BANKRUPTCY PREDICTION

A COMPARATIVE STUDY ON LOGIT AND NEURAL NETWORKS

By

Osama El-Temtamy

A DISSERTATION PRESENTED TO THE
GRADUATE FACULTY OF MIDDLE TENNESSEE STATE UNIVERSITY
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF DOCTOR OF ARTS

August 1995

UMI Number: 9602110

Bankruptcy Prediction

A Comparative Study of Logit and Neural Networks

Osama El-Temtamy

Approved:

____
Major Professor

____
Reader

____
Reader

____
Reader

____
Department Chair

____
Dean, College of Graduate Studies

ABSTRACT

Bankruptcy Prediction

A Comparative Study of Logit and Neural Networks

By

Dr. Osama El-Temtamy

This study extends the research of earlier studies on bankruptcy prediction. Logit models are built using different independent variables to predict the probability of bankruptcy in the oil and gas industry. Neural network models are then built to predict bankruptcies using the same independent variables used in the logit models. Each model is then ranked on the rate of prediction error on an outside sample using a cross-validation method.

The study will encompass six sets of data and two estimating methods. The six sets of data are from the oil and gas industry, and these sets are:

1. Accrual based ratios.
2. Accrual based ratios adjusted by interest rates and oil prices (real accrual ratios).
3. Cash flow based ratios.
4. Cash flow based ratios adjusted by interest rates and oil prices (real cash flow ratios).
5. Real accrual ratios with economic variables.
6. Real cash flow based ratios with economic variables.

The economic variables are the interest rate and oil price.

The two estimating methods are:

1. Logit model.
2. Neural networks.

The main finding of this study is that all of the models that were estimated with neural networks outperformed all of the models that were estimated with logit. This finding agrees with the findings of other studies that compared the two methods. The ability of neural networks to generalize and their freedom from the data characteristic and estimation assumptions that must be present for other estimation techniques to perform well, are the main reasons why neural networks outperformed logit models.

ACKNOWLEDGMENTS

In the name of Allah the most compassionate the most merciful

I would like to thank Allah for his mercy that he showed me by surrounding me with the most helpful people during this study. I would like to take this moment to thank them.

I would like to thank my committee chairman Dr. Anthon Eff for his timely feedback and courteous manners during all the time I spent at Middle Tennessee State University.

I would like to thank Dr. Joachim Zietz for his quick response to my questions and his constructive suggestions that he offered to improve my study.

Special thanks goes to Dr. Alfred Cripps who helped me a lot in the area of neural networks.

I would like to thank both Dr. Larry Farmer and Dr. Bob Womack for the role they took in finishing this study.

Special thanks goes to Dr. John Lee and Dr. Billy Balch whom made all of this possible.

Finally, I pray to Allah to reword my wife, kids, and my parents for their very valuable support.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION

Bankruptcy prediction has been researched extensively for the past 30 years or so. The ability to predict bankruptcy or financial distress is important for many parties. Owners, managers, potential investors and auditors would consider the ability to predict bankruptcy as very valuable information. Owners would consider the ability to predict bankruptcy important, because of their financial interest and the risk of losing that interest. Managers would consider the ability to predict bankruptcy important because planning and controlling the operations of a firm is part of their duties. If potential investors can predict bankruptcy, they would evaluate their investment decisions very critically.

When an independent auditor is called upon to provide an opinion on a firm's financial statements, he or she must evaluate the going concern of the firm under audit. An entity is a going concern if it is expected to continue in operation and "meet its obligations as they become due without substantial disposition of assets outside the ordinary course of business, restructuring of debt, externally forced revisions of its operations, or similar actions" (SAS 59, AU 341). If independent auditors have a tool that can signal the probability of bankruptcy, that tool will be very valuable to auditors.

After auditing a firm, an independent auditor issues an opinion on the firm's financial statements. If that opinion lacks any statement about the firm's continuation as a going concern, and the firm goes bankrupt, the auditor could be held liable if it is shown that the auditor did not show due care in following generally accepted auditing standards.

Auditors are not responsible "to design audit procedures solely to identify conditions and events that, when considered in the aggregate, indicate there could be substantial doubt about the firm's ability to continue as a going concern for a reasonable period of time" (SAS 59, AU 341). Nevertheless, using a model that can help the auditors to identify potential bankrupt firms could be part of the analytical procedures that auditors use in the first stages of planning an audit.

As more research was done in the area of bankruptcy prediction, the subject became more complex. Issues such as industry differences, accrual or cash flow financial data, data measured as real or nominal, and new estimation techniques, prompted researchers to try to find the best variables and estimation methods to predict bankruptcy.

Purpose of This Study

Building on the findings of past bankruptcy prediction studies, this study will try to find the best variables and estimation method to predict bankruptcy in the oil and gas industry. More specifically, this study will evaluate the usefulness of accrual versus cash flow financial ratios in predicting bankruptcy in the oil and gas industry. Because of the dependency of the oil and gas industry on the interest rate and the price of oil, this study will then evaluate the usefulness of nominal versus real financial ratios in predicting bankruptcy. Finally, this study will compare two estimation methods, logit and neural networks, in their ability to predict bankruptcy.

Limitations of the Study

This study is limited by the following factors. First, this study used financial data for firms operating in the United States which follow generally accepted accounting principles. Thus the results of the study could only be applied to firms using the same accounting rules.

Second, the economic environment in the United States during the 1980's and early 90s most probably had an effect on the performance of oil and gas firms.

Thus, this model should not be applied to oil and gas firms in other countries because of the different economic environments in those countries.

Third, the model developed in this study looked only at the oil and gas industry. Since bankruptcy studies indicate different industries have different performance measures, the results of this study should not be applied to other industries.

Fourth, a firm's bankruptcy could be due to factors other than financial performance, such as legal suits, natural disasters or new government regulations. This study did not use any variables that could reflect these factors.

Organization of the Study

This study is organized into six chapters. Chapter II includes a review of literature related to the issue of bankruptcy prediction. The review looks at variables and estimation methods used in past bankruptcy prediction studies.

Chapter III includes the research methodology and a description of the general models used in this study. Chapter III also includes a description of the population and sample, and a univariate analysis of the data used. The two estimation methods discussed are the logit model and neural networks.

Chapter IV presents the findings of this study. The estimation results for the logit and neural network models are presented. The models are then ranked according to their prediction ability using a v-fold cross validation method.

Chapter V presents the educational aspect of this study. It includes basic objectives and an outline for a presentation that is aimed to introduce neural network methodology to students.

Chapter VI presents a general summary, conclusions, and suggestions for future research.

CHAPTER II

REVIEW OF THE LITERATURE

Bankruptcy prediction has been researched extensively in the literature for the past thirty years or so. William H. Beaver (1966) examined the predictive power of thirty different financial ratios. His main finding was that the ratio of cash flow to total debt was the best ratio for predicting failure.

Bankruptcy prediction studies have mainly used three estimating techniques. These techniques are:

1. Multiple discriminant analysis.
2. The logit model.
3. Neural networks.

Section 1: DISCRIMINANT ANALYSIS

Altman (1968), tried to improve upon conventional ratio analysis by showing a way of combining several financial ratios into a single index. The "Z score," as he called it, is based on a statistical procedure known as "Multiple Discriminant Analysis" or MDA.

The lead given by Altman in applying the MDA technique to financial analysis was followed by several other writers, among them, Edward Deakin (1972) and Marc Blum (1974). Both authors claimed that they developed better models than that of Altman.

In spring 1977 R. Charles Moyer reexamined Altman's model. The results of his study showed that the accuracy of the model is highly dependent upon the parameters of a particular set of data. Problems were noted when the model was applied to data outside the original sample period. In addition, it was found that eliminating two of the five ratios from the original model increased its classification power. Altman's model included the following five ratios: working capital to total assets, retained earnings to total assets, earnings before interest and taxes to total assets, market value of equity to book-value of debt, and sales to total assets. The last two ratios are the ones that Moyer's study suggested to eliminate.

The methodology behind linear discriminant analysis in developing models that can predict possible business failures is based on assigning weights or coefficients to each variable or group of variables. One should expect that these variables should change from one model to another, when the estimation of these models is done in different environments, i.e., countries or industries.

MDA Applied in a Different Country:

Altman and Levallee (1980) developed a model to predict bankruptcies in Canada. They used a sample of fifty-four publicly traded Canadian firms, half of which went bankrupt. The Canadian Z-score model was developed. The score is expressed as an equation representing the inter-relationships of:

1. Sales / Total assets ratio.
2. Total debt / Total assets ratio.
3. Current assets / Current liabilities ratio.
4. Net profit after tax / Total debt ratio.
5. Rate of growth of equity vs. rate of assets growth.

Evaluation of the model, based on empirical data, showed an 80% accuracy level.

MDA Applied in Different Industries:

Altman's original model was applied to the Airline industry by Scaggs and Crawford (1986). Because the five variables used by Altman's model were not significantly dissimilar between the bankrupt and nonbankrupt airlines, Altman's model was not able to distinguish between the two groups of airlines. The model needed to be revised to include the *total operating expense / interest expense* ratio, reflecting the debt position of a firm. After the authors revised Altman's original model, it became more accurate. The authors concluded that Altman's model can be adjusted to reflect unique characteristics of a particular industry.

Realizing that a bankruptcy prediction model should be tailored for a specific industry, an attempt was made to find those characteristics of credit unions that affect their solvency. Sharma (1985) identified a set of variables that help in measuring a credit union's financial performance. Discriminant analysis (MDA) was applied to a sample of 247 credit unions, 120 of which were liquidated and 127 of which remained solvent. The MDA method was applied to the data of the year of bankruptcy. A holdout sample was used to address the predictive power of the model. In general, it was discovered that solvent credit unions had a longer history of operations, higher growth in shares, lower growth in loans, a lower rate of delinquent loans to total loans, a higher rate of retained earnings to assets, and a higher ratio of dividends to earnings than did liquidated credit unions over the sample period of 1973-1976.

