is equal to:

$$\begin{aligned} P(i \in B/S) &= \frac{P(i \in S/i \in B) P(i \in B)}{P(i \in S/i \in B) P(i \in B) + P(i \in S/i \in N) P(i \in N)} = \\ &= \frac{q_1 F(X_i b)}{q_1 F(X_i b) + q_2 [1 - F(X_i b)]} = \end{aligned}$$

$$= \frac{F(X_i b)}{F(X_i b) + q[1-F(X_i b)]} = G(X_i b)$$

where $q=q_2/q_1$. For logit, the function $F(X_i b)$ is the cumulative standard logistic distribution, while for probit this is equal to the cumulative standard normal distribution. The density function of the composite cumulative distribution $G(X_i b)$ is equal to:

$$g(X_i b) = \frac{q f(X_i b)}{\{F(X_i b) + q[1-F(X_i b)]\}^2}$$

where, $f(X_i b)$ is the density function of $F(X_i b)$.

The dichotomous variable Y_i is modeled as a Bernoulli random variable with probability distribution given by

$$P(Y_i) = G_i^{Y_i} (1-G_i)^{1-Y_i} \quad \text{for } Y_i = 0, 1$$

Given a stratified random sample of n firms (failed and non-failed), its log-likelihood function is written as

$$L = \sum_{i=1}^n \{Y_i \log G(X_i b) + (1-Y_i) \log [1-G(X_i b)]\}.$$

Differentiating with respect to b gives

$$S(b) = \sum_{i=1}^n \frac{Y_i - G(X_i b)}{G(X_i b) [1-G(X_i b)]} g(X_i b) X_i,$$

In the case of equal proportions ($q_1=q_2$), $G(X_i b)=F(X_i b)$ and $g(X_i b)=f(X_i b)$ thus the stratified log-likelihood function and the first order conditions collapse to those of random sampling. This shows that random estimation can be treated as a special case of stratified estimation.

The solution of $S(b)=0$ gives the maximum likelihood estimators (MLE) b . This system is highly non-linear for either logit or probit and its solution requires the use of a non-linear iterative procedure. In this paper we use the Newton-Rapson iterative method, programmed in SAS using the matrix procedure. This is necessary since a package for the stratified estimation of probit is not available.

The Fisher's information matrix is identical to that of random estimation, however the density and the cumulative distribution are substituted by their composite functions given above. The MLE are asymptotically minimum variance unbiased estimators (AMVUE) and follow normal distribution with mean and variance $I(b)^{-1}$, where $I(b)$ denotes the information matrix. This evaluated at b gives the estimated asymptotic variances of the MLE. The consistency and properties of the above estimators have been discussed by Manski and McFadden (1981) in a paper dealing with alternative sample designs and estimators for discrete choice models.

At this point we would like to highlight the difference between the sample dependent probability $G(\cdot)$ and the unconditional probability $F(\cdot)$. When stratified samples are treated in the estimation as random the estimated probability of failure is identical to $G(\cdot)$. The resulting bias is equal to,

$$\begin{aligned}
G - F &= \frac{q_1 F}{q_1 F + q_2(1-F)} - F = \\
&= \frac{(q_1 - q_2)(F - F^2)}{q_1 F + q_2(1-F)} \\
&= \frac{(1 - q)(F - F^2)}{F + q(1-F)} > 0 \quad \text{for } q_1 > q_2 \text{ or } q < 1.
\end{aligned}$$

In fact what we are interested is the estimated probability $F(\cdot)$ which is independent of the nature of the sample. An easy way to get this probability is to solve $G(\cdot)$ with respect to $F(\cdot)$. This yields,

$$F = \frac{G}{G + 1/q(1-G)}$$

In the case of logit the above equation reduces to,

$$\begin{aligned}
F &= \frac{1}{1 + 1/q \exp(-b_0 - X_i b)} \\
&= \frac{1}{1 + \exp(-[b_0 + \log(q)] - X_i b)}
\end{aligned}$$

The above implies that the logit coefficients excluding the intercept are the same, whether the sample is treated as random or stratified. The intercept is greater by an amount equal to $\log(q)$. In the case the proportion of failed firms (q_1) in the sample is greater than the proportion of healthy firms (q_2), then $q=q_2/q_1 < 1$ and the intercept will be smaller. In the opposite case it will be larger.

An easy way to recover the stratified estimators when the random estimators are available is to adjust the intercept by adding the $\log(q)$. This is not true for probit where the coefficients have to be estimated using by maximizing the stratified likelihood. However, if one is interested in the estimated probability, this can be obtained by solving G with respect to F.

3.2 Linear Probability Model (LPM)

In the case of stratified sampling, the weighted least-squares method can be used to estimate b by minimizing

$$S = \sum_{i=1}^n \frac{1}{q_i} (Y_i - X_i b)^2$$

where $q_i = q_1$ for $Y_i = 1$ and $q_i = q_2$ for $Y_i = 0$.

For a brief discussion see Maddala (1983) pp. 170-72. For a discussion on the applicability of probability weighted least squares see Holt et al. (1980).

The estimation of the linear probability is straight forward and does not involve any special difficulties. However in many occasions the estimated parameters provide counter intuitive signs. The cause of this are the weights attached to the observations. Specifically a large weight attached to the non-failed observations might cause the mean of a variable in one group to become larger, and more likely the sign of the coefficient associated with this variable will be reversed. For this reason we preferred discriminant analysis instead.

3.3 Discriminant Analysis

The Bayesian approach to discriminant analysis will not provide any counter intuitive results. The unequal weights will affect only the intercept of the model without alternating the signs of the other estimators. As in the case of logit the estimated intercept of discriminant analysis will be adjusted by adding to it a number equal to $\log(q)$.

4. Estimation

For the stratified estimation of our models we have used the same sample as the one used in chapter 3. This has been collected in a random stratified fashion from a population of 101 failed and 2008 healthy firms, and includes 74 failed firms ($q_1=.733$) and 1050 healthy firms ($q_2=.523$). We could have chosen equal proportions and thus avoid stratified estimation. However for the sake of exploring this technique we have not followed this approach.

Seven failed and 135 healthy did not have complete data, thus the sample used in the estimation includes 67 failed and 935 healthy firms. Tables 19-20 give the discriminant, probit and logit estimates for models 1 and 2 respectively. The discriminant coefficients have been obtained by using the regular formulas (see chapter 3), however, the intercept has been adjusted by adding the $\log(q)$. The logit and probit estimates have been obtained by maximizing the stratified log-likelihood function. Note that all coefficients have the expected signs.

The logit coefficients are almost identical to those in the random estimation case. The small deviations are due to some computational

error and are related to the convergence criterion used. Generally the lower this is the closer the estimates will be. Interestingly the probit estimators change in a non-systematic fashion, however, the sampling bias, as in the logit model, is concentrated in the intercept.

The probit and logit mean square error are approximately equal and they are both lower than that of discriminant analysis. Thus generally we can conclude that the two models are more efficient in the sense of mean square error. Paradoxically the mean square error of all three stratified models are higher to the corresponding mean square of the random estimation models. An explanation is the following. The variance of the estimated probabilities in the failed group is probably higher than the variance of the non-failed group. Thus including proportionally more failed firms in the sample increases the mean square error of our estimators under the stratified estimation scheme.

CHAPTER 5

EVALUATION OF THE MODELS

1. Introduction

The evaluation of the classification accuracy of corporate failure prediction models is a very serious issue and requires special attention. This typically involves reclassifying a group of failed and non-failed firms into the two groups based on the estimated probability failure and a cutoff probability. Specifically a firm is classified as failed if the estimated probability of failure is greater than a cutoff probability and as healthy otherwise. The model's predictive ability is measured by the percentage of firms classified correctly in their original groups.

Earlier studies have used arbitrarily chosen cutoff probabilities in order to evaluate the classification accuracy of their estimated models. Many times the cutoff probability was chosen as .5 and other times as that value which maximized the model's percentage of correct classification. Note that the predictive accuracy of the models depends on the value of the cutoff probability used. It is natural to assume that investors are associated with different cutoff points, thus results derived for a given cutoff probability do not necessarily help them decide which model fits their needs. Clearly the rewards or costs associated with the different types of correct or incorrect classification determine the investor's optimal cutoff probability. This issue is further explored in the next sections.

2. Cutoff Probability

The determination of an investor's optimal cutoff probability is exclusively based on the rewards or costs of the different types of correct or incorrect classification. Using a theoretical framework based on decision theory we derive an expression for the optimal cutoff probability to be used for the evaluation of the predictive ability of corporate failure prediction models. For this purpose we work as follows.

Let A be the space associated with a firm's attribute vector X . Suppose a decision rule exists which partitions A into two mutually exclusive regions denoted by A_f and A_h . Let A_f and A_h be associated with the groups of failed and healthy (non-failed) firms respectively. Further more, suppose that a firm is classified as failed ($Y=1$) or healthy ($Y=0$) if its attribute vector X lies in A_f or A_h respectively.

Let $P(F)$ and $P(H)$ be the prior probabilities that a firm comes from the two groups. Note that these probabilities are independent of X and known before the firm's attribute vector is measured. Moreover, let $P(F|X)$ and $P(H|X)=1-P(F|X)$ be the a posteriori probabilities for the two groups. In contrast to $P(F)$ and $P(H)$, the a posteriori probabilities depend on X and can be calculated only after the value of the X for a given firm has been realized. Such functions have been estimated in chapters 3 and 4.

The classification of a firm into one of the two groups is associated with a penalty (cost), or a reward. These can be summarized in the following payoff matrix.

	F	H
F	C_{FF}	C_{FH}
H	C_{HF}	C_{HH}

where, C_{FH} denotes the cost of misclassifying a failed firm, C_{HF} denotes the cost of misclassifying a healthy firm, C_{FF} , and C_{HH} denote the rewards of classifying a firm in their original groups correctly.

The expected cost of partitioning set A into A_f and A_h is equal to,

$$\begin{aligned}
 C &= C_{FF} P(F) \int_{A_f} P(X|F) dX + C_{FH} P(F) \int_{A_h} P(X|F) dX \\
 &+ C_{HF} P(H) \int_{A_f} P(X|H) dX + C_{HH} P(H) \int_{A_h} P(X|H) dX = \\
 &= \int_{A_f} [C_{FF} P(X|F) P(F) + C_{HF} P(X|H) P(H)] dX \\
 &+ \int_{A_h} [C_{FH} P(X|F) P(F) + C_{HH} P(X|H) P(H)] dX =
 \end{aligned}$$

The above will be minimized if A is partitioned to A_f and $A_h=A-A_f$ such that X is in A_f whenever,

$$C_{FF} P(X|F) P(F) + C_{HF} P(X|H) P(H) < C_{FH} P(X|F) P(F) + C_{HH} P(X|H) P(H)$$

Substituting $P(X|F) P(F) = P(F|X) P(X)$, $P(X|H) P(H) = P(H|X) P(X)$ and

$P(F|X)=1-P(h|X)$ above gives,

$$\{C_{FF} P(F|X) + C_{HF} [1 - P(F|X)]\} P(X) < \{C_{FH} P(F|X) + [1 - P(F|X)]\} P(X)$$

which if manipulated gives the following decision rule:

$$P(Y=1|X) = P(F|X) > \frac{C_{HF} - C_{HH}}{C_{FH} + C_{HF} - C_{FF} - C_{HH}} \implies X \in A_f \text{ or } Y=1.$$

The above rule states: "Classify a firm into the failed group (XEA_f) if its estimated probability is greater than the cutoff point, determined by the right hand side of the inequality. In the opposite case classify the firm into the healthy group (XEA_h)".

The range of the cutoff point will be the unit interval if both the numerator and denominator are positive. In this case this can be interpreted as a cutoff probability. If the numerator is a negative number ($C_{HH} > C_{HF}$) and the denominator is positive then the cutoff point takes the limiting value of one. If $C_{HH}=C_{FF}=0$ then the above classification rule reduces to,

$$P(Y=1|X) > \frac{C_{HF}}{C_{FH} + C_{HF}} \implies X \in A_f$$

In this case the optimal cutoff probability is positively related to the cost of misclassifying a healthy firm C_{HF} . It is intuitively clear that the higher C_{HF} the higher the cutoff probability. However, if the costs

of misclassification are symmetric, i.e. $C_{HF}=C_{FH}$, the above inequality reduces to Bayes' minimum error rule,

$$P(Y=1|X) > 1/2 \text{ then } X \in A_f$$

It is obvious that the optimal cutoff probability is determined completely by the values of the payoff matrix. The payoff matrix is subjective and it is not expected to be the same for all investors. Thus investors might prefer different corporate failure prediction models. Before further discussing this issue, let's introduce the concept of dominance.

Let $f_k(\bar{P})$ be a function of model's k percent of correct classification evaluated at a cutoff probability \bar{P} . A model k is said to dominate a model j if and only if,

$$f_k(\bar{P}) \geq f_j(\bar{P}) \quad \text{for any } \bar{P} \text{ in } (0,1)$$

If such a model exists, then any investor will prefer it. Specifically a model will be preferred by an investor with a cutoff probability \bar{P} if and only if

$$f_k(\bar{P}) > f_j(\bar{P})$$

A model will always be preferred, regardless of the investors payoff matrices if it dominates any model for any cutoff probability. Also we would like to indicate that for any a posteriori probability function with a linear index, the cutoff probability uniquely divides A into two mutually exclusive regions A_f and A_h . This can be shown as follows.

The rule for dividing A

$$P(Y=1|X) = F(X \cdot b) > \bar{P} \quad \text{then } X \in A_f$$

or,

$$X \cdot b > P^{-1}(\bar{P}),$$

where $P^{-1}(\cdot)$ is the inverse cumulative distribution. Note that $X \cdot b$ is a hyper plane separating the space A (this is assumed to be a Euclidian space) into two mutually exclusive regions.

3. Evaluation of the Models

For the evaluation of the predictive ability of our models we use two samples. The first called the initial sample is composed of 67 failed and 935 non-failed firms. We expect the results on this sample to be good since the coefficients of the models are derived from it.