MDA Applied to a Special Asset Size:

One study developed a model suited for small firms. Fulmer, Moon, Gavin, and Erwin (1984), presented a model that used data from firms having assets totaling less than $10 million. The authors obtained four financial statements, covering a span of two years, for clients that had failed from several southeast banks. They then matched the failed firms with nonfailed clients of similar size and industry. A total of 111 cases were analyzed using multiple discriminant analysis. Their results show that the model is quite accurate in distinguishing between failed and nonfailed firms. It correctly classifies 98% of the firms one year before failure and 81% of the firms two years before failure.

One year later a study by Crandall (1985) refuted the findings of the above study. Crandall argued that the model is not suitable for general use because:

1. Its overall accuracy is far lower than the authors' estimate.

2. The model's specific predictors are not stable over time and samples.

The general problem results from the fact that discriminant analysis is highly dependent on the sample of companies used, and inaccurate results will occur if the equation is applied to firms outside the study. There are two sources of imprecision in the specific equation:

1. The ability of small changes in the underlying data to shift the weights of each factor.

2. The lack of cross validation, a process of applying the model to an outside sample and measuring the accuracy of its prediction.

A new model should be cross validated on different data than those from which it is derived.

MDA Applied to Different Financial Statement Adjustments:

The endeavor to find the best variables for a particular industry led researchers to examine the hypothesis of whether adjusting the financial statements for a certain condition could produce a superior model. Mensah (1983) examined whether adjusting financial statements by Replacement Cost or Specific Price-Level (SPL) could produce a better bankruptcy prediction model. Assuming that SPL data might be regarded as a cost-effective surrogate for replacement cost data, he selected a set of nonbankrupt companies and matched them with a sample of companies that filed for bankruptcy in the period January 1975 to December 1978. The study evaluated the usefulness of specific price-level adjustments based on:

1. SPL indices for various industries, published by the US Department of Commerce.

2. Input-output indices for various industries, published by the US Department of Labor for the US economy of 1970.

Using discriminant analysis, the study concluded that the availability of SPL data may help to improve bankruptcy predictions.

In spring of 1992 a similar study was done by Aly, Barlow, and Jones (1992). In September 1979, the Financial Accounting Standards Board (FASB) issued a Statement of Financial Accounting Standards (SFAS) No. 33. which required large, publicly held corporations to issue supplementary financial statements that included both Constant-Dollars and Current-Cost information along with their primary financial statements. In 1984, the FASB issued SFAS 82 to eliminate some earlier requirements of SFAS 33. With this development in reporting requirements in mind, the authors developed three models based on Historical Cost (HC), Current Cost (CC), and HC-CC combined. Both multiple discriminant analysis and logistic regression analysis were used to derive the ex-post classification results. The authors' two main findings were:

1. The combined HC-CC model was found to have more discriminant power than did the HC model alone in each of the three years before bankruptcy.

2. The logistic regression analysis was found to have a better classification rate than MDA for the selected sample.

This second finding will be examined next.

The Shortcomings of Bankruptcy Studies That Use MDA:

From the above review, apparently a vast amount of research into bankruptcy prediction has involved the use of Fisher's (1936) Linear Discriminant Function (LDF). This model has been used to predict financial events and other variables (i.e., corporate failure, bank failure, and bond rating predictions) for use in particular decision models.

According to Taksuoka (1976), discriminant analysis is a useful technique in the solution of two distinct but interrelated problems:

1. To find if there are significant differences among two or more existing groups (populations) based on a combined set of descriptive variables.

2. To predict group membership of future observations, assuming such observations are truly members of one or another of the groups.

Optimal results are obtained with the LDF when the following data assumptions are met (Eisenbeis and Avery, 1972):

1. Partitioned groups are discrete and identifiable.

2. Each group member can be described by a measure that is a linear combination of several variables.

3. The linear combinations are multivariate normally distributed within each group population.

4. There is a single dispersion (variance-covariance) matrix that is common to all populations.

In the bankruptcy forecasting context, two important assumptions of multiple discriminant analysis (MDA) are violated. There is nothing wrong with viewing the future bankrupt and nonbankrupt firms as two populations, and two populations would be expected to have different means. The problem arises because the distribution of financial ratios is usually not normal. Furthermore, the variability of the financial ratios of future bankrupt firms is likely to be much different from the variability of successful firms, which means that the two groups will not have a common variance-covariance matrix.

Table 2.1 on the next page lists some studies that tested and did not test for the normality of the variables, and the common variance-covariance (VCV) assumptions of MDA.

Table 2.1.

Studies that tested for normality and VCV in the data that was used in MDA.

STUDY	TEST TYPE	
	NORMALITY	VCV
Altman, 1968		
Altman, 1970		
Altman, Haldman, and Naraganan, 1977	X	X
Bates, 1973	X	X
Blum, 1974		
Dambolena, Khoury, 1980		
Deakin, 1972		
Deakin, 1979		
Elam, 1975		

Notes: X for tested, blank for otherwise.

For a complete list see Frederic, Richardson, and Davidson, 1984.

Zavgren (1985) has argued that the above studies are deficient because they employ methodologies (i.e., discriminant analysis) which require variables in the sample data to be normally distributed. If all variables are not normally distributed, discriminant analysis may result in the selection of an inappropriate set of predictors. To correct for this problem, Zavgren used logit analysis to arrive at her bankruptcy prediction model. Logit is less affected by data sets that are not normally distributed, (Frederick, Richardson, and Davidson, 1984).

Section 2: THE LOGIT MODEL

Generally, conditional probability models estimate the probability of occurrence of a choice or outcome; they depend on the attribute vector of the individual and the choice or outcome set available. Although developed by a biologist (Finney, 1952), they can assay the probability of commercial failure. The logit model has been used to predict commercial bank failure (Ohlson, Santomero, and Vinson, 1977; Martin, 1977).

Conditional probability models derive the probability of an event for a dichotomous dependent variable by using the coefficients on the independent variables. The marginal effect of these coefficients can be interpreted as the effect of a unit change in an independent variable on the probability of the dependent variable. A cumulative probability distribution is necessary to constrain the predicted values within an acceptable range between [0,1] (Maddala 1977, pp.163-4).

One of the early studies of bankruptcy prediction that used the logit model as an estimation method is that of Ohlson (1980). Ohlson obtained data for the failed firms from their 10-K financial statements. He found four basic factors as being statistically significant in affecting the probability of failure within one year of bankruptcy. These four factors are:

1. The size of the company: bigger firms have a lower probability of bankruptcy.

2. The measure(s) of financial structure: higher financial leverage implies a higher probability of bankruptcy.

3. The measure(s) of performance: more positive measure(s) of performance lead to lower probability of bankruptcy.

4. The measure(s) of current liquidity: more liquid firms have a lower probability of bankruptcy.

Ohlson also found that the auditors' opinion reports for the misclassified bankrupt firms seemed to lack any warning signals of impending bankruptcy. Ohlson assumed that this could be due to the fact that all but two of the thirteen companies reported a profit. Other ratios showed the same healthy patterns, some even paid dividends in the year before bankruptcy.

These inconsistent results are not something new in bankruptcy prediction models. The process of building an econometric model is an evolutionary process. A model should be continually modified until it is not only significant but also consistent with both economic and econometric theories.

The literature review section on MDA shows that most of the studies did not follow econometric theory in building their models, thus resulting in many inconsistencies. Similarly, estimating problems in bankruptcy prediction studies using the logit estimation method might also give rise to inconsistencies caused by not following the econometric theories that relate to the logit estimation method.

Some of the data problems that might cause inconsistency in estimating results are:

1. Missing variables. Some important variables that should have been included among the independent variables were not included.

2. Multicollinearity: high intercorrelations among the explanatory variables.

These points were raised by Mensah (1984), who looked at three main issues:

1. Inconsistency both in the values of the coefficients reported and the relative importance of various financial ratios used.

2. Pooling of data across years without considering underlying economic events in those years.

3. Whether to control for multicollinearity.

Mensah investigated the following external economic factors by including them as independent variables in his model:

1. Inflation.

2. Interest rates and credit availability.

3. The business cycle.

Logit analysis was employed as the primary statistical tool. Mensah's analysis lead to three general conclusions:

1. The accuracy and structure of predictive models differ across different economic environments.

2. Different prediction models seem appropriate for firms in different industrial sectors, even for the same economic environment.

3. More useful results may be obtained by specifically considering multicollinearity in the intertemporal and intersectoral development of the models.

The above findings might be theoretically sound, especially controlling the bankruptcy prediction study for industry differences. But what about diversification? Many firms today are both very large and diversified. This fact makes controlling for industry differences a questionable method. A study appropriately entitled "The Dilemma of Matched Pairs and Diversified Firms in Bankruptcy Prediction Models," was done by Sheppard (1994) to examine this issue. Sheppard proposed a method by which industry norms could be used in bankruptcy prediction models. His model was found to be 86 percent accurate in differentiating survivors from failures one year before failure. The most significant predictive measures within the model were profitability and solvency ratios. However, it was also found that without adjustments made for industry differences the predictive validity of the model was not significantly reduced. Thus, Sheppard concludes that while industry differences are often argued to be important, their impact on the diversified firm may not be as important in deciding a firm's likelihood of failure as the simple profitability and solvency of the firm, regardless of the industry.

Although Sheppard's point of view is very interesting, controlling for industry differences may be very appropriate when dealing with a specialized industry. Some industries are so specialized that the simple comparison of financial ratios between two firms could be misleading if the firms were from two different industries. Furthermore, some special adjustments that a researcher could apply to a firm's financial statements in one industry, could not be applied to other firms in different industries.

A study that highlights this point was done by Platt, Platt, and Pedersen (1994). They reconsidered the usage of nondeflated financial ratios in statistical models to differentiate between failed and nonfailed firms. They hypothesized that nondeflated ratios inadequately reflect intertemporal macroeconomic fluctuations that affect the ability of firms to survive. Using a sample of 124 oil and gas companies between the period 1982-1988, they evaluated the going concern assumption (the accounting term for continued operations) with statistical logit models using either nondeflated or deflated financial ratios. Deflated company ratios were created by transforming the data with price indices or by creating market value ratios. Their results suggest that a superior bankruptcy early warning model could be developed for the oil and gas industry by creating real financial ratios. Real financial ratios were obtained by deflating nominal ratios by the prime interest rate and the price of oil.

Bankruptcy Prediction Using Cash Flow Ratios:

As researchers started to realize the superiority of the logit model over MDA in bankruptcy prediction models, they started to look for other variables that they could use in their models. This new direction was reinforced with the FASB changing the focus of the third financial statement to emphasize disclosure of detailed information on companies' current operating cash flow. Many studies were undertaken during the mid and late 80's to examine the usefulness of operating cash flow information in predicting bankruptcies. These studies ended with conflicting results.

In the mid 80's financial statement users and regulators of publicly reported financial accounting data argued in favor of the disclosure of detailed information on a company's current operating cash flows. The Financial Accounting Standards Board (FASB) holds that such disclosures will permit users to assess better the amount, timing, and uncertainty of future cash flows. A study by Casey and Bartczak (1985) was undertaken to find whether operating cash flow data and related measures lead to more accurate predictions of bankrupt and nonbankrupt companies. Their sample comprised sixty firms that had petitioned for bankruptcy during the period 1971-1982 and 230 nonfailed firms during the same period. Both multiple discriminant analysis and conditional stepwise logit analysis were applied to the sample. Their results show that operating cash flow data do not provide incremental predictive power over accrual-based ratios.

A study by Gentry, Newbold, and Whitford (1985) examined a cash-based funds flow model that was suggested by a FASB's Exposure Draft, and agreed with Casey and Bartczak's findings. The model was tested by determining whether cash-based funds flow ratios can adequately classify failed and nonfailed firms and serve as an alternative to financial ratios calculated using accrual accounting. The Standard & Poor's Compustat 1981 Industrial Annual Research File of firms and the Compustat Industrial Files were used to identify firms that failed during the period 1970-1981. Of the 114 firms found deleted from the Compustat Industrial File during that period, ninety-two were classified as failed. It was found that cash flow from operations alone does not improve the classification of failed and nonfailed firms. On the other hand, cash-based funds flow components did provide a viable alternative for classifying failed and nonfailed firms. The logit results revealed that the dividend funds flow component was the most significant variable in the classification model.

A few months later the same authors (1985) combined cash flow components with leading financial ratios to find if a more powerful model for predicting financial failure could be constructed. The analysis used twelve funds flow measures to distinguish between failed and nonfailed companies. As in their previous study, dividends were found to be an important variable in distinguishing between failed and nonfailed companies.

Their study's conclusions were that, although financial ratios were found to provide additional useful information, the funds flow components provide a slightly more reliable indication of financial health.

Using a Probit model, Gentry et al. (1987) found three funds flow components were significant for failed firms: 1. investment, 2. dividends, and 3. receivables. For nonfailed firms, the only significant components were the scale measure and dividends.

The examination of cash flow models continued with Aziz, Emanuel, and Lawson (1988). In their study, a cash flow identity that was developed by one of the authors was used to obtain a set of financial ratios and measures for generating a multivariate bankruptcy model. Matching nonbankrupt firms were selected on the criteria of industry classification and asset size to create a paired sample design. Multiple discriminant analysis and logistic regression techniques were used to evaluate the suitability of Lawson's identity components for discrimination between bankrupt and nonbankrupt firms. Their results confirmed the findings of Gentry et al. (1985) that logit models are somewhat better than discriminant models in the analysis of cash flow components models.

The contradictory results of cash flow based models to predict bankruptcy prompted Ward (1994) to examine if cash flow ratios were more important in certain industries than in others. Ward looked at the oil and gas industry. His main hypothesis was that contradictory results from past bankruptcy prediction studies using cash flow information were caused by pooling firms across industries into one sample. The results of his study suggest that cash flows are more useful to creditors in predicting financially distressed mining, oil and gas firms than they are in predicting financially distressed firms in other industries.

Section 3: NEURAL NETWORKS

Neural networks are a fairly new scientific concept. They have been used widely in character and voice recognition. A neural network's ability to generalize, coupled with its ability to classify, prompted researchers to examine neural networks' ability to classify firms as bankrupt or nonbankrupt from their financial ratios.

In a study by Fletcher and Goss (1993), the authors argued that, due to rapid hardware and software innovations, neural networks (NN) can now improve over the usual logit prediction model. Neural networks also provide a robust and less computationally demanding alternative to nonlinear regression methods. The authors applied a back-propagation neural network methodology to a sample of eighteen bankrupt and eighteen nonbankrupt firms. Their results showed that neural networks more accurately predict bankruptcy than the logit model.

In another study by Udo (1993), the author compared neural networks and multiple regression analysis in their ability to predict bankruptcy. The author applied neural networks methodology on a sample of 300 companies. The results show that (NN) is as accurate or more accurate than a multiple regression model in predicting bankruptcy, besides being easier to use and readily adapting to the changing environment.

The superiority of neural networks over the traditional statistical methodologies is not a perception shared by all researchers. In a study by Altman, Macro, and Varetto (1994), the authors compared the two methods. The study analyzed well over 1,000 healthy, vulnerable, and unsound industrial Italian firms from 1982-1992, using linear discriminant analysis, logit analysis and neural networks. Their results suggest a balanced degree of accuracy and other beneficial characteristics between linear discriminant analysis and neural networks. Both types of diagnostic techniques displayed acceptable, over 90%, classification and holdout sample accuracy. Their study concludes that there should be further studies and tests using the two techniques, and suggests a combined approach for predictive reinforcement.

Because neural network methodology is still in its infancy, not enough studies were found that apply neural network methodology to the problem of bankruptcy prediction.

Section 4: Summary of Literature Review

The literature review on bankruptcy prediction shows the complexity of this issue. By going through past bankruptcy prediction studies, one can see how this issue evolved over time. Bankruptcy prediction models became more complex with the introduction of new information and the development of new statistical and analytical methodologies. In general, past studies have found that certain measures of liquidity, performance, and capital structure are important discriminants of a firm's financial future.

These findings agree with McAuliffe's (1987) opinion on financial distress. McAuliffe found that corporate financial distress goes through three phases. The first phase is the incubation period, in which the conditions develop without recognition by management; signs include changes in product demand and some loss. The second phase is cash shortage, in which the company begins to have problems in meeting current financial obligations. During financial insolvency, the third phase, the company cannot obtain funds to meet obligations. If management cannot successfully secure the funds, the company goes on to total insolvency.

Trends in cash and working capital positions and indications in the company's operating statement can be used to detect impending failure. A good bankruptcy prediction model could detect financial difficulty by using financial measures that truly measure the financial performance of a firm.

Bankruptcy prediction studies suggest that firms included in a study should be from one industry. Controlling for industry differences should be even more important when dealing with a specialized industry, like the oil and gas industry. The way in which the oil and gas industry is affected by the price of oil and interest rates makes it a unique industry.

Choosing between accrual and cash flow ratios as predictor variables must be examined carefully within each industry. From the literature review, it is apparent that certain ratios could be important in one industry and not important in another.

Some issues regarding the best estimation method appear to have been resolved in the literature. Zavgren (1985) and Aziz et al.(1988) and others have found that the logit model outperformed multiple discriminant analysis. This is because the logit model is not affected by the distribution of the independent variables in the way discriminant analysis is. Discriminant analysis produces inconsistent parameters if the distribution of the independent variables is not normal, whereas the logit model produces consistent parameters. Nevertheless, there appears to be, as yet, no consensus regarding the superiority of logit relative to neural networks.

CHAPTER III

DATA PREPARATION AND ESTIMATING METHODS

This study extends the research of earlier studies on bankruptcy prediction. Logit models are built using different independent variables to predict the probability of bankruptcy in the oil and gas industry. Neural network models are then built to predict bankruptcies using the same independent variables used in the logit models. Each model is then ranked on the rate of prediction error on an outside sample using a cross-validation method.

The study will encompass six sets of data and two estimating methods. The six sets of data are from the oil and gas industry, and these sets are:

1. Accrual based ratios.
2. Accrual based ratios adjusted by interest rates and oil prices (real accrual ratios).
3. Cash flow based ratios.
4. Cash flow based ratios adjusted by interest rates and oil prices (real cash flow ratios).
5. Real accrual ratios with economic variables.
6. Real cash flow based ratios with economic variables.

The economic variables are the interest rate and oil price.

The two estimating methods are:

1. Logit model.

2. Neural networks.

Due to inconsistencies in past bankruptcy prediction studies in selecting the best variables and estimating methods, this study will try to answer the following questions:

1. Are nominal accrual ratios better predictors of bankruptcy than nominal cash flow ratios?

2. Are real accrual based ratios better predictors of bankruptcy than nominal accrual ratios?

3. Are real cash flow based ratios better predictors of bankruptcy than nominal cash flow ratios?

4. Are real accrual based ratios better predictors of bankruptcy than real cash flow ratios?

5. Does the inclusion of economic factors in models that use real variables improve prediction accuracy?

6. Are neural network models better predictors of bankruptcy than the logit model?

Section 1: THE SIX MODELS

MODEL I: ACCRUAL BASED RATIOS

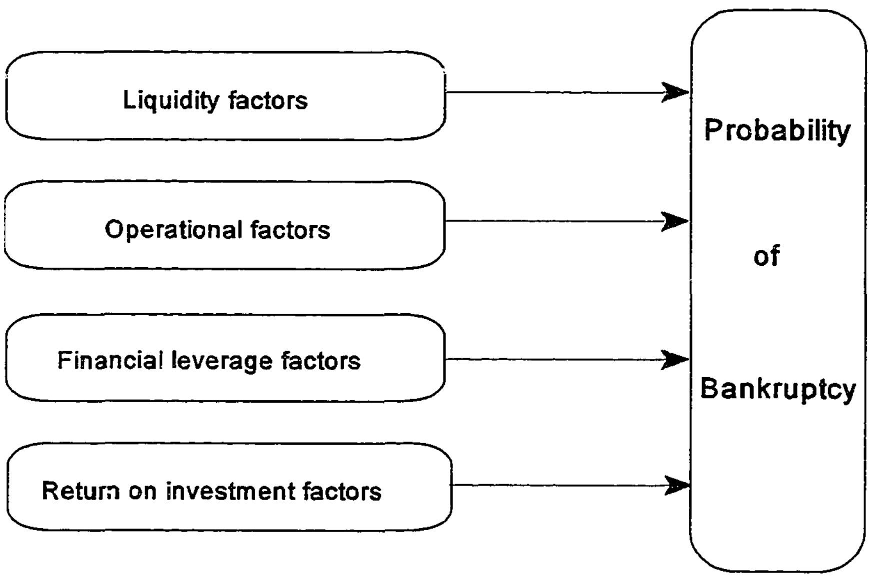
The objective of using a ratio when analyzing financial information is simply to standardize the information being analyzed so that comparisons can be made between ratios of different firms or possibly the same firm at different points in time. Ratio analysis can answer important questions about a firm's operations, such as:

1. How liquid is the firm?
2. Is management generating adequate operating profits from the firm's assets?
3. How is the firm financing its assets?
4. Are the owners (stockholders) receiving an adequate return on their investment?