To test the models more rigorously we also use a second sample called the holdout. This is composed of 25 failed and 818 non-failed firms. The two samples are mutually exclusive and they almost span the entire population of manufacturing and retailing firms in the COMPUSTAT files. Totally the compustat files include 2008 manufacturing and retailing firms. However some firms were excluded because of incomplete data. Data are extracted from the last financial statement of the firms at approximately two years prior to failure.

Using different cutoff probabilities we have tested the predictive accuracy of all models developed in chapters 3 and 4 on both samples. Along with overall percent of correct classification we also present the correct classification rates on the failed and non-failed groups. Note

that at the cutoff point of 0 we expect the LDA, probit, and logit, to classify all firms as failed, while at a cutoff point of 1 we expect all firms to be classified as healthy. In this case the overall percent of correct classification on the initial sample will be 6.87% and 93.31% respectively, while on the holdout sample this will be 2.96% and 97.19% respectively. For LPM, however, this is not true because in many cases the estimated probabilities do not lie on the unit interval.

Table 21 presents the classification accuracy of LPM1, LDA1, Probit1, and Logit1 on the initial sample (the number refers to model 1, see chapter 3 for the variables included in the model). In most cases the models have attained classification scores which are well above 95%. The highest percent of classification has been attained by logit at 95.91%. This is marginally above the highest percent of classification of the other models. No model dominates other models for every cutoff point. Note that logit and probit perform equally well and marginally better than LDA and LPM.

Table 22 shows the classification accuracy of the four statistical models when tested on the holdout sample. In most cases their accuracy is higher than 97% and in some cases exceeds 98%. These scores are higher to those of the initial sample, because the percentage of failed firms in the holdout sample is quite lower. As in the previous case no model dominates the other for every cutoff point. The highest percentage of correct classification is attained by both Logit and probit at 98.70%. The classification performance of the two models has been also found marginally better than those of LPM or LDA.

Table 23 and 24 present the classification accuracy of the unstandardized models (LPM1, LDA1, Logit1, Probit1) on the initial and holdout samples respectively. Specifically their performance scores range well above 94% (occasionally they reach 95%) on the initial sample, and well above 97% (occasionally they reach 98%) on the holdout sample. The highest scores are produced by the probit on the initial sample at 95.81%, probit and LPM on the holdout sample at 98.22%. Interestingly, all unstandardized models perform equally well on both samples and produce satisfactory results. However their predictive ability is weekly dominated by that of the unstandardized models.

Table 25 and 26 present the classification results of LPM2, LDA2, Logit2, and probit2 on the initial and holdout samples respectively. The overall classification accuracy of all models is around 95% for the initial sample, and well above 97% for the holdout sample. Note that the predictive ability of LPM, LDA, logit, and probit appears to be the same. Moreover their predictive ability is hardly dominated by those models which include the first profile of variables.

Table 27 and 28 show the results of the evaluation of the unstandardized models on the initial and holdout samples respectively. The overall classification of these models ranges between 93% and 95% on the initial sample and 97% to 98% on the holdout sample. Generally their predictive ability is lower to that of the standardized models.

Tables 29-32 show the classification accuracy of the stratified LDA, probit and logit. The classification accuracy of the stratified logit and LDA is equivalent to the corresponding random estimation models.

However this takes place at a lower cutoff point because the intercept of the models is lower. The same results appear for probit as well.

At this point we would like to summarize the above findings. It has been found that the logit and probit models have virtually the same classification performance. The same is true for the linear probability model and the linear discriminant analysis. None of the statistical models has been found to be dominant. However, logit and probit have produced better results for the majority of cutoff points. Thus the two statistical models have appeared slightly superior to LPM and LDA.

All models containing unstandardized variables have produced good classification results, but they have been generally dominated by the corresponding models containing standardized variables. All statistical models containing the first profile have been found slightly better than those containing the second profile of variables. Also the stratified and random estimation produced virtually the same results. Generally we conclude that the classification accuracy of the corporate failure prediction models developed in this study, either including profile 1, or profile 2, have been found very promising. This conclusion holds for all standardized or unstandardized models. We expect such models to be very useful tools in assessing the performance of any manufacturing and retailing firm.

At this point we would like to indicate that the classification performance of the LPM models is slightly biased in favor of them because regression analysis has been the primary tool used to identify the models.

APPENDIX 1

Manufacturing and Retailing Major Groups

SIC	Major Manufacturing Groups	# Firms
2000-99	Food and Kindred Products	99
2100-99	Tobacco Manufacturers	7
2200-99	Textile Mill Products	46
2300-99	Apparel and other Finished products Made From Fabrics and Similar Materials	49
2400-99	Lumber and Wood Products, Except Furniture	36
2500-99	Furniture and Fixtures	33
2600-99	Paper and Allied Products	47
2700-99	Printing, Publishing and Allied Prod.	65
2800-99	Chemicals and Allied Products	150
2900-99	Petroleum Refining and Related Indust.	45
3000-99	Rubber and Miscellaneous Plastic Products	58
3100-99	Leather and Leather Products	18
3200-99	Stone, Clay, Glass and Concrete Products	43
3300-99	Primary Metal Industries	69
3400-99	Fabricated Metal Products, Except Machinery and Transportation Equipment	103
3500-99	Machinery, Except Electrical	166

APPENDIX 1

Manufacturing and retailing Major Groups (Cont.)

SIC	Major Manufacturing Groups (Cont.)	# Firms
3600-99	Electrical and Electronic Machinery, Equipment and Supplies	360
3700-99	Transportation Equipment	81
3800-99	Measuring, Analyzing and Controlling Instruments	126
3900-99	Miscellaneous Manufacturing Industries from Fabrics and Similar Materials.	40
SIC	Major Retailing Groups	# Firms
5000-99	Wholesale Trade- Durable Goods	80
5100-99	Wholesale Trade- Nondurable goods	46
5200-99	Building Materials and hardware	13
5300-99	General Merchandise Stores	44
5400-99	Food Stores	46
5500-99	Automotive Dealers And Gasoline Stations	5
5600-99	Apparel and Accessory Stores	23
5700-99	Furniture, Home furniture and Equipment Stores.	10
5800-99	Eating and Drinking Places	46
5900-99	Miscellaneous Retail	51

APPENDIX 2

Failed Firms in the Manufacturing and Retailing Industries

NUM	CNUM	COMPANY NAME	SIC	FLR DATE	TA	TL	LTD
1	007551	Advent Corp	3651	03-17-81	13.45	10.068	1.000
2	007752	Aerodex Inc	3728	06-10-76	14.27	13.418	4.976
3	007806	Aerological Research Inc	3820	71	2.21	0.912	0.063
4	012644	Albee Homes inc	2450	10-09-79	8.94	7.276	5.316
5	018859	Allied Artists Industr.	3716	04-04-79	29.21	26.911	3.182
6	041321	Arlans Dept Stores Inc	5311	05-14-73	80.17	74.768	37.898
7	042078	Armac Enterprises Inc	3940	03-23-76	33.19	28.306	4.313
8	045609	Associated Food Stores	5140	06-16-75	11.63	12.329	2.105
9	053681	Avien Inc	3679	12-29-70	2.96	2.756	0.490
10	075581	Beck Inds Inc	3140	05-27-71	156.90	.	30.400
11	097309	Bohack Corp	5411	07-30-74	93.16	1.691	29.717
12	101241	Botany inds inc	2300	04-25-72	41.81	36.795	22.927
13	112061	Brody (B.) Seating Co	2510	02-04-80	3.99	2.402	0.464
14	126351	Cs Group Inc	2300	07-23-84	11.65	8.298	** 098
15	139579	Capehart Corp	5064	02-16-79	21.93	23.447	17.115
16	173000	Citation Mfg Inc	3580	10-24-78	6.74	4.016	0.163
17	233045	Dca Development Corp	3250	06-27-73	44.18	36.338	11.830
18	233191	Dei Industries Inc	3662	72	7.76	8.406	0.574
19	237570	Data Access Systems Inc	3573	01-.-83	48.01	27.396	16.210
20	243469	Decitron Electronics Co	3662	02-12-71	3.30	3.107	** 293
21	286155	Electrospace Corp	3662	04-28-74	44.34	30.521	11.144
22	294101	Eon Corp	3990	01-12-73	2.53	2.014	0.491
23	302819	Fabien Corp	2200	79	1.98	0.500	0.019
24	311729	Farrington Mfg Co	3573	01-19-71	37.64	39.141	22.827
25	314045	Federals Inc	5311	72	96.80	75.545	11.270
26	315666	Fiberstatics Corp	2200	03-06-74	1.86	1.655	0.744
27	320488	First Hartford Corp	2200	02-.-81	19.45	16.907	2.568
28	358604	Frier Industries Inc	3140	06-30-78	15.11	8.963	4.745
29	362235	GRT Corp	3652	07-18-79	23.78	18.157	1.630
30	366064	Garland Corp-C1 A	2300	04-29-80	25.42	14.028	6.383
31	368766	General Alloys Co	3320	73	3.32	2.301	0.384
32	370698	General Resources Corp	5030	79	19.58	16.369	3.428
33	374559	Giant Stores Corp	5311	03-13-74	31.26	18.149	5.978
34	375847	Gilman Services Inc	5120	05-13-82	32.57	30.339	4.806

NOTE: SIC = Standard Industrial Classification Code;

FLR DATE = Failure Date;

TL = Total Liabilities;

TA = Total Assets;

LTD = Long Term Debt.

APPENDIX 2

Failed Firms in the Manufacturing and Retailing Industries (Cont.)

NUM	CNUM	COMPANY NAME	SIC	FLR DATE	TA	TL	LTD
35	376424	Gladding Corp	3662	04-11-77	53.34	40.643	17.332
36	379848	Glover Inc	2010	07-30-80	23.08	19.246	9.835
37	382478	Goodway Inc	2731	03-25-74	13.61	9.805	4.286
38	387604	Grant (W.T.) Co	5331	04-13-76	1082.27	967.544	216.341
39	389370	Gray Mfg Co	3449	09-14-76	24.40	16.634	5.008
40	400118	Gruen Inds Inc	3870	04-15-77	15.16	10.452	2.701
41	417542	Harvest Markets Inc	5411	02-25-74	7.93	6.734	1.923
42	441764	House of Knitting Inc	2300	01-03-75	6.43	3.997	0.103
43	448519	Hy-Gain Electronics Corp	3662	01-05-78	40.96	34.751	0.052
44	461097	Interstate Stores Inc	5311	06-13-74	248.51	189.988	90.286
45	471134	Jarmel Fabrics Inc	2250	05-16-75	8.67	5.184	2.462
46	489355	Kennedy & Cohen Inc	5722	01-21-76	23.62	19.431	11.052
47	521687	Leader Intl Industries	3714	73	15.61	15.319	4.580
48	524166	Leeco Inc	3714	78	55.02	42.790	30.058
49	551675	Lynnwear Corp-C1 A	2300	02-25-81	18.77	14.090	3.171
50	559142	Magic Marker Corp	3950	07-...-80	15.61	18.657	14.085
51	577438	Maule Industries Inc	3270	07-22-76	188.91	121.761	16.740
52	585163	Mego International	3940	06-16-82	46.36	49.767	27.264
53	585310	Meister Brau Inc	2082	02-15-75	28.53	23.588	13.949
54	591846	Metropolitan Cons Inds	2771	01-18-79	14.22	11.678	0.496
55	601566	Milo Electronics Corp	5099	03-11-74	13.20	.	1.600
56	602805	Miner Industries Inc	3940	08-03-77	20.079	16.114	9.474
57	604611	Miracle Pet Products Inc	2721	12-10-71	8.024	3.453	0.610
58	610889	Monroe Group Inc	2250	01-27-75	25.486	17.658	8.610
59	634892	National Bellas Hess Inc	5311	10-29-74	42.826	40.310	15.879
60	637293	National Radio Inc	3662	08-11-70	8.462	7.916	2.880
61	6403903	Nelly Don Inc	2300	05-17-78	3.501	3.914	1.525
62	670096	Novo Corp	3713	78	55.020	47.501	24.851
63	680316	Old Town Corp	5080	06-01-73	7.307	4.248	0.569
64	683714	Open Road Inds	3792	11-15-76	57.096	55.116	4.033
65	686815	Ormont Drug & Chemical	5120	06-30-77	5.264	4.456	1.512
66	693299	Pec Electronics Corp	3670	70	5.100	.	1.000
67	701519	Parkview-G E M Inc	5912	12-19-73	70.155	7.726	11.617
68	703181	Paterson Parchment Paper	2650	12-20-74	18.482	11.171	*.338

NOTE: SIC = Standard Industrial Classification Code; YEAR = Data Year;
 FLR DATE: Date of Failure; TA = Total Assets;
 TL = Total Liabilities; LTD = Long Term
 Debt.

APPENDIX 2

Failed Firms in the Manufacturing and Retailing Industries (Cont.)

NUM	CNUM	COMPANY NAME	SIC	FLR DATE	TA	TL	LTD
69	703827	Pavelle Corp	3861	05-03-73	9.466	6.443	5.003
70	731588	Poloron Products Inc	2450	04-14-81	19.882	15.388	6.822
71	738102	Potter Instrument Inc	3570	04-18-75	43.816	39.246	1.835
72	742573	Printogs Ltd	2200	03-11-77	7.194	3.179	1.775
73	749222	RAI Inc	3140	..-02-73	14.221	11.921	1.546
74	761236	Responsive Environment	5099	05-30-73	10.126	9.417	7.077
75	779664	Rowland Inc	2890	75	8.138	3.606	1.628
76	780155	Royal Castle Systems Inc	5812	75	15.972	4.219	1.849
77	781768	Rusco Industries Inc	3442	02-22-82	39.040	32.192	12.105
78	805567	Saxon Industries	2600	..-04-82	486.617	361.968	213.852
79	810122	Scottex Corp	2200	01-15-74	30.702	22.656	9.775
80	817460	Sequoyah Industries Inc	2270	01-24-74	27.622	31.535	15.906
81	821328	Sheffield Watch Corp	5099	07-07-72	22.511	17.259	3.803
82	829880	Sitkin Smelting & Refin.	3341	03-13-78	26.657	22.529	3.631
83	846047	Sovereign Inds Inc	3728	..-10-76	18.909	9.765	1.337
84	858518	Stelber Industries Inc	3940	..-03-76	78.437	71.640	4.302
85	858552	Stellar Industries Inc	3714	04-08-75	7.958	7.823	3.160
86	862226	Story Chemical Corp	2844	02-22-77	11.551	6.336	0.004
87	863140	Stratton Group Ltd	5331	09-17-73	24.824	16.085	1.647
88	868647	Supronics Corp	2844	10-26-76	2.279	1.875	0.777
89	872415	TGC Inc	3940	08-08-78	80.783	67.953	10.518
90	872578	TMA Co	3651	07-28-72	3.526	2.976	1.750
91	879699	Teltronics Services	5063	80	12.431	9.340	4.959
92	880447	Tennessee Forging Steel	3310	12-05-77	44.143	36.866	1.826
93	888837	Tobin Packing Co Inc	2010	09-28-81	20.450	23.836	0.947
94	893842	Transogram Co	3940	02-26-71	21.520	16.688	8.418
95	901191	1225 Maple Corp	3940	78	11.904	8.218	6.115
96	913453	Universal Container Corp	3410	03-22-78	25.087	18.991	8.984
97	925385	Vesper Corp	3310	06-10-77	120.106	84.606	41.145
98	933246	Waltham Industries Corp	3699	07-15-71	44.995	43.795	10.586
99	950698	Wentworth Mfg Co	2300	72	3.791	1.858	0.326
100	959078	Western Orbis Co	2450	06-11-76	21.234	15.646	7.021
101	960691	Westminster Corp	3140	75	6.144	3.151	1.575

NOTE: SIC = Standard Industrial Classification Code;

FLR DATE: Date of Failure;

TL = Total Liabilities;

TA = Total Assets;

LTD = Long Term Debt.

APPENDIX 3

Definition of the Variables

Activity ratios

A1= SLS/TA : total assets turnover, Altman (68)
 A2= SLS/CA : current assets turnover, Deakin (77)
 A3= CGS/INV : inventory turnover.
 A4= SLS/FA :
 A5= RCV/CA :
 A6= INV/CAV :
 A7= FA/TA :
 A8= INV/TA :

Leverage ratios

LV1= LTD/TA : Debt ratio, Beaver(68)
 LV2= LTD/MVE : Debt to equity.
 LV3= IE/TA :
 LV4= IE/TL :
 LV5= TL/TA :
 LV6= TL/(MVE+TL) :
 LV7= MVE/TA :

Liquidity ratios

L1= CA/CL : Current ratio, Altman(77), Beaver(68), Deakin(77)
 L2= WC/TA : Working capital, Altman(68), Beaver(68), Blum(74)
 L3= CASH/TA :
 L4= (CA-INV)/CL : Quick ratio, Edmister(72)
 L5= CASH/TL : Beaver (68), Deakin(72)
 L6= CA/TA : Deakin(77)

Profitability ratios

P1= EBIT/TA : Return on total assets Altman (68), (73), (77)
 P2= NI/TA : Net return Beaver (68), Deakin (77)
 P3= OPI/TA :
 P4= GP/SLS :
 P5= RE/TA : Cumulative profitability, Altman (68), (77)
 P6= OPI/SLS : net operating margin.
 P7= EPS/PSHARE : earnings to price ratio
 P8= DPS/PSHARE : Price-earning ratio.

Note: For more details, see next page.

APPENDIX 3 (Cont.)

COMPUSTAT Definition of the Variables

CA=V4	: current assets (p.20).
CASH=V1	: cash or short-term investments (p.14).
CEX=V30	: capital expenditures (p.13).
CGS=V41	: cost of goods sold (p. ?)
CL=V5	: current liabilities (p.20).
DEP=V14	: depreciation and amortization (p.24).
DPS=V26	: dividend per share (p. ?)
EBIT=V13-V14	: earnings before interest and taxes or
EPS=V58	: earnings per share
EBT=V16+V18+V49	: earnings before tax and after interest pre tax income (p.43).
FA=V8	: fixed assets or net plant (p.41).
FG=V78	: finished goods (p.29).
GP=V12-V41	: gross profit on sales (p.18 and 48)
INV=V3	: inventories (p.33).
IE=V15	: interest expense on short and LTD (p.32).
IELTD=V101	: interest expense on LTD (p.32).
LTD=V9	: long term debt (p.36).
MVE=(V25*V27)/1000	: market value of common shares.
NI=V18	: net income (p.29).
NSHARE=V25	: number of shares outstanding (p.16).
NW=V60+V130	: book value of equity or net worth (p.50-A)
OPI=V13	: operating income before depreciation (p.38).
PSHARE=V24	:
RCV=V2	: accounts receivables (p.45).
RCVD=V67	: accounts receivables, estimated doubtful (p.45).
RE=V36	: retained earnings (p.47).
RDE=V46	: research and development expense (p.46).
SLS=V12	: net sales (p.48).
TA=V6	: total assets.
TL=V6-V60-V130	: total liabilities.
WC=V4-V5	: working capital.

Note: For more details see the corresponding page in COMPUSTAT given in the parentheses.

TABLE 1

Failed firms by Standard Industrial Classification Code (SIC).

SIC	# FIRMS	SIC	# FIRMS	SIC	# FIRMS
2000-99	3	3000-99	0	5000-99	7
2100-99	0	3100-99	4	5100-99	3
2200-99	8	3200-99	2	5200-99	0
2300-99	7	3300-99	4	5300-99	7
2400-99	3	3400-99	3	5400-99	2
2500-99	1	3500-99	4	5500-99	0
2600-99	2	3600-99	12	5600-99	0
2700-99	3	3700-99	8	5700-99	1
2800-99	3	3800-99	3	5800-99	1
2900-99	0	3900-99	9	5900-99	1
TOTAL	30		49		22 = 101

TABLE 2

Number of firms in the COMPUSTAT research file,
filed for bankruptcy liquidation each year.

YEAR	# FAILED	YEAR	# FAILED
1964-68	1	1975	7
1969	11	1976	7
1970	6	1977	10
1971	12	1978	3
1972	10	1979	6
1973	9	1980	6
1974	13		
TOTAL	62		39 = 101

TABLE 3

Test for the Differences in the Means of Each Group,
Unstandardized Variables.

VARIAB.	FAILED MEANS n=101	NON-FAIL MEANS n=2008	T VALUES	VARIAB.	FAILED MEANS n=101	NON-FAIL MEANS n=2008	T VALUES
A ₁	1.692	1.553	-1.15*	L ₁	1.534	3.654	2.46
A ₂	2.826	2.864	0.18*	L ₂	.154	.329	7.62
A ₃	.369	.298	-1.56*	L ₃	.039	.120	16.0
A ₄	10.776	7.214	-2.93	L ₄	.742	2.462	2.33
A ₅	.360	.354	-0.39*	L ₅	.057	.459	13.4
A ₆	.529	.411	-6.36	L ₆	.632	.601	-1.66*
A ₇	.267	.316	2.80	LTA	2.959	4.907	15.8
A ₈	.340	.249	-5.78	P ₁	-.068	.082	10.0
LV ₁	.268	.169	-5.30	P ₂	-.102	.033	9.72
LV ₂	2.341	.415	-6.94	P ₃	-.036	.123	10.9
LV ₃	.048	.026	-8.40	P ₄	.190	-2.090	-0.94*
LV ₄	.060	.048	-4.03	P ₅	-.127	.252	9.74
LV ₅	.780	.491	-14.8	P ₆	-.057	-2.331	-0.94*
LV ₆	.744	.400	-15.7	P ₇	-1.066	-0.005	5.22
LV ₇	.388	1.037	11.3	P ₈	.005	.020	4.70

Note: * Statistically insignificant

TABLE 4

Means of the Standardized Variables Two Years Prior to Failure.

----- FSN=1 -----

VAR	N	MEAN	T-VALUE	PR> T	SE(MEAN)
A1	101	-0.07114451	-0.50	0.6161	0.14145614
A2	101	0.04439577	0.27	0.7895	0.16588729
A3	101	0.36597515	1.46	0.1465	0.25010572
A4	101	0.35148188	1.60	0.1131	0.21991723
A5	101	0.05318612	0.38	0.7084	0.14177876
A6	101	0.37060842	2.75	0.0070	0.13462455
A7	101	-0.09997446	-0.76	0.4481	0.13126784
A8	101	0.27036062	2.01	0.0469	0.13434365
LV1	101	0.70715318	4.91	0.0001	0.14415752
LV2	101	1.58369151	6.29	0.0001	0.25164964
LV3	96	1.79435427	10.80	0.0001	0.16618885
LV4	95	0.86990106	7.77	0.0001	0.11201953
LV5	98	1.73194599	15.09	0.0001	0.11474691
LV6	98	1.22508150	13.19	0.0001	0.09289211
LV7	101	0.61388341	-7.97	0.0001	0.07705428
L1	101	-0.89960198	-13.20	0.0001	0.06815491
L2	101	-1.45351006	-9.88	0.0001	0.14708498
L3	101	-0.50627220	-8.17	0.0001	0.06197578
L4	101	-0.73041584	-8.19	0.0001	0.08919888
L5	98	-0.42918669	-6.55	0.0001	0.06552641
L6	101	-0.08706030	-0.71	0.4811	0.12312287
P1	101	-2.05698044	-12.65	0.0001	0.16263039
P2	101	-2.60418097	-10.90	0.0001	0.23882149
P3	101	-2.05403698	-13.18	0.0001	0.15579678
P4	101	-0.79423197	-5.69	0.0001	0.13958538
P5	98	-1.84872569	-11.44	0.0001	0.16159902
P6	101	-1.99612842	-9.18	0.0001	0.21732866
P7	101	-6.56904400	-5.67	0.0001	1.15928832
P8	101	-0.91782910	-12.61	0.0001	0.07280311

A1=SLS/TA	A2=SLS/CA	A3=INV/CGS	A4=SLS/FA	A5=RCV/CA
A6=INV/CA	A7=FA/TA	A8=INV/TA	LV1=LTD/TA	LV2=LTD/MVE
LV3=IE/TA	LV4=IE/TL	LV5=TL/TA	LV6=TL/(TL+MVE)	LV7=MVE/TA
L1=CA/CL	L2=WC/TA	L3=CASH/TA	L4=(CA-INV)/CL	L5=CASH/TL
L6=CA/TA	P1=EBIT/TA	P2=NI/TA	P3=OPI/TA	P3=OPI/TA
P4=GP/SLS	P5=RE/TA	P6=OPI/SLS	P7=EPS/PSHARE	P8=DPS/PSHARE

TABLE 5

Means of the Standardized Variables Three Years Prior to Failure.

----- FSN=2 -----

VAR	N	MEAN	T-VALUE	PR> T	SE(MEAN)
A1	98	-0.19719050	-1.54	0.1264	0.12791221
A2	98	-0.21685278	-1.67	0.0982	0.12987684
A3	98	0.36927139	1.93	0.0560	0.19095309
A4	98	0.33036440	1.96	0.0534	0.16892210
A5	98	0.16851898	1.33	0.1879	0.12707371
A6	98	0.12100350	0.93	0.3547	0.13010716
A7	98	-0.25729127	-2.12	0.0369	0.12160001
A8	98	0.17188787	1.31	0.1947	0.13162787
LV1	98	0.67961884	4.38	0.0001	0.15529840
LV2	98	1.38881110	3.59	0.0005	0.38735317
LV3	95	1.24931938	8.25	0.0001	0.15139545
LV4	88	0.74394171	4.17	0.0001	0.17834951
LV5	90	1.32624485	9.77	0.0001	0.13573441
LV6	90	1.033643	10.47	0.0001	0.09871792
LV7	98	-0.44063593	-2.94	0.0041	0.14987679
L1	98	-0.73093641	-10.84	0.0001	0.06741605
L2	98	-0.91285659	-7.41	0.0001	0.12326457
L3	98	-0.33468574	-3.54	0.0006	0.09461384
L4	98	-0.52000599	-6.77	0.0001	0.07685110
L5	90	-0.22684706	-1.32	0.1905	0.17197955
L6	98	0.07138105	0.61	0.5460	0.11779852
P1	98	-1.46589279	-8.81	0.0001	0.16637575
P2	98	-1.72130668	-6.48	0.0001	0.26574862
P3	98	-1.50965377	-8.99	0.0001	0.16798110
P4	98	-0.61426668	-3.21	0.0018	0.19140907
P5	87	-1.40681901	-8.90	0.0001	0.15801330
P6	98	-1.57230650	-4.91	0.0001	0.31994925
P7	98	-2.18045649	-5.77	0.0001	0.37804876
P8	98	-0.70393039	-6.24	0.0001	0.11278548

A1=SLS/TA	A2=SLS/CA	A3=INV/CGS	A4=SLS/FA	A5=RCV/CA
A6=INV/CA	A7=FA/TA	A8=INV/TA	LV1=LTD/TA	LV2=LTD/MVE
LV3=IE/TA	LV4=IE/TL	LV5=TL/TA	LV6=TL/(TL+MVE)	LV7=MVE/TA
L1=CA/CL	L2=WC/TA	L3=CASH/TA	L4=(CA-INV)/CL	L5=CASH/TL
L6=CA/TA	P1=EBIT/TA	P2=NI/TA	P3=OPI/TA	P3=OPI/TA
P4=GP/SLS	P5=RE/TA	P6=OPI/SLS	P7=EPS/PSHARE	P8=DPS/PSHARE

TABLE 6

Means of the Standardized Variables Four Years Prior to Failure.