The liquidity of a business is defined as its ability to meet maturing debt obligations. That is, does or will the firm have the resources to pay the creditors when the debt comes due? The second question deals with whether profits are sufficient relative to the assets invested. The question is similar to a question one might ask about the interest earned on a savings account at a bank. The main issue raised by the third question is: how does the firm finance its assets? Does it finance the assets by debt or by equity? Management has to find the best mix between debt and equity to benefit from the rewards of financial leverage and at the same time not take on more debt that might lead to its bankruptcy. The last question's answer tells us if the earnings available to the firm's owners or common equity investors are attractive when compared with returns to owners of similar companies in the same industry.

The model using accrual based ratios can be illustrated in Figure 3.1.

Figure 3.1 Accrual based factors that affect the probability of bankruptcy



This model assumes that the probability of bankruptcy is the output of a joint effect among its determinants. These determinants can be categorized into four groups: liquidity, operational, financial leverage, and return on investment factors. Table 3.1 summarizes the factors and the accrual ratios used.

Table 3.1-- Accrual based factors to be tested as determinants of the probability of bankruptcy.

FACTOR	RATIOS
Liquidity	1. Working Capital / Total Assets
Operational	1. Retained Earnings / Total Assets 2. Earnings Before Interest and Taxes / Total Assets
Financial Leverage	1. Total Debt / Total Assets 2. Total Debt / Equity
Return on Investment	1. Net Income / Equity

MODEL II: CASH FLOW BASED RATIOS

In a discussion memorandum by FASB in December 1980, the FASB suggested that cash flow data are a useful supplemental disclosure because they:

1. Provide feedback on actual cash flows.

2. Help to identify the relationship between accounting income and cash flows.

3. Provide information about the quality of income. A firm's quality of earnings increases as the correlation between accounting income and cash flows increases.

4. Improve comparability of information in financial reports.

5. Aid in assessing flexibility and liquidity.

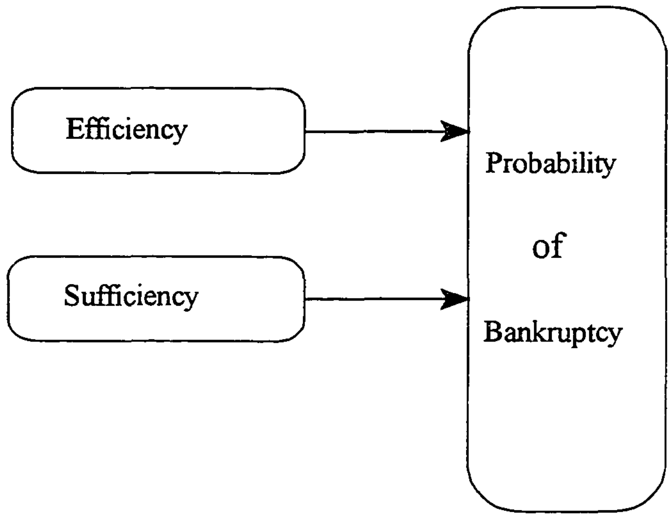
6. Assist in predicting future cash flows.

Cash flow from operations is not a measure of profitability. It is a net measure of the liquidity aspects of operations, i.e., cash collections from customers due to sales or services on account, and other cash receipts (e.g., interest and dividend income), and payments to suppliers due to purchases or services on account, and other cash disbursements (e.g., labor, utilities, rent, and taxes). Cash flow from operations does not include cash transactions related to investment in assets and financing activities. Cash flows from investment and financing activities are reported under separate sections in the Statement of Cash Flows.

A recent study (Giacomino and Mielke, 1993) classified the scattered cash flows based ratios into two categories: efficiency ratios and sufficiency ratios. Efficiency ratios would reflect how well a company generates cash flows relative both to other years and to other companies. Sufficiency ratios would show the adequacy of cash flows for meeting a company's needs.

The model using cash flow based ratios can be illustrated by Figure 3.2.

Figure 3.2 Cash flow based factors that affect the probability of bankruptcy



This model assumes that the probability of bankruptcy is the output of a joint effect among its determinants. These determinants can be categorized into two categories: efficiency ratios and sufficiency ratios. Table 3.2 summarizes the categories and the cash flow ratios within each category.

Table 3.2-- Cash flow based categories to be tested as determinants of the probability of bankruptcy.

CATEGORY	RATIOS
Efficiency	1. Cash from operations / Sales 2. Cash from operations / Net Income 3. Cash from operations / Total Assets
Sufficiency	1. Dividends / Cash from operations 2. Cash from operations / Current liabilities

MODEL III: REAL ACCRUAL BASED RATIOS

and

MODEL IV: REAL CASH FLOW BASED RATIOS

This study will continue the research into the use of real financial ratios. The method of adjusting nominal financial ratios of oil and gas companies into real financial ratios was introduced by Platt, Platt, and Pedersen (1994). The deflators designated for assets, liabilities, and income statement items are described in table 3.3.

Table 3.3 -- Variable-specific deflator

VARIABLE	DEFLATOR
Assets from Balance Sheet	1 / Oil Price
Liabilities from Balance Sheet	Interest Rate (YTM AAA)
Income Statement Items	Oil Price

Models III and IV use real financial ratios, which were obtained by deflating the ratios used in models I and II. Deflating the ratios was done in the following manner.

If, for a given year, the interest rate and oil price were 9.93% and $24.09, respectively, and a firm has a debt ratio of 80% (total debt / total assets), then:

real debt = total debt/interest rate = 80/.0993 = 805.64

real assets = total assets/[1/oil price]

= 100/[1/24.09] = 100 * 24.09 = 2409

thus, the real debt ratio = 805.64/2409 = .33

So, a firm that has a nominal debt ratio of 80% will have a real debt ratio of 33%.

In Platt et al's (1994) study the authors used this deflating example to reflect the inverse relationship between the value of debt and the interest rate, and the appreciation in the value of the firm's assets when the price of oil rises.

Thus, models III and IV will have the same diagrams as in Figures 3.1 and 3.2, except that they will be using real variables instead of nominal ones.

MODELS V AND VI: REAL FINANCIAL RATIOS AND ECONOMIC FACTORS

Models V and VI will add both the interest rate and oil price as extra variables on models III and IV.

Section 2: POPULATION AND SAMPLE

The COMPUSTAT PC Plus database is used to get the data necessary for this study. The database allows the user to query for records that meet some certain criteria. By searching the database for companies deleted at some point in time for bankruptcy reasons, a total of 539 companies were found. Out of these 539 companies only 43 were from the oil and gas industry.

Searching the database for companies that were in the oil and gas industry and were still active resulted in the location of 318 companies. Financially weak firms were then extracted from the active oil and gas companies. A total of 41 firms were classified as financially weak. A company was classified as financially weak, if it had both a negative *working capital / total assets* ratio and a negative *retained earnings / total assets* ratio for the most recent consecutive three years.

The first ratio can only be negative if the firm's current liabilities are more that its current assets, thus there is a chance that the firm cannot meet its current obligations. The second ratio can only be negative if the firm's retained earnings are negative. This could happen if the firm had to close its losses against its retained earnings account. Having a negative *retained earnings / total assets* ratio for three consecutive years could suggest that the firm had been running losses.

After including the financially weak firms with the bankrupt firms, a total of 84 firms could be classified as bankrupt or financially distressed. After eliminating the firms that had missing data, this number came down to 56 firms. From the remaining 277 active firms, a sample of 128 firms was selected. After eliminating the firms that had missing data, the sample of active healthy firms was reduced to 106 firms. Thus, the study has a total sample of 162 firms, with 56 classified as bankrupt or financially weak firms and 106 active healthy firms.

Section 3: UNIVARIATE ANALYSIS OF FINANCIAL RATIOS

All financial data required to calculate the financial ratios are extracted from the COMPUSTAT database. Ratios are calculated for the three years before bankruptcy. Data for cash flows from operations were not available before 1987. The FASB did not require that the Statement of Cash Flows be issued before 1987. Cash flows from operations had to be calculated by the indirect method for firms that went bankrupt before 1987. Oil prices are taken from the *Wall Street Journal*, and the interest rate used is the calculated yield to maturity for a AAA long-term bond issued by the firm Exxon.

In the following section, simple descriptive statistics are calculated for each variable used, and a significance level for the Shapiro-Wilk test for normality (Royston, 1982) is given for each variable. The Shapiro-Wilk test for normality is used to provide evidence that a logit model is more appropriate to use than discriminant analysis when the independent variables are not normally distributed. According to Zavgren (1985), financial ratios usually are not normally distributed. A significance level of less than 5 percent indicates that the null hypothesis of normality could be rejected.