----- FSN=3 -----

VAR	N	MEAN	T-VALUE	PR> T	SE(MEAN)
A1	89	-0.01636246	-0.12	0.9013	0.13161063
A2	89	-0.13900507	-1.13	0.2624	0.12323628
A3	89	0.23188380	1.34	0.1839	0.17314615
A4	89	0.50806104	2.45	0.0161	0.20713132
A5	89	0.22695938	1.67	0.0985	0.13590997
A6	89	0.07103167	0.57	0.5678	0.12387020
A7	89	-0.31192205	-2.54	0.0128	0.12277135
A8	89	0.19466757	1.48	0.1419	0.13135076
LV1	89	0.46377876	3.60	0.0005	0.12887858
LV2	89	0.82800474	4.02	0.0001	0.20622203
LV3	85	0.98221121	6.56	0.0001	0.14967296
LV4	77	0.68851725	5.07	0.0001	0.13574216
LV5	78	1.03303293	9.29	0.0001	0.11117152
LV6	78	0.77139765	6.89	0.0001	0.11192352
LV7	89	-0.41566865	-4.44	0.0001	0.09356954
L1	89	-0.53988103	-4.96	0.0001	0.10886924
L2	89	-0.58081064	-4.79	0.0001	0.12123310
L3	89	-0.27293014	-2.18	0.0320	0.12527676
L4	89	-0.36165350	-2.83	0.0057	0.12773749
L5	78	-0.13182273	-0.47	0.6381	0.27911356
L6	89	0.21107496	1.77	0.0810	0.11957752
P1	89	-1.06798388	-6.83	0.0001	0.15632236
P2	89	-1.32305367	-5.79	0.0001	0.22833335
P3	89	-1.10602748	-7.17	0.0001	0.15433597
P4	89	-0.44684390	-3.69	0.0004	0.12108615
P5	72	-1.12570863	-7.20	0.0001	0.15643033
P6	89	-1.25735782	-3.85	0.0002	0.32664352
P7	89	-1.37269955	-4.01	0.0001	0.34195088
P8	89	-0.82792966	-10.79	0.0001	0.07670218

A1=SLS/TA	A2=SLS/CA	A3=INV/CGS	A4=SLS/FA	A5=RCV/CA
A6=INV/CA	A7=FA/TA	A8=INV/TA	LV1=LTD/TA	LV2=LTD/MVE
LV3=IE/TA	LV4=IE/TL	LV5=TL/TA	LV6=TL/(TL+MVE)	LV7=MVE/TA
L1=CA/CL	L2=WC/TA	L3=CASH/TA	L4=(CA-INV)/CL	L5=CASH/TL
L6=CA/TA	P1=EBIT/TA	P2=NI/TA	P3=OPI/TA	P3=OPI/TA
P4=GP/SLS	P5=RE/TA	P6=OPI/SLS	P7=EPS/PSHARE	P8=DPS/PSHARE

TABLE 7

Means of the Standardized Variables Five Years Prior to Failure.

----- FSN=4 -----

VAR	N	MEAN	T-VALUE	PR> T	SE(MEAN)
A1	80	0.05624853	0.40	0.6886	0.13985747
A2	80	-0.06128507	-0.45	0.6570	0.13750198
A3	80	0.13333223	0.71	0.4809	0.18828122
A4	80	0.54497792	2.59	0.0115	0.21052394
A5	80	0.24280398	1.53	0.1296	0.15853266
A6	80	-0.08667022	-0.62	0.5390	0.14046420
A7	80	-0.31479167	-2.42	0.0177	0.12996914
A8	80	0.08751461	0.60	0.5509	0.14610878
LV1	80	0.33292951	2.45	0.0167	0.13612338
LV2	80	0.75640880	3.79	0.0003	0.19979704
LV3	76	0.66029354	4.29	0.0001	0.15394168
LV4	70	0.46444806	3.76	0.0004	0.12347760
LV5	72	0.76453026	5.93	0.0001	0.12890203
LV6	72	0.85956836	6.18	0.0001	0.13912758
LV7	80	-0.36428793	-3.30	0.0014	0.11024216
L1	80	-0.43428179	-4.90	0.0001	0.08864566
L2	80	-0.37204799	-2.96	0.0040	0.12560635
L3	80	-0.04914122	-0.28	0.7778	0.17353242
L4	80	-0.16993613	-1.17	0.2437	0.14468463
L5	72	0.12189559	0.31	0.7600	0.39752608
L6	80	0.22109203	1.70	0.0933	0.13016506
P1	80	-0.82587463	-6.50	0.0001	0.12706761
P2	80	-0.95679925	-5.09	0.0001	0.18793538
P3	80	-0.87183745	-6.78	0.0001	0.12866030
P4	80	-0.37133389	-2.81	0.0063	0.13232903
P5	61	-0.93087761	-7.78	0.0001	0.11958475
P6	80	-1.06092904	-4.22	0.0001	0.25135458
P7	80	-0.55822634	-2.72	0.0081	0.20534873
P8	80	-0.79017486	-7.41	0.0001	0.10669606

A1=SLS/TA	A2=SLS/CA	A3=INV/CGS	A4=SLS/FA	A5=RCV/CA
A6=INV/CA	A7=FA/TA	A8=INV/TA	LV1=LTD/TA	LV2=LTD/MVE
LV3=IE/TA	LV4=IE/TL	LV5=TL/TA	LV6=TL/(TL+MVE)	LV7=MVE/TA
L1=CA/CL	L2=WC/TA	L3=CASH/TA	L4=(CA-INV)/CL	L5=CASH/TL
L6=CA/TA	P1=EBIT/TA	P2=NI/TA	P3=OPI/TA	P3=OPI/TA
P4=GP/SLS	P5=RE/TA	P6=OPI/SLS	P7=EPS/PSHARE	P8=DPS/PSHARE

TABLE 8

Means of the Standardized Variables Six Years Prior to Failure.

----- FSN=5 -----

VAR	N	MEAN	T-VALUE	PR> T	SE(MEAN)
A1	71	0.30537343	2.16	0.0345	0.14161913
A2	71	0.17686485	1.22	0.2248	0.14440900
A3	71	-0.07060981	-0.48	0.6341	0.14768281
A4	71	0.68347675	3.28	0.0016	0.20842549
A5	71	0.24090189	1.47	0.1459	0.16382311
A6	71	0.02963439	0.21	0.8345	0.14128047
A7	71	-0.36757451	-2.67	0.0094	0.13771830
A8	71	0.19523205	1.29	0.1997	0.15080516
LV1	71	0.09820568	0.79	0.4296	0.12360534
LV2	71	0.40196307	2.62	0.0107	0.15335029
LV3	69	0.69555597	4.72	0.0001	0.14739712
LV4	63	0.52797118	3.44	0.0010	0.15337558
LV5	64	0.62627953	4.74	0.0001	0.13199321
LV6	64	0.67478213	4.29	0.0001	0.15746167
LV7	71	-0.27605996	-1.88	0.0645	0.14696727
L1	71	-0.51386648	-6.22	0.0001	0.08256324
L2	71	-0.40654104	-2.93	0.0046	0.13893763
L3	71	-0.15006942	-1.02	0.3119	0.14731954
L4	71	-0.33487958	-2.71	0.0084	0.12337580
L5	64	0.06999367	0.21	0.8354	0.33552946
L6	71	0.29325980	2.07	0.0426	0.14198200
P1	71	-0.76600626	-6.54	0.0001	0.11709371
P2	71	-0.78402091	-5.72	0.0001	0.13711326
P3	71	-0.80315640	-6.80	0.0001	0.11815972
P4	71	-0.38264704	-3.25	0.0018	0.11779666
P5	50	-0.75109094	-6.75	0.0001	0.11123246
P6	71	-0.66818768	-5.96	0.0001	0.11215717
P7	71	-0.58102058	-3.87	0.0002	0.15004647
P8	71	-0.77281688	-7.81	0.0001	0.09890463

A1=SLS/TA	A2=SLS/CA	A3=INV/CGS	A4=SLS/FA	A5=RCV/CA
A6=INV/CA	A7=FA/TA	A8=INV/TA	LV1=LTD/TA	LV2=LTD/MVE
LV3=IE/TA	LV4=IE/TL	LV5=TL/TA	LV6=TL/(TL+MVE)	LV7=MVE/TA
L1=CA/CL	L2=WC/TA	L3=CASH/TA	L4=(CA-INV)/CL	L5=CASH/TL
L6=CA/TA	P1=EBIT/TA	P2=NI/TA	P3=OPI/TA	P3=OPI/TA
P4=GP/SLS	P5=RE/TA	P6=OPI/SLS	P7=EPS/PSHARE	P8=DPS/PSHARE

TABLE 9

Means of the Standardized Variables Seven Years Prior to Failure.

----- FSN=6 -----

<u>VAR</u>	<u>N</u>	<u>MEAN</u>	<u>T-VALUE</u>	<u>PR> T </u>	<u>SE(MEAN)</u>
A1	63	0.43084479	2.38	0.0206	0.18134687
A2	63	0.20787377	1.15	0.2549	0.18088872
A3	63	-0.03843878	-0.20	0.8384	0.18766307
A4	63	0.97383104	3.55	0.0007	0.27398189
A5	63	0.26297690	1.47	0.1454	0.17834898
A6	63	0.01025295	0.07	0.9466	0.15234859
A7	63	-0.46074097	-3.24	0.0019	0.14231340
A8	63	0.24203770	1.45	0.1515	0.16668796
LV1	63	0.13018630	0.94	0.3503	0.13833590
LV2	63	0.62064462	2.92	0.0049	0.21247511
LV3	61	0.43602779	3.05	0.0034	0.14307267
LV4	55	0.27791539	2.00	0.0504	0.13888749
LV5	56	0.70734269	3.60	0.0007	0.19663450
LV6	56	0.67531034	3.77	0.0004	0.17905782
LV7	63	-0.23912616	-1.63	0.1085	0.14684345
L1	63	-0.26517276	-1.37	0.1766	0.19401286
L2	63	-0.12994711	-0.88	0.3811	0.14732177
L3	63	-0.06753697	-0.36	0.7180	0.18617912
L4	63	-0.23076963	-1.72	0.0906	0.13422542
L5	56	0.25055094	0.46	0.6474	0.54480609
L6	63	0.40499890	2.69	0.0092	0.15054438
P1	63	-0.72197401	-3.09	0.0030	0.23339426
P2	63	-0.88663200	-2.85	0.0059	0.31097987
P3	63	-0.75868638	-3.19	0.0022	0.23748417
P4	63	-0.29316484	-2.43	0.0181	0.12075611
P5	42	-0.75049731	-5.23	0.0001	0.14347668
P6	63	-0.65934782	-4.46	0.0001	0.14789761
P7	63	-1.06579181	-2.26	0.0271	0.47079103
P8	63	-0.89651449	-8.15	0.0001	0.11002247

A1=SLS/TA	A2=SLS/CA	A3=INV/CGS	A4=SLS/FA	A5=RCV/CA
A6=INV/CA	A7=FA/TA	A8=INV/TA	LV1=LTD/TA	LV2=LTD/MVE
LV3=IE/TA	LV4=IE/TL	LV5=TL/TA	LV6=TL/(TL+MVE)	LV7=MVE/TA
L1=CA/CL	L2=WC/TA	L3=CASH/TA	L4=(CA-INV)/CL	L5=CASH/TL
L6=CA/TA	P1=EBIT/TA	P2=NI/TA	P3=OPI/TA	P3=OPI/TA
P4=GP/SLS	P5=RE/TA	P6=OPI/SLS	P7=EPS/PSHARE	P8=DPS/PSHARE

TABLE 10

Means of the Standardized Variables Eight Years Prior to Failure.

----- FSN=7 -----

<u>VAR</u>	<u>N</u>	<u>MEAN</u>	<u>T-VALUE</u>	<u>PR> T </u>	<u>SE(MEAN)</u>
A1	57	0.56544097	2.85	0.0061	0.19847769
A2	57	0.35637293	2.04	0.0461	0.17474598
A3	57	0.83512375	0.81	0.4229	1.03451631
A4	57	1.00266608	2.96	0.0045	0.33885438
A5	57	0.22698926	1.59	0.1173	0.14267602
A6	57	0.05269259	0.36	0.7230	0.14790568
A7	57	-0.35619174	-2.27	0.0272	0.15699416
A8	57	0.28177724	1.75	0.0859	0.16116991
LV1	57	0.07659065	0.55	0.5854	0.13959068
LV2	57	0.19091272	1.19	0.2403	0.16085244
LV3	56	0.52394231	2.72	0.0088	0.19293499
LV4	54	0.33631136	2.16	0.0355	0.15582117
LV5	55	0.47002655	2.70	0.0092	0.17410358
LV6	55	0.47341915	2.96	0.0047	0.16064516
LV7	57	-0.23419339	-2.04	0.0459	0.11469065
L1	57	-0.24325283	-1.39	0.1696	0.17480439
L2	57	-0.16430811	-0.99	0.3254	0.16560386
L3	57	-0.17415165	-0.92	0.3616	0.18930921
L4	57	-0.16921409	-1.03	0.3093	0.16491208
L5	55	0.24485924	0.46	0.6485	0.53418609
L6	57	0.35885052	2.29	0.0256	0.15652538
P1	57	-0.46027884	-2.89	0.0054	0.15907614
P2	57	-0.55076534	-3.27	0.0018	0.16824283
P3	57	-0.48906434	-3.02	0.0038	0.16207026
P4	57	-0.29481555	-1.94	0.0574	0.15195454
P5	38	-0.72023388	-3.92	0.0004	0.18371284
P6	57	-0.44843661	-3.07	0.0033	0.14615324
P7	57	-0.67812533	-2.55	0.0135	0.26570471
P8	57	-0.80995058	-8.02	0.0001	0.10101938

A1=SLS/TA	A2=SLS/CA	A3=INV/CGS	A4=SLS/FA	A5=RCV/CA
A6=INV/CA	A7=FA/TA	A8=INV/TA	LV1=LTD/TA	LV2=LTD/MVE
LV3=IE/TA	LV4=IE/TL	LV5=TL/TA	LV6=TL/(TL+MVE)	LV7=MVE/TA
L1=CA/CL	L2=WC/TA	L3=CASH/TA	L4=(CA-INV)/CL	L5=CASH/TL
L6=CA/TA	P1=EBIT/TA	P2=NI/TA	P3=OPI/TA	P3=OPI/TA
P4=GP/SLS	P5=RE/TA	P6=OPI/SLS	P7=EPS/PSHARE	P8=DPS/PSHARE

TABLE 11

Means of the Standardized Variables Nine Years Prior to Failure.

----- FSN=8 -----

VAR	N	MEAN	T-VALUE	PR> T	SE(MEAN)
A1	50	0.54340318	2.79	0.0074	0.19445375
A2	50	0.35486051	1.83	0.0735	0.19402294
A3	49	1.32231734	0.86	0.3915	1.52913519
A4	50	1.00121514	1.88	0.0664	0.53331069
A5	50	0.13799226	1.12	0.2662	0.12270068
A6	50	0.08219847	0.54	0.5889	0.15111284
A7	50	-0.34576466	-2.11	0.0397	0.16360291
A8	50	0.30988362	1.81	0.0760	0.17096550
LV1	50	0.01496610	0.09	0.9250	0.15817226
LV2	50	0.29418823	1.40	0.1669	0.20967026
LV3	49	0.61022465	3.10	0.0032	0.19667541
LV4	47	0.42990934	2.47	0.0173	0.17414157
LV5	48	0.52322935	2.62	0.0118	0.19972129
LV6	48	0.48194804	2.85	0.0065	0.16933921
LV7	50	-0.11725207	-0.74	0.4601	0.15749647
L1	50	-0.36350080	-1.71	0.0928	0.21203493
L2	50	-0.33454756	-1.94	0.0579	0.17229381
L3	50	-0.04084092	-0.22	0.8234	0.18200767
L4	50	-0.31555132	-1.78	0.0805	0.17678493
L5	48	0.37077843	0.69	0.4942	0.53812940
L6	50	0.33941928	2.12	0.0390	0.16000639
P1	50	-0.49763914	-3.04	0.0038	0.16362122
P2	50	-0.67035886	-3.10	0.0032	0.21630892
P3	50	-0.52830022	-3.14	0.0028	0.16799299
P4	49	-0.25198641	-1.46	0.1513	0.17280047
P5	31	-0.70970043	-3.27	0.0027	0.21716166
P6	50	-0.58999032	-3.81	0.0004	0.15493537
P7	50	-0.69921319	-2.19	0.0329	0.31856035
P8	50	-0.83781960	-7.87	0.0001	0.10639294

A1=SLS/TA	A2=SLS/CA	A3=INV/CGS	A4=SLS/FA	A5=RCV/CA
A6=INV/CA	A7=FA/TA	A8=INV/TA	LV1=LTD/TA	LV2=LTD/MVE
LV3=IE/TA	LV4=IE/TL	LV5=TL/TA	LV6=TL/(TL+MVE)	LV7=MVE/TA
L1=CA/CL	L2=WC/TA	L3=CASH/TA	L4=(CA-INV)/CL	L5=CASH/TL
L6=CA/TA	P1=EBIT/TA	P2=NI/TA	P3=OPI/TA	P3=OPI/TA
P4=GP/SLS	P5=RE/TA	P6=OPI/SLS	P7=EPS/PSHARE	P8=DPS/PSHARE

TABLE 12

Means of the Standardized Variables Ten Years Prior to Failure.

----- FSN=9 -----

VAR	N	MEAN	T-VALUE	PR> T	SE(MEAN)
A1	37	0.54707433	2.35	0.0244	0.23275984
A2	37	0.28430578	1.34	0.1896	0.21262448
A3	37	6.99705830	0.96	0.3415	7.25864734
A4	37	1.40086615	2.10	0.0428	0.66721134
A5	37	0.21337650	1.57	0.1249	0.13581873
A6	37	0.04176163	0.23	0.8163	0.17842248
A7	37	-0.42793548	-2.26	0.0301	0.18946788
A8	37	0.27333937	1.32	0.1944	0.20672111
LV1	37	0.05893779	0.30	0.7627	0.19374372
LV2	37	0.52119946	1.54	0.1330	0.33909000
LV3	33	0.36551217	1.65	0.1086	0.22143030
LV4	32	0.09839292	0.50	0.6188	0.19579023
LV5	36	0.48106699	2.13	0.0402	0.22574566
LV6	36	0.48494623	2.49	0.0178	0.19496872
LV7	37	-0.25369582	-1.50	0.1433	0.16956969
L1	37	-0.42175004	-2.84	0.0073	0.14830098
L2	37	-0.21215821	-1.11	0.2723	0.19030481
L3	37	-0.04621158	-0.18	0.8560	0.25279883
L4	37	-0.28666878	-1.72	0.0949	0.16711288
L5	36	0.71289515	0.73	0.4729	0.98256551
L6	37	0.37259081	2.00	0.0531	0.18627266
P1	37	-0.80910646	-4.29	0.0001	0.18874399
P2	37	-0.92772843	-3.62	0.0009	0.25624721
P3	37	-0.88078752	-4.61	0.0001	0.19124471
P4	37	-0.21410079	-0.92	0.3632	0.23245070
P5	25	-0.77330484	-3.03	0.0058	0.25547511
P6	37	-0.68358254	-2.41	0.0210	0.28327392
P7	37	-1.48196996	-2.32	0.0261	0.63870524
P8	37	-0.68230798	-4.50	0.0001	0.15149373

A1=SLS/TA	A2=SLS/CA	A3=INV/CGS	A4=SLS/FA	A5=RCV/CA
A6=INV/CA	A7=FA/TA	A8=INV/TA	LV1=LTD/TA	LV2=LTD/MVE
LV3=IE/TA	LV4=IE/TL	LV5=TL/TA	LV6=TL/(TL+MVE)	LV7=MVE/TA
L1=CA/CL	L2=WC/TA	L3=CASH/TA	L4=(CA-INV)/CL	L5=CASH/TL
L6=CA/TA	P1=EBIT/TA	P2=NI/TA	P3=OPI/TA	P3=OPI/TA
P4=GP/SLS	P5=RE/TA	P6=OPI/SLS	P7=EPS/PSHARE	P8=DPS/PSHARE

TABLE 13

Means of the Standardized Variables Eleven Years Prior to Failure

----- FSN=10 -----

VAR	N	MEAN	T-VALUE	PR> T	SE(MEAN)
A1	32	0.33854869	2.06	0.0475	0.16403588
A2	32	0.16835272	1.11	0.2756	0.15167784
A3	32	0.47479697	0.49	0.6262	0.96515621
A4	32	1.29308672	2.42	0.0218	0.53537304
A5	32	0.38729615	2.09	0.0453	0.18570628
A6	32	-0.06377412	-0.33	0.7425	0.19234640
A7	32	-0.43566918	-2.07	0.0473	0.21086661
A8	32	0.10250436	0.47	0.6413	0.21787215
LV1	32	0.13892429	0.57	0.5753	0.24537128
LV2	32	0.48265679	1.27	0.2135	0.37998556
LV3	25	0.80522573	2.03	0.0538	0.39713300
LV4	24	0.54512444	1.68	0.1058	0.32376728
LV5	31	0.36584370	1.59	0.1233	0.23069646
LV6	31	0.38518174	1.70	0.0985	0.22591527
LV7	32	-0.11587883	-0.59	0.5618	0.19758959
L1	32	-0.26391941	-1.52	0.1380	0.17335834
L2	32	-0.15299689	-0.80	0.4300	0.19132243
L3	32	-0.02102375	-0.05	0.9601	0.41644902
L4	32	-0.14819154	-0.78	0.4424	0.19046046
L5	31	0.81387815	0.71	0.4861	1.15408158
L6	32	0.26368178	1.33	0.1925	0.19794264
P1	32	-0.66939472	-4.52	0.0001	0.14825348
P2	32	-0.69433342	-4.14	0.0002	0.16771064
P3	32	-0.73684874	-5.00	0.0001	0.14749700
P4	32	-0.50082549	-2.62	0.0136	0.19137406
P5	23	-0.71008095	-3.27	0.0035	0.21714313
P6	32	-0.60951668	-2.51	0.0173	0.24244846
P7	32	-0.53798933	-2.22	0.0337	0.24214097
P8	32	-0.39824858	-1.61	0.1167	0.24675032

A1=SLS/TA	A2=SLS/CA	A3=INV/CGS	A4=SLS/FA	A5=RCV/CA
A6=INV/CA	A7=FA/TA	A8=INV/TA	LV1=LTD/TA	LV2=LTD/MVE
LV3=IE/TA	LV4=IE/TL	LV5=TL/TA	LV6=TL/(TL+MVE)	LV7=MVE/TA
L1=CA/CL	L2=WC/TA	L3=CASH/TA	L4=(CA-INV)/CL	L5=CASH/TL
L6=CA/TA	P1=EBIT/TA	P2=NI/TA	P3=OPI/TA	P3=OPI/TA
P4=GP/SLS	P5=RE/TA	P6=OPI/SLS	P7=EPS/PSHARE	P8=DPS/PSHARE

TABLE 14

CORRELATION MATRIX

	A ₁	A ₂	A ₃	A ₄	A ₅	A ₆	A ₇	A ₈
A ₁	1	.762	-.420	.559	-.012	.056	-.099	.138
A ₂		1	-.510	.161	-.019	-.011	.374	-.228
A ₃			1	-.146	-.226	.323	-.021	.260
A ₄				1	.066	-.047	-.524	.189
A ₅					1	-.800	-.081	-.578
A ₆						1	.012	.803
A ₇							1	-.434
A ₈								1
L ₁	-.140	-.252	.065	-.072	.040	-.047	-.110	.102
L ₂	.007	-.275	.115	.131	.004	.012	-.380	.316
L ₃	-.111	-.092	-.114	.047	-.106	-.362	-.061	-.257
L ₄	-.159	-.202	-.119	.000	.527	-.634	-.127	-.405
L ₅	-.155	-.055	-.120	-.068	-.093	-.232	.138	-.180
L ₆	.266	-.325	.093	.473	-.035	.173	-.752	.675
LV ₁	-.006	.085	-.051	-.128	-.032	.023	.088	-.075
LV ₂	.127	.218	-.127	-.051	.076	-.014	.120	-.056
LV ₃	.243	.266	.019	.030	-.305	.348	.067	.201
LV ₄	.220	.204	.098	.021	-.296	.406	.120	.281
LV ₅	.197	.157	-.089	.083	-.090	.117	-.171	.083
LV ₆	.207	.104	-.027	.076	.001	.175	-.197	.266
LV ₇	-.104	-.009	-.024	-.068	-.129	-.015	.153	-.118

TABLE 14 (Cont.)
CORRELATION MATRIX

	P ₁	P ₂	P ₃	P ₄	P ₅	P ₆	P ₇	P ₈
A ₁	-.083	-.181	-.068	-.088	-.043	.209	-.244	-.124
A ₂	-.169	-.323	-.118	-.069	-.208	.107	-.376	-.131
A ₃	.135	.145	.107	.121	.073	-.169	.149	.025
A ₄	-.090	-.059	-.129	-.094	.013	.033	-.037	-.076
A ₅	.070	.204	.070	.063	.156	-.143	.056	.014
A ₆	.061	-.060	.066	-.015	-.080	.229	-.034	-.005
A ₇	-.196	-.259	-.114	-.146	-.104	-.177	-.199	-.048
A ₈	.110	.053	.083	-.019	.122	.238	.008	.053
L ₁	.242	.275	.238	.274	.331	.053	.221	.138
L ₂	.274	.331	.246	.184	.403	.095	.257	.062
L ₃	-.235	-.188	-.260	-.216	-.013	-.335	.077	.062
L ₄	.097	.213	.085	.274	.260	-.188	.177	.145
L ₅	-.373	-.320	-.384	-.493	.011	-.431	.042	-.006
L ₆	.096	.158	.041	-.042	.227	.160	.069	.111
LV ₁	.056	-.042	.064	.223	-.291	.061	-.045	-.047
LV ₂	-.088	-.096	-.072	-.020	-.028	.006	-.383	-.060
LV ₃	-.347	-.414	-.336	-.118	-.467	-.175	-.268	.048
LV ₄	-.192	-.239	-.175	-.075	-.196	-.087	-.171	.054
LV ₅	-.138	-.264	-.146	.099	-.603	.041	-.317	-.054
LV ₆	.063	.019	.066	.144	.115	.179	-.378	.036
LV ₇	-.176	-.209	-.186	-.149	-.416	-.208	.243	-.015

TABLE 14 (Cont.)
CORRELATION MATRIX

	LV ₁	LV ₂	LV ₃	LV ₄	LV ₅	LV ₆	LV ₇
LV ₁	1	.587	.350	.237	.392	.156	-.011
LV ₂		1	.289	.264	.217	.511	-.388
LV ₃			1	.874	.663	.308	-.049
LV ₄				1	.324	.300	-.131
LV ₅					1	.412	-.110
LV ₆						1	-.839
LV ₇							1
L ₁	.315	.069	-.285	-.184	-.374	-.114	.016
L ₂	.351	.227	-.229	-.060	-.350	-.005	-.057
L ₃	-.033	-.085	-.126	-.237	-.137	-.314	.269
L ₄	.116	.077	-.341	-.332	-.286	-.132	.009
L ₅	-.206	-.126	-.244	-.296	-.392	-.437	.389
L ₆	-.178	-.114	.028	.071	.108	.260	-.191

TABLE 14 (Cont.)
CORRELATION MATRIX

	P ₁	P ₂	P ₃	P ₄	P ₅	P ₆	P ₇	P ₈
P ₁	1	.849	.987	.551	.410	.722	.532	-.130
P ₂		1	.818	.400	.541	.572	.678	.018
P ₃			1	.556	.404	.736	.490	-.150
P ₄				1	.096	.387	.146	.044
P ₅					1	.238	.261	.176
P ₆						1	.219	-.096
P ₇							1	.070
P ₈								1

	L ₁	L ₂	L ₃	L ₄	L ₅	L ₆
L ₁	1	.732	.145	.675	.120	.137
L ₂		1	.171	.458	.040	.452
L ₃			1	.371	.727	-.047
L ₄				1	.238	.002
L ₅					1	-.145
L ₆						1

TABLE 15

Linear Probability Model Estimates

VARIABLES	STANDARDIZED VARIABLES		UNSTANDARDIZED VARIABLES	
	MODEL ₁	MODEL ₂	MODEL ₁	MODEL ₂
INTERCEPT	.155745 (9.13)	.140991 (8.21)	.502045 (12.5)	.504092 (11.6)
LTA	-.023902 (-6.88)	-.020715 (-5.93)	-.028824 (7.82)	-.027791 (-7.36)
A ₁	-.022893 (-3.55)	-.019458 (-2.98)	-.035101 (-4.99)	-.029587 (-4.14)
A ₇	-.033614 (-4.56)	-.030492 (-4.12)	-.273233 (-4.77)	-.237299 (-4.10)
A ₈	.021553 (2.97)	.013451 (1.77)*	.135352 (2.28)	.121134 (1.94)
L ₂	-.075007 (-10.6)	-.062979 (-8.16)	-.516493 (-10.0)	-.514994 (-9.31)
LV ₂	.022823 (4.21)		.032939 (6.06)	
LV ₃		.028133 (4.21)		.147323 (.379)**
P ₆	-.037466 (-6.14)	-.036420 (-5.52)	-.431322 (-5.32)	-.460822 (-5.46)
P ₇	-.029845 (-10.3)	-.030833 (-10.8)	-.111182 (-7.77)	-.137591 (-9.82)
F-VALUE	95.285	90.607	86.376	76.596
MSE	.03680	.03639	.038345	.038935
R-SQUARE	.4304	.4220	.4065	.3816
ADJ R-SQR	.4258	.4173	.4018	.3766

Note: The t-values are given in parentheses. All coefficients are significant at 5 percent unless otherwise noted.