ACCRUAL BASED RATIOS

WORKING CAPITAL / TOTAL ASSETS

The working capital to total assets ratio is used to measure the liquidity of the firm. The numerator is equal to the firm's Current Assets minus its Current Liabilities. A firm's current assets are all the assets that could be turned into cash within a short period, usually one year. Its current liabilities are obligations that the firm has to meet within a one year period. This ratio evaluates the firm's liquidity relative to its total assets. An inverse relationship exists between the value of the ratio and the likelihood of liquidity problems. Thus the coefficient of this ratio should be negative, indicating an inverse relationship with the probability of bankruptcy. Tables 3.4 and 3.5 present nominal and real summary statistics for this ratio.

Table 3.4 -- Working Capital / Total Assets (Nominal)

SAMPLE	BANKRUPT			NON-BANKRUPT			OVERALL		
PERIOD	WC1	WC2	WC3	WC1	WC2	WC3	WC1	WC2	WC3
MEAN	-0.49	-0.31	-0.26	0.18	0.19	0.18	-0.05	0.01	0.03
STD. DV.	0.72	0.57	0.43	0.16	0.18	0.18	0.55	0.44	0.36
MEDIAN	-0.23	-0.11	-0.10	0.15	0.14	0.13	0.05	0.06	0.07
MIN	-3.58	-2.64	-2.13	0.00	5.94	0.00	-3.58	-2.64	-2.1
MAX	-0.01	0.17	0.28	0.97	0.94	0.93	0.97	0.94	0.93
Prob_N							0.00	0.00	0.00

Notes: WC1, WC2, and WC3 stand for the time lag. Prob_N is the significance level for the Shapiro-Wilk test for normality.

Table 3.5 -- Working Capital / Total Assets (Real)

SAMPLE	BANKRUPT			NON-BANKRUPT			OVERALL		
PERIOD	WCr1	WCr2	WCr3	WCr1	WCr2	WCr3	WCr1	WCr2	WCr3
MEAN	0.12	0.15	0.17	0.30	0.31	0.32	0.24	0.26	0.27
STD. DV.	0.12	0.14	0.15	0.18	0.19	0.19	0.19	0.19	0.20
MEDIAN	0.09	0.11	0.13	0.27	0.27	0.27	0.20	0.21	0.23
MIN	-0.14	-0.05	0.00	0.06	0.06	0.06	-0.14	-0.05	0.00
MAX	0.49	0.64	0.69	0.99	0.99	0.98	0.99	0.98	0.98
Prob_N							0.00	0.00	0.00

Notes: WCr1, WCr2, and WCr3 stand for the time lag. Prob_N is the significance level for the Shapiro-Wilk test for normality.

RETAINED EARNINGS / TOTAL ASSETS

The retained earnings to total assets ratio is classified in the operational factors. The retained earnings account is where the firm closes its income or losses every year. It does not have any cash in it. It only indicates the cumulative total amount of earnings that the firm kept for reinvestment and did not pay out as dividends. This ratio evaluates the retained earnings of the firm relative to its assets. The higher this ratio, the less likely it is that the firm will go bankrupt, indicating an inverse relationship between this ratio and the probability of bankruptcy. Tables 3.6 and 3.7 present nominal and real summary statistics for this ratio.

Table -- 3.6 Retained Earnings / Total Assets (Nominal)

SAMPLE	BANKRUPT			NON-BANKRUPT			OVERALL		
PERIOD	RE1	RE2	RE3	RE1	RE2	RE3	RE1	RE2	RE3
MEAN	-1.70	-1.40	-1.22	-0.89	-0.62	-0.62	-1.17	-0.89	-0.83
STD. DV.	2.21	2.01	2.06	3.88	3.10	3.32	3.43	2.81	2.97
MEDIAN	-0.70	-0.47	-0.31	0.03	0.02	0.01	-0.19	-0.16	-0.10
MIN	-9.84	-9.43	-9.00	-26.0	-29.5	-32.2	-26.0	-29.5	-32.2
MAX	-0.03	0.14	0.28	0.79	0.86	0.84	0.79	0.86	0.84
Prob_N							0.00	0.00	0.00

Notes: RE1, RE2, and RE3 stand for the time lag. Prob_N is the significance level for the Shapiro-Wilk test for normality.

Table -- 3.7 Retained Earnings / Total Assets (Real)

SAMPLE	BANKRUPT			NON-BANKRUPT			OVERALL		
PERIOD	REr1	REr2	REr3	REr1	REr2	REr3	REr1	REr2	REr3
MEAN	-0.09	-0.06	-0.05	-0.05	-0.03	-0.03	-0.06	-0.04	-0.04
STD. DV.	0.12	0.10	0.09	0.22	0.16	0.16	0.19	0.14	0.14
MEDIAN	-0.04	-0.02	-0.01	0.00	0.00	0.00	-0.01	-0.01	-0.00
MIN	-0.56	-0.48	-0.43	-1.49	-1.50	-1.53	-1.49	-1.50	-1.53
MAX	-0.00	0.01	0.01	0.05	0.04	0.04	0.05	0.04	0.04
Prob_N							0.00	0.00	0.00

Notes: REr1, REr2, and REr3 stand for the time lag. Prob_N is the significance level for the Shapiro-Wilk test for normality.

EARNINGS BEFORE INTEREST AND TAXES / TOTAL ASSETS

The earnings before interest and taxes to total assets ratio is also an operational ratio, measureing the earning power of the firm. The ratio measures the earning power relative to the total assets of the firm. Thus, it can give a measure of how well the firm is using its assets. There is an inverse relationship between this ratio and the probability of bankruptcy. Tables 3.8 and 3.9 give nominal and real statistical summaries for this ratio.

Table 3.8 -- Earnings Before Interest and Taxes / Total Assets (Nominal)

SAMPLE	BANKRUPT			NON-BANKRUPT			OVERALL		
PERIOD	EB1	EB2	EB3	EB1	EB2	EB3	EB1	EB2	EB3
MEAN	-0.16	-0.08	-0.03	-0.02	0.02	0.03	-0.07	-0.02	0.01
STD. DV.	0.30	0.42	0.36	0.27	0.19	0.15	0.29	0.30	0.25
MEDIAN	-0.13	-0.04	-0.01	0.04	0.03	0.04	0.01	0.02	0.03
MIN	-1.01	-2.31	-1.12	-1.78	-1.29	-0.83	-1.78	-2.31	-1.12
MAX	1.36	1.85	1.99	0.48	0.61	0.61	1.36	1.85	1.99
Prob_N							0.00	0.00	0.00

Notes: EB1, EB2, and EB3 stand for the time lag. Prob_N is the significance level for the Shapiro-Wilk test for normality.

Table 3.9 -- Earnings Before Interest and Taxes / Total Assets (Real)

SAMPLE	BANKRUPT			NON-BANKRUPT			OVERALL		
PERIOD	EBr1*	EBr2*	EBr3*	EBr1*	EBr2*	EBr3*	EBr1*	EBr2*	EBr3*
MEAN	-0.42	-0.12	-0.015	-0.054	0.05	0.056	-0.18	-0.009	0.031
STD. DV.	0.928	0.934	0.54	0.874	0.45	0.319	0.912	0.664	0.411
MEDIAN	-.23	-0.072	-0.008	0.126	0.088	0.089	0.012	0.044	0.05
MIN	-3.31	-5.21	-1.12	-5.83	-2.92	-1.86	-5.83	-5.21	-1.86
MAX	3.495	4.182	3.414	1.562	1.372	1.044	3.495	4.182	3.414
Prob_N							0.00	0.00	0.00

Notes: EBr1, EBr2, and EBr3 stand for the time lag. Prob_N is the significance level for the Shapiro-Wilk test for normality. * Figures in thousandths.

TOTAL DEBT / TOTAL ASSETS

The total debt to total assets ratio measures the financial structure of the firm. It is a measurement of how the firm is financing its assets. This ratio calculates the percent of the firm's assets financed by debt. The higher this ratio, the riskier the firm becomes. There is a direct relationship between this ratio and the probability of bankruptcy. Tables 3.10 and 3.11 present nominal and real summary statistics for this ratio.

Table 3.10 -- Total Debt / Total Assets (Nominal)

SAMPLE	BANKRUPT			NON-BANKRUPT			OVERALL		
PERIOD	DB1	DB2	DB3	DB1	DB2	DB3	DB1	DB2	DB3
MEAN	0.50	0.53	0.42	0.17	0.17	0.20	0.28	0.30	0.27
STD. DV.	0.48	0.45	0.36	0.18	0.19	0.22	0.36	0.35	0.30
MEDIAN	0.43	0.41	0.34	0.11	0.12	0.12	0.20	0.22	0.19
MIN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MAX	3.06	2.28	1.61	0.81	0.77	1.09	3.06	2.28	1.61
Prob_N							0.00	0.00	0.00

Notes: DB1, DB2, and DB3 stand for the time lag. Prob_N is the significance level for the Shapiro-Wilk test for normality.

Table 3.11 -- Total Debt / Total Assets (Real)

SAMPLE	BANKRUPT			NON-BANKRUPT			OVERALL		
PERIOD	DBr1	DBr2	DBr3	DBr1	DBr2	DBr3	DBr1	DBr2	DBr3
MEAN	0.35	0.30	0.19	0.18	0.13	0.14	0.24	0.19	0.15
STD. DV.	0.41	0.28	0.17	0.19	0.15	0.15	0.30	0.21	0.16
MEDIAN	0.24	0.23	0.12	0.12	0.09	0.09	0.17	0.14	0.10
MIN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MAX	2.52	1.43	0.69	0.89	0.60	0.77	2.52	1.43	0.77
Prob_N							0.00	0.00	0.00

Notes: DBr1, DBr2, and DBr3 stand for the time lag. Prob_N is the significance level for the Shapiro-Wilk test for normality.

TOTAL DEBT / EQUITY

There are two main sources of financing for a firm, debt or equity. Equity capital is provided by the firm's owners as common or preferred stocks. The total debt to equity ratio measures the firm's debt relative to capital provided by the firm's owners. There is a direct relationship between this ratio and the probability of bankruptcy. Tables 3.12 and 3.13 present nominal and real statistical summaries for this ratio.

Table 3.12 -- Total Debt / Total Equity (Nominal)

SAMPLE	BANKRUPT			NON-BANKRUPT			OVERALL		
PERIOD	DQ1	DQ2	DQ3	DQ1	DQ2	DQ3	DQ1	DQ2	DQ3
MEAN	0.88	2.10	1.78	0.48	0.69	0.60	0.62	1.18	1.01
STD. DV.	6.25	10.4	4.55	1.18	2.78	1.42	3.80	6.53	2.97
MEDIAN	0.41	0.61	0.58	0.15	0.16	0.18	0.22	0.22	0.24
MIN	-25.8	-18.7	-2.65	0.00	0.00	-4.13	-25.8	-18.7	-4.13
MAX	28.5	54.2	30.8	11.1	28.0	8.8	28.5	54.2	30.8
Prob_N							0.00	0.00	0.00

Notes: DQ1, DQ2, and DQ3 stand for the time lag. Prob_N is the significance level for the Shapiro-Wilk test for normality.

Table 3.13 -- Total Debt / Total Equity (Real)

SAMPLE	BANKRUPT			NON-BANKRUPT			OVERALL		
PERIOD	DQr1	DQr2	DQr3	DQr1	DQr2	DQr3	DQr1	DQr2	DQr3
MEAN	8.84	16.94	20.62	9.08	10.73	8.86	8.94	12.84	12.87
STD. DV.	76.46	98.75	52.19	22.61	43.18	21.14	48.56	67.91	35.61
MEDIAN	6.62	7.95	6.45	2.87	2.40	2.53	3.30	3.10	3.43
MIN	-401.0	-279.0	-29.39	0.00	0.00	-61.50	-401.0	-279.0	-61.50
MAX	245.1	465.3	341.4	212.9	434.7	130.9	245.1	465.3	341.4
Prob_N							0.00	0.00	0.00

Notes: DQr1, DQr2, and DQr3 stand for the time lag. Prob_N is the significance level for the Shapiro-Wilk test for normality.

NET INCOME / EQUITY

The net income to equity ratio measures the return on investment for the owners of the firm. The higher this ratio, the less likely that the firm will go bankrupt. Thus, there is an inverse relationship between this ratio and the probability of bankruptcy. Tables 3.14 and 3.15 present nominal and real statistical summaries for this ratio.

Table 3.14 -- Net Income / Equity (Nominal)

SAMPLE	BANKRUPT			NON-BANKRUPT			OVERALL		
PERIOD	IQ1	IQ2	IQ3	IQ1	IQ2	IQ3	IQ1	IQ2	IQ3
MEAN	-0.24	-0.59	-0.29	-0.15	0.07	-0.01	-0.19	-0.16	-0.11
STD. DV.	1.61	3.82	1.03	1.15	0.42	0.46	1.33	2.29	0.72
MEDIAN	-0.17	-0.06	-0.06	0.04	0.03	0.02	0.01	0.02	0.01
MIN	-4.43	-23.4	-6.04	-11.0	-1.24	-3.81	-11.0	-23.4	-6.04
MAX	7.90	5.19	1.40	0.74	3.27	2.10	7.90	5.19	2.10
Prob_N							0.00	0.00	0.00

Notes: IQ1, IQ2, and IQ3 stand for the time lag. Prob_N is the significance level for the Shapiro-Wilk test for normality.

Table 3.15 -- Net Income / Equity (Real)

SAMPLE	BANKRUPT			NON-BANKRUPT			OVERALL		
PERIOD	IQr1*	IQr2*	IQr3*	IQr1*	IQr2*	IQr3*	IQr1*	IQr2*	IQr3*
MEAN	-15.73	-16.24	-12.47	-8.65	3.385	-0.73	-11.18	-3.38	-4.8
STD. DV.	67.02	127.14	42.27	65.47	20.87	21.709	66.29	77.21	30.98
MEDIAN	-6.88	-2.8	-2.05	2.051	1.527	0.96	0.762	1.107	0.602
MIN	-212.25	-753.9	-250.48	-630.0	-62.67	-180.81	-630.83	-753.9	-250.48
MAX	250.14	246.3	47.33	4.246	165.97	99.96	250.14	246.39	99.96
Prob_N							0.00	0.00	0.00

Notes: IQr1, IQr2, and IQr3 stand for the time lag. Prob_N is the significance level for the Shapiro-Wilk test for normality. * Figures are in thousandths.

CASH FLOW BASED RATIOS

CASH FROM OPERATIONS / SALES

The cash from operations to sales ratio shows the percentage of cash realized from each dollar sale. An inverse relationship exists between the value of this ratio and the likelihood of bankruptcy. Tables 3.16 and 3.17 present nominal and real statistical summaries for this ratio.

Table 3.16 -- Cash From Operations / Sales (Nominal)

SAMPLE	BANKRUPT			NON-BANKRUPT			OVERALL		
PERIOD	CS1	CS2	CS3	CS1	CS2	CS3	CS1	CS2	CS3
MEAN	-0.84	0.24	-0.19	0.32	0.12	0.19	-0.08	0.16	0.06
STD. DV.	1.88	4.34	3.61	2.89	1.04	0.30	2.65	2.69	2.14
MEDIAN	-0.05	-0.02	0.13	0.23	0.21	0.20	0.15	0.16	0.17
MIN	-8.49	-5.16	-22.86	-12.00	-6.06	-1.34	-12.00	-6.06	-22.86
MAX	1.03	31.58	12.18	26.87	4.12	0.87	26.87	31.58	12.18
Prob_N							0.00	0.00	0.00

Notes: CS1, CS2, and CS3 stand for the time lag. Prob_N is the significance level for the Shapiro-Wilk test for normality.

Table 3.17 -- Cash From Operations / Sales (Real)

SAMPLE	BANKRUPT			NON-BANKRUPT			OVERALL		
PERIOD	CSr1	CSr2	CSr3	CSr1	CSr2	CSr3	CSr1	CSr2	CSr3
MEAN	-0.84	0.24	-0.19	0.32	0.12	0.19	-0.08	0.16	0.06
STD. DV.	1.88	4.34	3.61	2.89	1.04	0.30	2.65	2.69	2.14
MEDIAN	-0.05	-0.02	0.13	0.23	0.21	0.20	0.15	0.16	0.17
MIN	-8.49	-5.16	-22.86	-12.00	-6.06	-1.34	-12.00	-6.06	-22.86
MAX	1.03	31.58	12.18	26.87	4.12	0.87	26.87	31.58	12.18
Prob_N							0.00	0.00	0.00

Notes: CSr1, CSr2, and CSr3 stand for the time lag. Prob_N is the significance level for the Shapiro-Wilk test for normality.

CASH FROM OPERATIONS / NET INCOME

The cash from operations to net income ratio shows the percentage of cash generated from operating income. An inverse relationship exists between the value of this ratio and the likelihood of bankruptcy. Tables 3.18 and 3.19 present nominal and real statistical summaries for this ratio.

Table 3.18 -- Cash From Operations / Net Income (Nominal)

SAMPLE	BANKRUPT			NON-BANKRUPT			OVERALL		
PERIOD	CI1	CI2	CI3	CI1	CI2	CI3	CI1	CI2	CI3
MEAN	1.60	0.63	1.75	5.47	3.48	5.39	4.18	2.49	4.07
STD. DV.	6.29	3.66	8.10	33.14	10.74	32.99	27.25	9.09	27.27
MEDIAN	0.38	0.31	0.51	1.47	1.45	1.19	0.79	0.85	0.84
MIN	-3.31	-17.04	-38.00	-8.41	-13.23	-18.16	-8.41	-17.04	-38.00
MAX	47.00	12.00	38.29	342.41	62.50	335.31	342.41	62.50	335.31
Prob_N							0.00	0.00	0.00

Notes: CI1, CI2, and CI3 stand for the time lag. Prob_N is the significance level for the Shapiro-Wilk test for normality.

Table 3.19 -- Cash From Operations / Net Income (Real)

SAMPLE	BANKRUPT			NON-BANKRUPT			OVERALL		
PERIOD	CI1	CI2	CI3	CI1	CI2	CI3	CI1	CI2	CI3
MEAN	1.60	0.63	1.75	5.47	3.48	5.39	4.18	2.49	4.07
STD. DV.	6.29	3.66	8.10	33.14	10.74	32.99	27.25	9.09	27.27
MEDIAN	0.38	0.31	0.51	1.47	1.45	1.19	0.79	0.85	0.84
MIN	-3.31	-17.04	-38.00	-8.41	-13.23	-18.16	-8.41	-17.04	-38.00
MAX	47.00	12.00	38.29	342.41	62.50	335.31	342.41	62.50	335.3
Prob_N							0.00	0.00	0.00

Notes: CIr1, CIr2, and CIr3 stand for the time lag. Prob_N is the significance level for the Shapiro-Wilk test for normality.

CASH FROM OPERATIONS / TOTAL ASSETS

The cash from operations to total assets ratio indicates the percentage of cash generated from total assets. An inverse relationship exists between the value of this ratio and the likelihood of bankruptcy. Tables 3.20 and 3.21 present nominal and real statistical summaries for this ratio.

Table 3.20 -- Cash From Operations / Total Assets (Nominal)

SAMPLE	BANKRUPT			NON-BANKRUPT			OVERALL		
PERIOD	CA1	CA2	CA3	CA1	CA2	CA3	CA1	CA2	CA3
MEAN	-0.13	0.02	0.03	0.08	0.11	0.09	0.01	0.08	0.07
STD. DV.	0.52	0.23	0.25	0.15	0.16	0.11	0.35	0.19	0.17
MEDIAN	-0.01	-6E-04	0.05	0.09	0.10	0.07	0.06	0.06	0.06
MIN	-3.54	-0.59	-0.67	-0.85	-0.23	-0.31	-3.54	-0.59	-0.67
MAX	0.76	0.94	1.25	0.35	1.07	0.57	0.76	1.07	1.25
Prob_N							0.00	0.00	0.00

Notes: CA1, CA2, and CA3 stand for the time lag. Prob_N is the significance level for the Shapiro-Wilk test for normality.