* significant at 7 percent. ** insignificant.

LTA=LOG(TA) A1=SLS/TA A7=FA/TA A8=INV/TA
L2=WC/TA LV2=LTD/TA LV3=IE/TA P6=OPI/SLS P7=EPS/PSHARE

TABLE 16

Linear Discriminant Analysis Estimates

VARIABLES	STANDARDIZED VARIABLES		UNSTANDARDIZED VARIABLES	
	MODEL ₁	MODEL ₂	MODEL ₁	MODEL ₂
INTERCEPT	-1.4903	-1.66065	3.74259	3.88568
LTA	-.361269	-.316663	-.418131	-.397092
A ₁	-.346021	-.297430	-.509196	-.422765
A ₇	-.508064	-.466109	-3.96363	-3.39070
A ₈	.325768	.205607	1.96347	1.73085
L ₂	-1.1337	-.962700	-7.49246	-7.3586
LV ₂	.34496		.477826	
LV ₃		.430047		2.10506
P ₆	-.566279	-.556728	-6.25694	-6.58454
P ₇	-.451104	-.471318	-1.61286	-1.96600
-2 Logl	350.48	358.12	369.51	377.27
MSE	.03951	.04055	.03993	.039999
Efron R ²	.3831	.3501	.3763	.3589
Pseudo R ²	.3126	.2719	.2753	.2351

Note: Efron's R-square is based on the MSE while the Pseudo R-square is based on the loglikelihood ratio test.

LTA=LOG(TA) A1=SLS/TA A7=FA/TA A8=INV/TA
L2=WC/TA LV2=LTD/TA LV3=1E/TA P6=OPI/SLS P7=EPS/PSHARE

TABLE 17

Probit Model Estimates

VARIABLES	STANDARDIZED VARIABLES		UNSTANDARDIZED VARIABLES	
	MODEL ₁	MODEL ₂	MODEL ₁	MODEL ₂
INTERCEPT	-.886125 (-7.72)	-1.16786 (-10.6)	1.42464 (7.22)	.960069 (4.92)
LTA	-.384011 (-11.9)	-.281792 (-10.1)	-.406104 (-12.9)	-.311040 (-11.5)
A ₁	-.168979 (-4.78)	-.165022 (-4.67)	-.210387 (-5.31)	-.129177 (-3.52)
A ₇	-.282225 (-6.68)	-.246491 (-5.95)	-2.46079 (-8.23)	-1.85963 (-6.44)
A ₈	.259937 (6.47)	.177646 (4.37)	1.88589 (2.48)	1.04457 (3.40)
L ₂	-.626771 (-6.47)	-.509667 (-13.2)	-4.18609 (-3.67)	-3.43875 (-13.4)
LV ₂	.266196 (9.99)		.287647 (12.9)	
LV ₃		.208854 (6.85)		6.74289 (3.98)
P ₆	-.275433 (-7.99)	-.281847 (-8.18)	-2.38838 (-5.59)	-2.28907 (-5.30)
P ₇	-.080405 (-4.69)	-.112150 (-7.11)	-.213285 (-2.86)	-.548349 (-7.26)
L-Ratio	301.87	278953	284.72	244.65
MSE	.02989	.03047	.03210	.03524
Efron R ²	.5332	.5117	.4986	.4352
Pseudo R ²	.5921	.5671	.5584	.4973

Note: The t-values are given in parentheses. All coefficients are significant at 5 percent unless otherwise noted.

* significant at 7 percent. ** insignificant.

LTA=LOG(TA) A1=SLS/TA A7=FA/TA A8=INV/TA
L2=WC/TA LV2=LTD/TA LV3=IE/TA P6=OPI/SLS P7=EPS/PSHARE

TABLE 18

Logit Model Estimates

VARIABLES	STANDARDIZED VARIABLES		UNSTANDARDIZED VARIABLES	
	MODEL ₁	MODEL ₂	MODEL ₁	MODEL ₂
INTERCEPT	-.928143 (-2.97)	-1.18092 (-3.88)	1.6331 (3.10)	1.24936 (2.36)
LTA	-.401465 (-4.63)	-.303729 (-3.95)	-.429041 (-4.88)	-.343569 (-4.47)
A ₁	-.147439 (-1.58)	-.138803 (-1.48)	-.201359 (-1.98)	-.127425 (-1.30)
A ₇	-.319422 (-2.89)	-.293700 (-2.65)	-2.68607 (-3.44)	-2.02113 (-2.58)
A ₈	.286209 (2.69)	.195013 (1.78)	2.02626 (2.49)	1.18187 (1.40)
L ₂	-.691392 (-6.56)	-.554134 (-5.38)	-4.50339 (-6.27)	-3.73992 (-5.41)
LV ₂	.296084 (4.30)		.292729 (5.14)	
LV ₃		.219666 (2.80)		5.71148 (1.27)
P ₆	-.299962 (-3.22)	-.294886 (-3.16)	-3.21485 (-2.70)	-3.06610 (-2.57)
P ₇	-.063895 (-1.47)	-.102689 (-2.59)	-.202271 (-.945)	-.522489 (-2.62)
L-Ratio	299.45	275.95	282.59	241.26
MSE	.03017	.03071	.03162	.03493
Efron R ²	.5288	.5079	.5062	.4402
Pseudo R ²	.5873	.5610	.5542	.4905

Note: The t-values are given in parentheses. All coefficients are significant at 5 percent unless otherwise noted.

* significant at 7 percent. ** insignificant.

LTA=LOG(TA) A1=SLS/TA A7=FA/TA A8=INV/TA
L2=WC/TA LV2=LTD/TA LV3=IE/TA P6=OPI/SLS P7=EPS/PSHARE

TABLE 19

Stratified Estimation of Model 1

VARIABLES	LDA ₁	PROBIT ₁	LOGIT ₁
INTERCEPT	-1.66016	-1.0526 (-9.38)	-1.11389 (-3.57)
LTA	-.361269	-.37562 (-11.9)	-.401635 (-4.63)
A ₁	-.346021	-.168754 (-4.86)	-.147493 (-1.58)*
A ₇	-.508064	-.272034 (-6.58)	-.319482 (-2.89)
A ₈	.325768	.25036 (6.40)	.286263 (2.69)
L ₂	-1.13370	-.612033 (-16.1)	-.691506 (-6.56)
LV ₂	.344960	.261208 (10.0)	-.296174 (-4.30)
P ₆	-.566279	-.272098 (-7.84)	-.299928 (-3.22)
P ₇	-.451104	-.0791126 (-4.67)	-.063912 (-1.47)*
L-Ratio	168.29	310.14	307.63
MSE	.03867	.03057	.03087
Efron R ²	.3961	.5226	.5178
Pseudo R ²	.34849	.5993	.5938

Note: The proportions sampled from the failed and healthy groups are .725 and .523 respectively.

The t-values are given in parentheses. All coefficients are significant at 5 percent unless otherwise noted.

* insignificant.

LTA=LOG(TA) A1=SLS/TA A7=FA/TA A8=INV/TA
L2=WC/TA LV2=LTD/TA P6=OPI/SLS P7=EPS/PSHARE

TABLE 20

Stratified Estimation of Model 2

VARIABLES	LDA ₂	PROBIT ₂	LOGIT ₂
INTERCEPT	-1.83047	-1.32473 (-12.3)	-1.36685 (-4.50)
LTA	-.316663	-.275259 (-10.0)	-.303695 (-3.95)
A ₁	-.29743	-.164490 (-4.76)	-.138752 (-1.48)*
A ₇	-.466109	-.234257 (-5.78)	-.293696 (-2.65)
A ₈	.205607	.170518 (4.31)	.195017 (1.78) *
L ₂	-.962700	-.496962 (-13.1)	-.554073 (-5.38)
LV ₃	.430047	.200824 (6.74)	.219623 (2.80)
P ₆	-.556728	-.280108 (-8.07)	-.294908 (-3.16)
P ₇	-.471318	-.109683 (-7.03)	-.102695 (-2.59)
L-Ratio	171.86	286.53	283.80
MSE	.03956	.03089	.03109
Efron R ²	.36597	.5049	.5017
Pseudo R ²	.31033	.5739	.5679

Note: The proportions sampled from the failed and healthy groups are .725 and .523 respectively.

The t-values are given in parentheses. All coefficients are significant at 5 percent unless otherwise noted.

* insignificant.

LTA=LOG(TA) A1=SLS/TA A7=FA/TA A8=INV/TA
L2=WC/TA LV2=LTD/TA P6=OPI/SLS P7=EPS/PSHARE

TABLE 21

Evaluation of the Models on the Initial Sample,
(Standardized Variables).

CUTOFF	LPM ₁			LDA ₁			PROBIT ₁			LOGIT ₁		
	FAIL	HLTH	ALL	FAIL	HLTH	ALL	FAIL	HLTH	ALL	FAIL	HLTH	ALL
.00	100	36.2	40.5	100	0.00	6.68	100	0.00	6.68	100	0.00	6.68
.05	97.0	62.0	64.3	94.0	88.9	89.3	95.5	88.1	88.6	95.5	88.6	89.1
.10	95.5	79.1	80.2	94.0	92.4	92.5	92.5	93.0	93.0	91.0	94.0	93.8
.15	94.0	89.4	89.7	89.5	93.4	93.2	88.0	95.1	94.7	83.5	95.9	95.1
.20	88.0	94.0	93.6	85.0	94.1	93.5	80.5	96.6	95.6	79.1	96.6	95.5
.25	77.6	96.5	95.3	82.0	94.8	94.0	77.6	96.8	95.6	77.6	97.2	95.9
.30	65.6	97.6	95.5	80.5	95.2	94.3	71.6	97.4	95.7	70.1	97.4	95.6
.35	56.7	98.0	95.3	79.1	95.9	94.8	65.6	97.5	95.4	65.6	97.5	95.4
.40	52.2	98.9	95.8	79.1	96.2	95.1	61.1	97.8	95.4	62.6	97.8	95.5
.45	46.2	99.2	95.7	77.6	96.5	95.3	58.2	98.5	95.8	59.7	98.1	95.6
.50	38.8	99.6	95.6	77.6	96.5	95.3	52.2	98.7	95.6	56.7	98.7	95.9
.55	29.8	99.7	95.1	73.1	96.7	95.2	49.2	98.9	95.6	49.2	98.7	95.4
.60	23.8	99.7	94.7	70.1	97.0	95.2	46.2	99.1	95.6	49.2	98.9	95.6
.65	17.9	99.8	94.4	70.1	97.1	95.3	46.2	99.2	95.7	47.7	99.2	95.8
.70	14.9	100	94.3	65.6	97.2	95.1	44.7	99.5	95.9	44.7	99.3	95.7
.75	13.4	100	94.2	65.6	97.4	95.3	40.2	99.5	95.6	43.2	99.5	95.8
.80	10.4	100	94.0	65.6	97.7	95.6	37.3	99.6	95.5	38.8	99.6	95.6
.85	8.95	100	93.9	64.1	97.8	95.6	32.8	99.7	95.3	35.8	99.7	95.5
.90	8.95	100	93.9	58.2	97.9	95.3	26.8	99.8	95.0	31.3	99.7	95.2
.95	7.46	100	93.8	55.2	98.1	95.3	17.9	99.8	94.4	19.4	99.8	94.5
1.0	5.97	100	93.7	1.49	100	93.4	0.00	100	93.3	0.00	100	93.3

Note:

FAIL: Percent of failed firms classified correctly
 HLTH: Percent of non-failed firms classified correctly
 ALL : Overall percent of correct classification

TABLE 22

Evaluation of the Models on the Holdout Sample,
(Standardized Variables).