Table 3.21 -- Cash From Operations / Total Assets (Real)

SAMPLE	BANKRUPT			NON-BANKRUPT			OVERALL		
PERIOD	CArl*	CAr2*	CAr3*	CArl*	CAr2*	CAr3*	CArl*	CAr2*	CAr3*
MEAN	-0.36	0.096	0.082	0.243	0.279	0.186	0.036	0.208	0.15
STD. DV.	1.917	0.401	0.386	0.481	0.375	0.224	1.227	0.398	0.294
MEDIAN	-0.04	-0.016	0.063	0.295	0.254	0.166	0.18	0.138	0.125
MIN	-13.93	-0.68	-0.68	-2.78	-0.52	-0.54	-13.93	-0.68	-0.68
MAX	1.953	2.122	2.151	1.137	2.412	0.981	1.953	2.412	2.151
Prob_N							0.00	0.00	0.00

Notes: CArl, CAr2, and CAr3 stand for the time lag. Prob_N is the significance level for the Shapiro-Wilk test for normality. * Figures are in thousandths.

DIVIDENDS / CASH FROM OPERATIONS

The dividends to cash from operations ratio shows the portion of cash from operations applied to dividend payments. The higher this ratio, the less likely the probability of bankruptcy, because payment of dividends is a sign of financial strength. Tables 3.22 and 3.23 present nominal and real statistical summaries of this ratio.

Table 3.22 -- Dividends / Cash From Operations (Nominal)

SAMPLE	BANKRUPT			NON-BANKRUPT			OVERALL		
PERIOD	CD1	CD2	CD3	CD1	CD2	CD3	CD1	CD2	CD3
MEAN	-0.01	-2E-04	0.01	0.05	0.06	0.04	0.03	0.04	0.03
STD. DV.	0.10	0.01	0.07	0.19	0.15	0.17	0.17	0.13	0.15
MEDIAN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MIN	-0.74	-0.02	-0.01	-0.57	-0.29	-0.65	-0.74	-0.29	-0.65
MAX	0.01	0.04	0.49	1.47	0.91	0.70	1.47	0.91	0.70
Prob_N							0.00	0.00	0.00

Notes: CD1, CD2, and CD3 stand for the time lag. Prob_N is the significance level for the Shapiro-Wilk test for normality.

Table 3.23 -- Dividends / Cash From Operations (Real)

SAMPLE	BANKRUPT			NON-BANKRUPT			OVERALL		
PERIOD	CDr1	CDr2	CDr3	CDr1	CDr2	CDr3	CDr1	CDr2	CDr3
MEAN	-0.43	-0.01	0.19	0.87	1.26	0.95	0.44	0.83	0.70
STD. DV.	3.04	0.14	1.37	3.63	3.05	3.68	3.49	2.55	3.12
MEDIAN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MIN	-22.96	-0.40	-0.18	-10.00	-5.77	-13.62	-22.96	-5.77	-13.62
MAX	0.26	0.86	10.34	28.95	19.13	14.69	28.95	19.13	14.69
Prob_N							0.00	0.00	0.00

Notes: CDr1, CDr2, and CDr3 stand for the time lag. Prob_N is the significance level for the Shapiro-Wilk test for normality.

CASH FROM OPERATIONS / CURRENT LIABILITIES

The cash from operations to current liabilities ratio addresses the issues of actual convertability to cash, turnover, and the need for a minimum level of cash to maintain operations. It measures liquidity by comparing actual cash flows from operations with current liabilities. Tables 3.24 and 3.25 present nominal and real statistical summaries for this ratio.

Table 3.24 -- Cash From Operations / Current Liabilities (Nominal)

SAMPLE	BANKRUPT			NON-BANKRUPT			OVERALL		
PERIOD	CL1	CL2	CL3	CL1	CL2	CL3	CL1	CL2	CL3
MEAN	-0.08	0.06	0.12	0.96	1.09	0.81	0.61	0.74	0.57
STD. DV.	0.51	0.52	0.59	1.60	2.37	1.19	1.42	2.01	1.07
MEDIAN	-0.06	8E-04	0.14	0.91	0.70	0.57	0.44	0.40	0.37
MIN	-1.24	-1.58	-2.37	-8.35	-12.36	-2.57	-8.35	-12.36	-2.57
MAX	1.74	1.50	1.31	5.09	14.83	5.20	5.09	14.83	5.20
Prob_N							0.00	0.00	0.00

Notes: CL1, CL2, and CL3 stand for the time lag. Prob_N is the significance level for the Shapiro-Wilk test for normality.

Table 3.25 -- Cash From Operations / Current Liabilities (Real)

SAMPLE	BANKRUPT			NON-BANKRUPT			OVERALL		
PERIOD	Clr1*	Clr2*	CLr3*	CLr1*	CLr2*	CLr3*	CLr1*	CLr2*	CLr3*
MEAN	-3.13	4.219	6.43	53.69	54.701	37.426	34.53	37.50	26.70
STD. DV.	25.90	23.89	23.63	89.49	116.89	53.506	78.95	98.97	47.97
MEDIAN	-2.4	0.033	4.74	51.76	34.306	27.37	22.78	19.57	16.25
MIN	-77.92	-46.49	-63.68	-478.31	-587.35	-106.49	-478.3	-587.3	-106.49
MAX	88.25	110.55	109.42	258.17	751.7	215.58	258.1	751.7	215.58
Prob_N							0.00	0.00	0.00

Notes: CLr1, CLr2, and CLr3 stand for the time lag. Prob_N is the significance level for the Shapiro-Wilk test for normality. * Figures are in thousandths.

Section 4: INTRODUCTION TO ESTIMATION METHODS

LOGIT MODEL

The logit model belongs in a group of models called qualitative response models. These models use a discrete outcome for the dependent variable, such as a yes or no decision, so that the conventional regression methods are inappropriate (Greene, 1993).

In this study, the dependent variable is dichotomous. If (Y = 1) then the firm is bankrupt and financially distressed, or if (Y = 0) then the firm is healthy and active. Estimating a logit model is based on the method of maximum likelihood. "Each observation is treated as a single draw from a Bernoulli distribution" Greene, pp. 643, 1993).

The likelihood function is:

$$\text{Prob}\ (Y = 1) = \prod_{y_i = 0} [1 - F(\beta' X_i)] \prod_{y_i = 1} F(\beta' X_i)$$

Where:

F	Cumulative distribution function of the error term
β	Coefficient matrix
X	Matrix of independent variables
Y	Dependent variable
i	Index for observations

The functional form for F will depend on the assumption made about the error term. If the cumulative distribution of the error term is logistic, the resulting model will be the logit model:

$$\text{Prob}\ (Y = 1) = \frac{e^{\beta' X}}{1 + e^{\beta' X}}$$

Where:

Prob   Probability of outcome

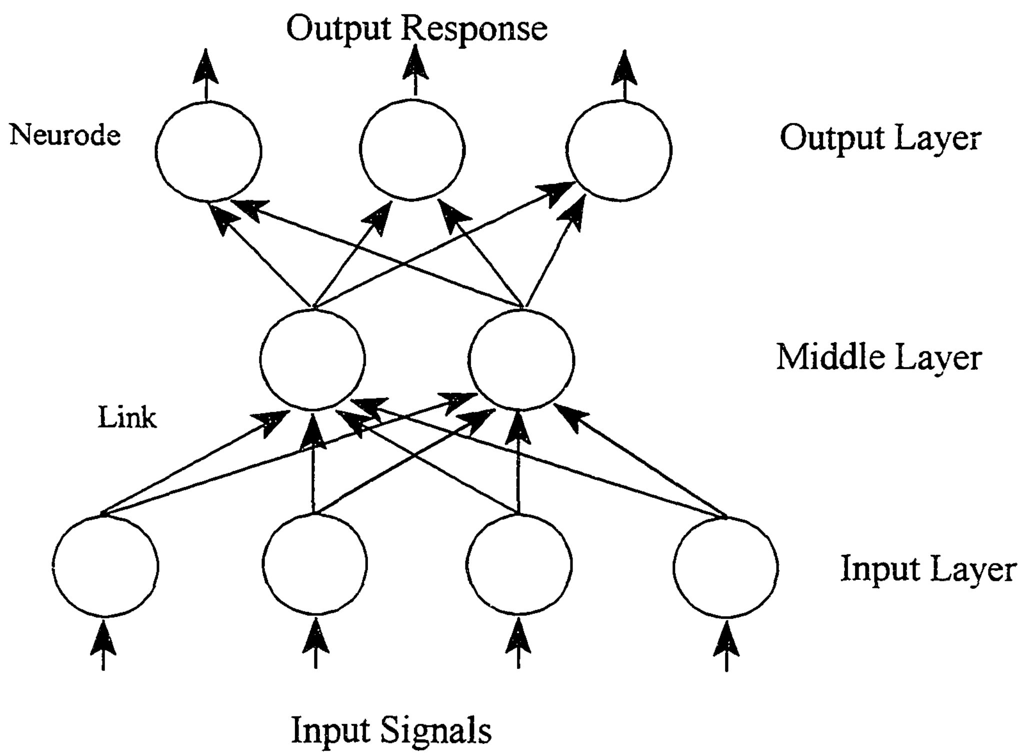
NEURAL NETWORKS

Background:

A neural network is an information processing system that is nonlogarithmic, nondigital, and intensely parallel. It consists of simple, highly interconnected processors called neurodes or units, which are the analogs of the biological neural cells, or neurons, in the brain. The neurodes or units are connected by a large number of weighted links, over which signals can pass. Each neurode receives signals over its incoming connections; some of these incoming signals may arise from other neurodes, and others may come from the outside world. The neurode usually has many of these incoming signal connections; however, it never produces more than a single outgoing signal. An output signal is then transmited over the neurode's outgoing connection. A neurode's connection is split into a very large number of smaller connections, each of which terminates at a different destination. Each of these branches of the single outgoing connection transmits the same signal; the signal is not split or divided among them in any way. Most of these outgoing branches terminate at the incoming connection of some other neurode in the network.