CUTOFF	LPM ₁			LDA ₁			PROBIT ₁			LOGIT ₁		
	FAIL	HLTH	ALL	FAIL	HLTH	ALL	FAIL	HLTH	ALL	FAIL	HLTH	ALL
.00	100	37.8	39.7	100	0.00	2.96	100	0.00	2.96	100	0.00	2.96
.05	100	61.6	62.7	100	88.6	88.9	100	88.1	88.4	96	89.3	89.5
.10	100	77.9	78.6	96	92.6	92.7	88	93.7	93.5	84	94.3	94.0
.15	100	89.1	89.4	92	94.4	94.4	84	96.4	96.0	84	96.9	96.5
.20	92	95.5	95.4	88	95.8	95.6	84	97.6	97.2	84	97.8	97.3
.25	84	97.5	97.1	84	96.3	95.9	80	98.1	97.6	80	98.2	97.7
.30	84	98.6	98.2	84	96.5	96.2	80	98.5	97.9	80	98.7	98.2
.35	72	99.3	98.5	84	96.6	96.3	80	99.1	98.5	80	99.0	98.4
.40	40	99.8	98.1	84	96.8	96.4	80	99.2	98.6	76	99.3	98.6
.45	40	99.8	98.1	84	97.3	96.9	72	99.5	98.6	68	99.5	98.5
.50	40	99.8	98.1	84	97.6	97.2	64	99.5	98.4	68	99.5	98.5
.55	32	100	97.9	84	97.8	97.3	52	99.5	98.1	56	99.5	98.2
.60	24	100	97.7	84	98.0	97.6	44	99.5	97.8	56	99.5	98.2
.65	20	100	97.6	84	98.1	97.7	44	99.5	97.8	48	99.5	97.9
.70	20	100	97.6	84	98.1	97.7	40	99.6	97.8	40	99.5	97.7
.75	20	100	97.6	84	98.4	97.9	32	99.7	97.7	40	99.6	97.8
.80	20	100	97.6	80	98.6	98.1	32	99.7	97.7	36	99.7	97.8
.85	20	100	97.6	80	98.9	98.3	32	99.8	97.8	32	99.7	97.7
.90	20	100	97.6	72	99.3	98.5	28	100	97.8	28	99.8	97.7
.95	16	100	97.5	60	99.6	98.4	20	100	97.6	24	100	97.7
1.0	16	100	97.5	8	100	97.2	0	100	97.0	0	100	97.0

Note:

FAIL: Percent of failed firms classified correctly
 HLTH: Percent of non-failed firms classified correctly
 ALL : Overall percent of correct classification

TABLE 23

Evaluation of the Models on the Initial Sample,
(Unstandardized Variables).

CUTOFF	LPM ₁			LDA ₁			PROBIT ₁			LOGIT ₁		
	FAIL	HLTH	ALL	FAIL	HLTH	ALL	FAIL	HLTH	ALL	FAIL	HLTH	ALL
.00	100	35.4	39.7	100	0.00	6.68	100	0.00	6.68	100	0.00	6.68
.05	98.5	60.7	63.2	95.5	85.2	85.9	94.0	85.8	86.4	83.5	91.4	90.9
.10	97.0	77.8	79.1	94.0	90.0	90.3	89.5	92.9	92.7	73.1	96.3	94.8
.15	95.5	88.4	88.9	92.5	92.7	92.7	86.5	95.6	95.0	68.6	97.2	95.3
.20	88.0	94.4	94.0	89.5	93.9	93.6	80.5	96.3	95.3	62.6	97.9	95.6
.25	77.6	96.3	95.1	86.5	94.5	94.0	79.1	97.2	96.0	55.2	98.2	95.4
.30	67.1	97.4	95.4	85.0	95.2	94.6	70.1	97.4	95.6	46.2	98.3	94.9
.35	52.2	98.3	95.3	83.5	95.6	94.8	58.2	97.7	95.1	41.7	98.7	94.9
.40	47.7	99.0	95.6	83.5	95.7	94.9	55.2	98.3	95.5	38.8	99.0	95.0
.45	34.3	99.4	95.1	82.0	96.0	95.1	53.7	98.7	95.7	35.8	99.1	94.9
.50	26.8	99.5	94.7	79.1	96.2	95.1	49.2	99.1	95.8	31.3	99.2	94.7
.55	25.3	99.6	94.7	74.6	96.4	95.0	44.7	99.1	95.5	29.8	99.3	94.7
.60	20.8	99.6	94.4	73.1	96.7	95.2	43.2	99.1	95.4	28.3	99.4	94.7
.65	20.8	99.7	94.5	73.1	96.8	95.3	40.2	99.1	95.2	26.8	99.4	94.6
.70	20.8	99.7	94.5	73.1	96.8	95.3	37.3	99.3	95.2	26.8	99.5	94.7
.75	16.4	99.8	94.3	70.1	97.1	95.3	32.8	99.3	94.9	22.3	99.5	94.4
.80	11.9	99.8	94.0	67.1	97.2	95.2	28.3	99.6	94.9	20.8	99.6	94.4
.85	8.95	99.8	93.8	64.1	97.7	95.5	23.8	99.6	94.6	14.9	99.6	94.0
.90	7.46	99.8	93.7	59.7	97.9	95.4	22.3	99.7	94.6	10.4	99.8	93.9
.95	7.46	99.8	93.7	52.2	98.5	95.4	17.9	99.7	94.3	8.95	99.8	93.8
1.0	5.97	100	93.7	0.00	100	93.3	0.00	100	93.3	0.00	100	93.3

Note:

FAIL: Percent of failed firms classified correctly
 HLTH: Percent of non-failed firms classified correctly
 ALL : Overall percent of correct classification

TABLE 24

Evaluation of the Models on the Holdout Sample,
(Unstandardized Variables).

CUTOFF	LPM ₁			LDA ₁			PROBIT ₁			LOGIT ₁		
	FAIL	HLTH	ALL	FAIL	HLTH	ALL	FAIL	HLTH	ALL	FAIL	HLTH	ALL
.00	100	37.1	39.0	100	0.00	2.96	100	0.00	2.96	100	0.00	2.96
.05	100	60.5	61.6	100	85.5	86.0	100	85.9	86.3	92	91.1	91.2
.10	100	77.6	78.2	100	90.5	90.8	96	93.6	93.7	76	95.3	94.7
.15	100	89.1	89.4	96	93.0	93.1	88	95.5	95.3	64	96.9	95.9
.20	92	95.1	95.0	92	94.3	94.3	80	97.1	96.6	60	98.1	97.0
.25	84	97.5	97.1	92	95.3	95.2	68	98.0	97.1	56	98.9	97.6
.30	76	98.9	98.2	92	95.8	95.7	68	98.4	97.5	56	99.0	97.7
.35	64	99.3	98.3	88	96.5	96.3	68	98.7	97.8	56	99.0	97.7
.40	56	99.5	98.2	84	96.6	96.3	68	99.1	98.2	52	99.3	97.9
.45	44	99.8	98.2	84	96.9	96.5	60	99.1	97.9	52	99.5	98.1
.50	28	100	97.8	84	97.3	96.9	60	99.3	98.2	52	99.5	98.1
.55	28	100	97.8	84	97.5	97.1	52	99.3	97.9	44	99.5	97.8
.60	24	100	97.7	84	98.0	97.6	44	99.3	97.7	32	99.5	97.5
.65	20	100	97.6	84	98.0	97.6	44	99.5	97.8	28	99.6	97.5
.70	20	100	97.6	84	98.2	97.8	44	99.7	98.1	28	99.7	97.6
.75	16	100	97.5	80	98.5	97.9	32	99.7	97.7	28	99.7	97.6
.80	16	100	97.5	76	98.9	98.2	32	100	97.9	28	99.7	97.6
.85	16	100	97.5	72	99.0	98.2	24	100	97.7	24	100	97.7
.90	12	100	97.3	68	99.2	98.3	16	100	97.5	16	100	97.5
.95	12	100	97.3	64	99.3	98.3	16	100	97.5	12	100	97.3
1.0	12	100	97.3	8	100	97.2	0	100	97.0	0	100	97.0

Note:

FAIL: Percent of failed firms classified correctly
 HLTH: Percent of non-failed firms classified correctly
 ALL : Overall percent of correct classification

TABLE 25

Evaluation of the Models on the Initial Sample,
(Standardized Variables).

CUTOFF	LPM ₂			LDA ₂			PROBIT ₂			LOGIT ₂		
	FAIL	HLTH	ALL	FAIL	HLTH	ALL	FAIL	HLTH	ALL	FAIL	HLTH	ALL
.00	100	35.0	39.4	100	0.00	6.68	100	0.00	6.68	100	0.00	6.68
.05	95.5	62.8	65.0	92.5	89.1	89.4	92.5	88.3	88.6	92.5	89.6	89.8
.10	92.5	80.4	81.2	91.0	91.5	91.5	91.0	92.6	92.5	86.5	93.4	93.0
.15	92.5	90.0	90.2	86.5	93.0	92.6	80.5	94.6	93.7	80.5	96.0	95.0
.20	86.5	93.9	93.4	86.5	93.9	93.4	77.6	96.6	95.4	71.6	97.0	95.3
.25	73.1	96.8	95.3	83.5	94.5	93.8	68.6	97.3	95.4	67.1	97.3	95.3
.30	62.6	97.4	95.1	83.5	94.8	94.1	64.1	97.5	95.3	64.1	97.4	95.2
.35	56.7	98.2	95.5	82.0	95.6	94.7	62.6	97.6	95.3	64.1	97.7	95.5
.40	50.7	98.9	95.7	79.1	96.3	95.2	62.6	98.2	95.9	62.6	98.2	95.9
.45	47.7	99.2	95.8	76.1	96.6	95.3	56.7	98.2	95.5	59.7	98.2	95.7
.50	40.2	99.7	95.8	73.1	96.8	95.3	52.2	98.7	95.6	53.7	98.5	95.5
.55	31.3	99.7	95.2	71.6	97.0	95.3	52.2	98.9	95.8	52.2	98.8	95.7
.60	25.3	100	95.0	70.1	97.0	95.2	50.7	99.1	95.9	52.2	99.1	96.0
.65	19.4	100	94.6	68.6	97.0	95.1	49.2	99.3	96.0	50.7	99.2	96.0
.70	16.4	100	94.4	65.6	97.2	95.1	43.2	99.5	95.8	44.7	99.5	95.9
.75	13.4	100	94.2	62.6	97.2	94.9	37.3	99.6	95.5	41.7	99.5	95.7
.80	11.9	100	94.1	62.6	97.4	95.1	35.8	99.7	95.5	35.8	99.6	95.4
.85	10.4	100	94.0	58.2	97.6	95.0	32.8	99.8	95.4	35.8	99.8	95.6
.90	8.95	100	93.9	56.7	98.0	95.3	26.8	100	95.1	29.8	99.8	95.2
.95	8.95	100	93.9	56.7	98.3	95.6	22.3	100	94.8	22.3	100	94.8
1.0	7.46	100	93.8	1.49	100	93.4	0.00	100	93.3	0.00	100	93.3

Note:

FAIL: Percent of failed firms classified correctly
 HLTH: Percent of non-failed firms classified correctly
 ALL : Overall percent of correct classification

TABLE 26

Evaluation of the Models on the Holdout Sample,
(Standardized Variables).

CUTOFF	LPM ₂			LDA ₂			PROBIT ₂			LOGIT ₂		
	FAIL	HLTH	ALL	FAIL	HLTH	ALL	FAIL	HLTH	ALL	FAIL	HLTH	ALL
.00	100	37.6	39.5	100	0.00	2.96	100	0.00	2.96	100	0.00	2.96
.05	100	62.7	63.8	100	88.8	89.2	100	87.0	87.4	96	88.5	88.7
.10	100	78.8	79.4	96	92.9	93.0	88	93.8	93.7	88	95.5	95.3
.15	100	89.7	90.0	96	94.6	94.6	84	96.8	96.4	84	97.5	97.1
.20	84	95.8	95.4	84	95.7	95.3	84	97.8	97.3	80	98.0	97.5
.25	84	97.9	97.5	84	96.3	95.9	80	98.6	98.1	80	98.7	98.2
.30	80	99.2	98.6	84	97.0	96.6	80	99.0	98.4	76	99.0	98.3
.35	68	99.6	98.6	84	97.1	96.7	80	99.1	98.5	72	99.1	98.3
.40	48	99.7	98.2	84	97.4	97.0	72	99.3	98.5	72	99.3	98.5
.45	36	99.8	97.9	84	97.6	97.2	68	99.5	98.5	64	99.5	98.4
.50	36	100	98.1	84	97.9	97.5	52	99.5	98.1	56	99.5	98.2
.55	24	100	97.7	84	98.1	97.7	48	99.7	98.2	48	99.5	97.9
.60	24	100	97.7	84	98.1	97.7	44	99.8	98.2	44	99.8	98.2
.65	20	100	97.6	84	98.2	97.8	40	99.8	98.1	44	99.8	98.2
.70	20	100	97.6	84	98.5	98.1	40	99.8	98.1	44	99.8	98.2
.75	20	100	97.6	84	99.1	98.6	32	99.8	97.8	40	99.8	98.1
.80	20	100	97.6	80	99.2	98.6	28	99.8	97.7	36	99.8	97.9
.85	20	100	97.6	80	99.2	98.6	28	100	97.8	28	100	97.8
.90	16	100	97.5	72	99.6	98.8	24	100	97.7	24	100	97.7
.95	16	100	97.5	68	99.6	98.6	16	100	97.5	16	100	97.5
1.0	16	100	97.5	8	100	97.2	0	100	97.0	0	100	97.0

Note:

FAIL: Percent of failed firms classified correctly
 HLTH: Percent of non-failed firms classified correctly
 ALL : Overall percent of correct classification

TABLE 27

Evaluation of the Models on the Initial Sample,
(Unstandardized Variables).

CUTOFF	LPM ₂			LDA ₂			PROBIT ₂			LOGIT ₂		
	FAIL	HLTH	ALL	FAIL	HLTH	ALL	FAIL	HLTH	ALL	FAIL	HLTH	ALL
.00	100	33.7	38.2	100	0.00	6.68	100	0.00	6.68	100	0.00	6.68
.05	95.2	61.4	63.7	94.0	85.6	86.2	91.0	84.7	85.1	91.0	85.3	85.7
.10	94.0	81.1	82.0	88.0	90.2	90.1	86.5	92.6	92.2	85.0	93.3	92.8
.15	86.5	90.8	90.5	85.0	92.4	91.9	79.1	95.2	94.2	79.1	96.0	94.9
.20	77.6	95.0	93.9	80.5	93.5	92.7	73.1	96.0	94.5	74.6	96.6	95.2
.25	71.6	97.3	95.6	80.5	94.1	93.2	65.6	97.2	95.1	68.6	97.4	95.5
.30	55.2	98.0	95.2	77.6	95.0	93.9	58.2	97.8	95.2	61.1	97.7	95.3
.35	47.7	98.7	95.3	77.6	95.7	94.5	53.7	97.9	95.0	55.2	98.0	95.2
.40	41.7	99.2	95.4	76.1	96.1	94.8	50.7	98.7	95.5	52.2	98.6	95.5
.45	34.3	99.3	95.0	74.6	96.4	95.0	47.7	98.9	95.5	52.2	98.9	95.8
.50	25.3	99.5	94.6	74.6	96.6	95.2	38.8	99.0	95.0	46.2	98.9	95.4
.55	20.8	99.5	94.3	73.1	96.8	95.3	37.3	99.1	95.0	41.7	99.0	95.2
.60	19.4	99.6	94.3	71.6	97.2	95.5	34.3	99.1	94.8	37.3	99.1	95.0
.65	19.4	99.6	94.3	70.1	97.3	95.5	32.8	99.2	94.8	34.3	99.1	94.8
.70	17.9	99.7	94.3	68.6	97.4	95.5	29.8	99.3	94.7	34.3	99.1	94.8
.75	16.4	99.7	94.2	65.6	97.8	95.7	28.3	99.4	94.7	32.8	99.3	94.9
.80	13.4	99.8	94.1	61.1	97.0	95.5	22.3	99.5	94.4	31.3	99.3	94.8
.85	8.95	100	93.9	55.2	98.0	95.2	19.4	99.6	94.3	23.8	99.3	94.3
.90	8.95	100	93.9	53.7	98.5	95.5	17.9	99.7	94.3	19.4	99.6	94.3
.95	7.46	100	93.8	52.2	98.7	95.6	16.4	99.8	94.3	16.4	99.8	94.3
1.0	7.46	100	93.8	0.00	100	93.3	0.00	100	93.3	0.00	100	93.3

Note:

FAIL: Percent of failed firms classified correctly
 HLTH: Percent of non-failed firms classified correctly
 ALL : Overall percent of correct classification

TABLE 28

Evaluation of the Models on the Holdout Sample,
(Unstandardized Variables).

CUTOFF	LPM ₂			LDA ₂			PROBIT ₂			LOGIT ₂		
	FAIL	HLTH	ALL	FAIL	HLTH	ALL	FAIL	HLTH	ALL	FAIL	HLTH	ALL
.00	100	34.4	36.4	100	0.00	2.96	100	0.00	2.96	100	0.00	2.96
.05	100	60.5	61.6	100	85.5	86.0	100	83.3	83.8	100	84.2	84.6
.10	100	79.4	80.0	100	89.7	90.0	96	92.5	92.6	96	93.2	93.3
.15	100	89.8	90.1	100	91.8	92.0	84	95.3	95.0	84	95.4	95.1
.20	88	95.5	95.3	96	93.3	93.4	72	96.8	96.0	68	96.8	95.9
.25	84	98.2	97.8	92	94.4	94.4	68	98.0	97.1	68	97.9	97.0
.30	68	99.1	98.2	88	95.4	95.2	68	98.9	97.9	68	98.7	97.8
.35	68	99.5	98.5	88	96.3	96.0	64	99.0	97.9	64	98.9	97.8
.40	48	99.5	97.9	88	96.6	96.4	64	99.3	98.3	64	99.0	97.9
.45	48	99.6	98.1	88	97.3	97.0	64	99.3	98.3	64	99.3	98.3
.50	32	99.8	97.8	84	97.4	97.0	64	99.5	98.4	64	99.3	98.3
.55	24	100	97.7	84	97.5	97.1	44	99.5	97.8	60	99.5	98.3
.60	16	100	97.5	84	98.2	97.8	36	99.6	97.7	52	99.5	98.1
.65	16	100	97.5	84	98.2	97.8	32	99.8	97.8	40	99.5	97.7
.70	16	100	97.5	84	98.2	97.8	28	99.8	97.7	36	99.6	97.7
.75	16	100	97.5	76	98.6	97.9	28	100	97.8	32	99.7	97.7
.80	16	100	97.5	68	98.6	97.7	28	100	97.8	32	100	97.9
.85	16	100	97.5	68	99.1	98.2	20	100	97.6	28	100	97.8
.90	12	100	97.3	68	99.2	98.3	16	100	97.5	24	100	97.7
.95	12	100	97.3	68	99.5	98.5	16	100	97.5	16	100	97.5
1.0	12	100	97.3	8	100	97.2	0	100	97.0	0	100	97.0

Note:

FAIL: Percent of failed firms classified correctly
 HLTH: Percent of non-failed firms classified correctly
 ALL : Overall percent of correct classification

TABLE 29

Evaluation of the Models on the Initial Sample,
(Stratified Estimation).

CUTOFF	LDA ₁			PROBIT ₁			LOGIT ₁		
	FAIL	HLTH	ALL	FAIL	HLTH	ALL	FAIL	HLTH	ALL
.00	100	0.00	6.68	100	0.00	6.68	100	0.00	6.68
.05	94.0	90.8	91.0	95.5	89.9	90.3	95.5	91.2	91.5
.10	92.5	93.1	93.1	88.0	94.5	94.1	86.5	95.0	94.5
.15	85.0	94.0	93.4	82.0	96.5	95.6	79.1	96.6	95.5
.20	82.0	94.8	94.0	76.1	96.8	95.5	77.6	97.3	96.0
.25	80.5	95.7	94.7	70.1	97.4	95.6	70.1	97.4	95.6
.30	79.1	96.0	94.9	64.1	97.5	95.3	64.1	97.7	95.5
.35	79.1	96.5	95.4	61.1	98.0	95.6	59.7	97.9	95.4
.40	77.6	96.5	95.3	56.7	98.5	95.7	58.2	98.5	95.8
.45	73.1	96.7	95.2	50.7	98.7	95.5	52.2	98.7	95.6
.50	71.6	96.8	95.2	49.2	98.9	95.6	49.2	98.8	95.5
.55	70.1	97.1	95.3	46.2	99.2	95.7	47.7	99.1	95.7
.60	68.6	97.2	95.3	44.7	99.3	95.7	46.2	99.3	95.8
.65	65.6	97.2	95.1	43.2	99.5	95.8	44.7	99.5	95.9
.70	65.6	97.4	95.3	38.8	99.6	95.6	43.2	99.5	95.8
.75	65.6	97.7	95.6	35.8	99.7	95.5	38.8	99.6	95.6
.80	64.1	97.8	95.6	31.3	99.7	95.2	35.8	99.7	95.5
.85	59.7	97.8	95.3	28.3	99.8	95.1	31.3	99.7	95.2
.90	56.7	98.0	95.3	22.3	99.8	94.7	26.8	99.8	95.0
.95	53.7	98.3	95.4	13.4	100	94.2	14.9	99.8	94.2
1.0	1.49	100	93.4	0.00	100	93.3	0.00	100	93.3

Note:

FAIL: Percent of failed firms classified correctly
 HLTH: Percent of non-failed firms classified correctly
 ALL : Overall percent of correct classification

TABLE 30

Evaluation of the Models on the Holdout Sample,
(Stratified Estimation).

CUTOFF	LDA ₁			PROBIT ₁			LOGIT ₁		
	FAIL	HLTH	ALL	FAIL	HLTH	ALL	FAIL	HLTH	ALL
.00	100	0.00	2.96	100	0.00	2.96	100	0.00	2.96
.05	100	90.2	90.5	96	91.3	91.4	92	92.7	92.7
.10	92	93.7	93.7	84	95.5	95.2	84	96.6	96.3
.15	92	95.8	95.7	84	97.6	97.2	84	97.8	97.3
.20	84	96.3	95.9	80	98.1	97.6	80	98.4	97.8
.25	84	96.5	96.2	80	98.7	98.2	80	98.9	98.3
.30	84	96.6	96.3	80	99.1	98.5	80	99.2	98.6
.35	84	97.0	96.6	80	99.3	98.8	72	99.3	98.5
.40	84	97.5	97.1	68	99.5	98.5	68	99.5	98.5
.45	84	97.6	97.2	60	99.5	98.3	64	99.5	98.4
.50	84	97.9	97.5	48	99.5	97.9	56	99.5	98.2
.55	84	98.0	97.6	44	99.5	97.8	52	99.5	98.1
.60	84	98.1	97.7	40	99.5	97.7	40	99.5	97.7
.65	84	98.2	97.8	40	99.7	97.9	40	99.5	97.7
.70	84	98.4	97.9	32	99.7	97.7	36	99.7	97.8
.75	80	98.6	98.1	32	99.8	97.8	36	99.7	97.8
.80	80	98.9	98.3	32	99.8	97.8	32	99.7	97.7
.85	76	99.3	98.6	28	100	97.8	28	99.8	97.7
.90	72	99.3	98.5	28	100	97.8	28	100	97.8
.95	60	99.8	98.6	16	100	97.5	16	100	97.5
1.0	8	100	97.2	0	100	97.0	0	100	97.0

Note:

FAIL: Percent of failed firms classified correctly
 HLTH: Percent of non-failed firms classified correctly
 ALL : Overall percent of correct classification

TABLE 31

Evaluation of the Models on the Initial Sample,
(Stratified Estimation).

CUTOFF	LDA ₁			PROBIT ₁			LOGIT ₁		
	FAIL	HLTH	ALL	FAIL	HLTH	ALL	FAIL	HLTH	ALL
.00	100	0.00	6.68	100	0.00	6.68	100	0.00	6.68
.05	92.5	90.3	90.5	92.5	91.0	91.1	92.5	91.8	91.9
.10	89.5	92.8	92.6	85.0	93.6	93.1	80.5	95.0	94.1
.15	86.5	93.7	93.3	77.6	96.6	95.4	71.6	97.0	95.3
.20	83.5	94.5	93.8	68.6	97.3	95.4	67.1	97.3	95.3
.25	83.5	94.9	94.2	64.1	97.6	95.4	64.1	97.5	95.3
.30	80.5	95.9	94.9	62.6	97.7	95.4	62.6	97.9	95.6
.35	76.1	96.5	95.2	56.7	98.2	95.5	61.1	98.2	95.8
.40	74.6	96.8	95.4	53.7	98.3	95.4	55.2	98.3	95.5
.45	71.6	96.8	95.2	52.2	98.9	95.8	52.2	98.6	95.5
.50	70.1	97.0	95.2	52.2	99.0	95.9	52.2	98.9	95.8
.55	68.6	97.0	95.1	49.2	99.2	95.9	50.7	99.2	96.0
.60	67.1	97.2	95.2	46.2	99.3	95.8	47.7	99.4	96.0
.65	64.1	97.2	95.0	43.2	99.5	95.8	43.2	99.5	95.8
.70	62.6	97.2	94.9	35.8	99.6	95.4	37.3	99.6	95.5
.75	62.6	97.4	95.1	35.8	99.7	95.5	35.8	99.6	95.4
.80	58.2	97.6	95.0	31.3	99.8	95.3	35.8	99.8	95.6
.85	56.7	97.8	95.1	28.3	99.8	95.1	32.8	99.8	95.4
.90	56.7	98.1	95.4	22.3	100	94.8	23.8	100	94.9
.95	55.2	98.8	95.9	14.9	100	94.3	14.9	100	94.3
1.0	1.49	100	93.4	0.00	100	93.3	0.00	100	93.3

Note:

FAIL: Percent of failed firms classified correctly
 HLTH: Percent of non-failed firms classified correctly
 ALL : Overall percent of correct classification

TABLE 32

Evaluation of the Models on the Holdout Sample,
(Stratified Estimation).

CUTOFF	LDA ₂			PROBIT ₂			LOGIT ₂		
	FAIL	HLTH	ALL	FAIL	HLTH	ALL	FAIL	HLTH	ALL
.00	100	0.00	2.96	100	0.00	2.96	100	0.00	2.96
.05	100	90.4	90.7	100	90.3	90.6	96	91.9	92.0
.10	96	94.4	94.5	84	95.9	95.6	84	96.9	96.5
.15	84	95.7	95.3	84	97.8	97.3	80	98.0	97.5
.20	84	96.4	96.0	80	98.6	98.1	80	98.9	98.3
.25	84	97.0	96.6	80	99.0	98.4	76	99.0	98.3
.30	84	97.1	96.7	80	99.2	98.6	72	99.3	98.5
.35	84	97.5	97.1	72	99.5	98.6	64	99.5	98.4
.40	84	97.8	97.3	64	99.5	98.4	56	99.5	98.2
.45	84	98.0	97.6	48	99.7	98.2	52	99.5	98.1
.50	84	98.1	97.7	44	99.8	98.2	44	99.8	98.2
.55	84	98.2	97.8	44	99.8	98.2	44	99.8	98.2
.60	84	98.4	97.9	40	99.8	98.1	44	99.8	98.2
.65	84	98.7	98.3	36	99.8	97.9	40	99.8	98.1
.70	84	99.1	98.6	32	99.8	97.8	40	99.8	98.1
.75	80	99.2	98.6	28	99.8	97.7	32	99.8	97.8
.80	80	99.2	98.6	28	100	97.8	28	100	97.8
.85	76	99.6	98.9	24	100	97.7	28	100	97.8
.90	68	99.6	98.6	20	100	97.6	24	100	97.7
.95	60	99.7	98.5	16	100	97.5	16	100	97.5
1.0	8	100	97.2	0	100	97.0	0	100	97.0

Note:

FAIL: Percent of failed firms classified correctly
 HLTH: Percent of non-failed firms classified correctly
 ALL : Overall percent of correct classification

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