Figure 3.3 illustrates the physical connections of a typical neural network.

Figure 3.3 -- Physical connections of a simple neural network



Neural Network in Operation:

A neurode in a neural network is an extremely simple device. It receives input stimuli along its input connections and translates those stimuli into an output response, which is transmitted along the neurode's output connection.

The mathematical expression that describes the translation of input stimulus pattern to output response signal is called the *transfer function* of the neurode, and it consists of a three-step process. First, the neurode computes the net weighted input (I) it is receiving along its input connections. Most commonly I for neurode i is computed as:

$$I_i = \sum_{j=1}^{n} w_{ij} X_j$$

Where:

I_i	Total input signal for unit i
X_j	Incoming signal from unit j
W_{ij}	Weight of the link from unit i to unit j
j	Index for all units in the net linked to unit i

Once I_i is computed, all information about which input signals were strong and which were weak has been lost. A strong input signal arriving over a weakly weighted connection may have less effect than a weaker signal arriving over a strongly weighted connection. Thus, it is the net stimulus that matters, not the value of any particular one. A weight may be negative instead of positive. In this case the connection is said to be inhibitory; that is, it tends to reduce the overall stimulation of the receiving neurode.

The second step of the translation operation represented by the neurode's transfer function consists of converting the net input to an activation level for the neurode. The activation level of the neurode is equivalent to the level of excitement of a biological neuron. The default activation function in the software used is *Logistic.*

$$a_j(t+1) = \frac{1}{1 + e^{-(\sum W_{ij} O_i(t))}}$$

Where:

$a_j(t)$	Activation of unit j in step t
$O_i(t)$	Output of unit i in step t
W_{ij}	Weight of the link from unit i to unit j

With this function, the network computes the network input simply by summing over all weighted activations and then containing the results with the logistic function. The final step accomplished by the transfer function is to convert the neurode's activation level to an output signal. Most commonly, this is done by setting the output signal to the following expression:

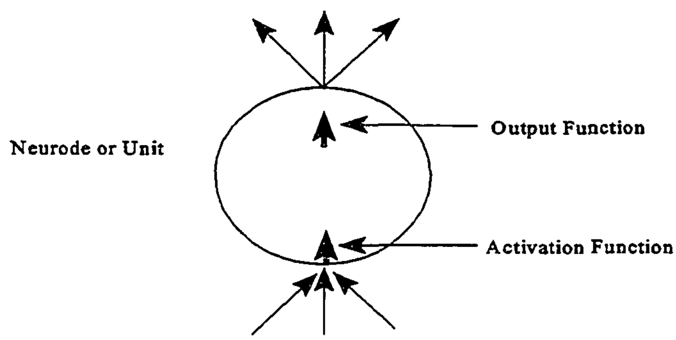
$$O_i = \begin{cases} a_i(t), \text{ if } a_i(t) > T \\ \text{or} \\ 0 \text{ , otherwise} \end{cases}$$

Where:

T Threshold value

The neurode's output is its activation level, or a user defined output value, as long as the activation value exceeds a given threshold, otherwise the neurode outputs nothing. The software used, SNNS (Stuttgart Neural Network Simulator) allows the user to specify an activation function and an output function for each neurode or unit. This feature allows for great flexibility in building a neural network. Figure 3.4 presents this feature graphically:

Figure 3.4 -- A graphical presentation of the Activation and Output functions within a unit in a network



Training a Neural Network:

Neural networks learn to solve a problem; they are not programmed to do so. Learning is achieved not by modifying the neurodes in the network but by modifying the weights on the interconnections in the network. Each neurode's output is determined by two things only: the incoming signal and the weights on the input connections to the neurode. If the neurode is to learn to respond correctly to a given incoming signal pattern, the only possible element that can be used to improve the neurode's performance is the weight on the connection. Learning in neural networks consists of making systematic changes to these weights to improve the network's response performance to acceptable levels.

Training is done by example, and it can take place in three distinct ways.

The most common training method is supervised training. In this technique, the network is provided with an input stimulus pattern along with the corresponding desired output pattern. The learning law for such networks typically computes an error, which is the difference between the desired output and the network's actual output. This error is then used to modify the weights on the interconnections between the neurodes.

The second procedure is graded training, sometimes called reinforcement training. This is similar to supervised training except that the exact desired output is not provided, only a "grade" on how well the network is doing.

The third training procedure is called unsupervised training, or self organization. In this procedure the network is presented only with a series of input patterns and is given no information or feedback at all about its performance levels. Networks that use this kind of training procedure are most often used only for categorization or statistical modeling applications because the network's specific responses cannot be determined by the designer.

This chapter included the research methodology and a description of the general models used in this study. The chapter also included a description of the population and the steps followed in choosing the sample of companies used in this study. Each variable was analyzed and a table of descriptive statistics was developed for each. Finally, the two estimation methods were discussed.

As expected, the descriptive statistics for variables that measure performance for bankrupt firms generally were lower than those of nonbankrupt firms. Variables that measure financial leverage were generally higher for bankrupt firms. The Shapiro-Wilk test for normality indicated that all the variables were not normally distributed, thus, using a logit model is a better predictor of bankruptcy than discriminant analysis.

CHAPTER IV

EMPIRICAL ANALYSIS

The purpose of this chapter is to report the process and findings of the empirical analysis. The first part of this chapter discusses the estimation of the logit model. The second part discusses the estimation of the neural network models. Finally, the last part evaluates and ranks all of the models.

The six general models and the variables used are listed below. The dependent variable in all of the models is dichotomous, taking the value of 1 and 0, for bankrupt (or financially-distressed) and nonbankrupt, respectively.
Each model has the following format:

Probability (Prob.) of bankruptcy = f (independent variables)

Model I:

Prob. of Bankruptcy = f(Nominal accrual ratios)

Model II:

Prob. of Bankruptcy = f(Nominal cash flow ratios)

Model III:

Prob. of Bankruptcy = f(Real accrual ratios)

Where the variables are the same as the variables in model I, except they are adjusted by interest rates and oil prices in the way described in chapter three.

Model IV:

Prob. of Bankruptcy = f(Real cash flow ratios)

Where the variables are the same as the variables in model II, except they are adjusted by interest rates and oil prices in the way described in chapter three.

Model V:

Prob. of Bankruptcy = f(Real accrual ratios; economic factors)

The interest rate and oil price for the year before bankruptcy are added as extra independent variables on model III. The reason for including these variables, is to test the hypothesis that oil and gas firms are affected directly by these variables. Only one lag year is used for these variables because it is assumed that the effect of these variables is immediate on the current operations of the firm. The lagged effect of interest rates and oil price is assumed to be captured by the use of real variables in the model.

Model VI:

Prob. of Bankruptcy = f(Real cash flow ratios; economic factors)

Interest rate and oil price for the year before bankruptcy are added as extra independent variables on model IV.

Section 1: THE LOGIT MODELS

Selection of the Preferred Model:

This study uses the top-down approach suggested by D.F. Hendry (1979). This approach starts with a very general model with many variables. The model is then simplified with a simplification test (Maddala 1992).

Likelihood Ratio:

The simplification test is done, using the likelihood ratio (LR) procedure in the following way. Let the hypothesis be that K variables do not belong in the model, taking the form H_0: $\beta_i = 0$, where β_i is the parameter being estimated for variable K. Let L_u be the maximum likelihood estimate for the model without any restriction on variable K, and let L_r denote the restricted maximum likelihood estimate, that is, the estimates obtained while imposing the null hypothesis. Then the likelihood ratio is calculated as:

$$LR = -2 * [\mathit{ln}\, L_r - \mathit{ln}\, L_u]$$

Where:

LR	Likelihood ratio
ln	Natural logarithm
L_r	Maximum likelihood estimate with restrictions
L_u	Maximum likelihood estimate without restrictions

The LR test has a χ^2 distribution with degrees of freedom equal to the number of restrictions (Greene 1993, pg. 380).

Measuring Goodness of Fit:

To measure the goodness of fit for the logit models, this study uses the Count R^2, defined as:

$$\text{Count } R^2 = \frac{\text{number of correct predictions}}{\text{total number of observations}}$$

According to Maddala (1992) this measurement of goodness of fit could be a good discriminator between models in certain problems. Since the purpose of this study is to classify firms as bankrupt and nonbankrupt, the count R^2 is a good measurement of the goodness of fit.

Condition Number:

To test for multicollinearity, this study calculates the condition number, a measurement suggested by D.E. Belsley et al. (1980). The condition number of a data matrix is the square root of the ratio of the largest to the smallest characteristic root (Greene 1993, pg. 33):

$$\gamma = \sqrt{\frac{\lambda \ max}{\lambda \ min}}$$

Where:

γ Condition number

λ Characteristic root of the data matrix

The rule of thumb is that values more than 20 for the condition number are considered to be large. Thus, if a model's calculated condition number is larger than 20, then multicollinearity might be present. According to Maddala (1992), multicollinearity is caused by high intercorrelation between the explanatory variables. The resulting effect of multicollinearity is that the standard errors will be very high and the t-ratios will be very low, thus the confidence interval for the parameters of interest will be very wide.

Marginal Effects:

Marginal effects are the effect of a unit change in the independent variable on the change in the probability of the dependent variable. In a nonlinear regression like the logit model, the marginal effects are not the parameters of the model.

In this study, the marginal effects for the logit model are calculated at the mean of the independent variables. For specific purposes marginal effects could be calculated at different values of the independent variables. Marginal effects are important when speaking about what will happen to the probability of bankruptcy if the value of one ratio changes by one unit. Marginal effects for the logit model are calculated as (Greene 1993, pg. 639):

$$\frac{\partial E[Y]}{\partial X} = \Lambda(\beta' X)\ (1 - \Lambda(\beta' X))\,\beta$$

Where:

E[.]	Expectation operator
$\Lambda(.)$	Logistic cumulative distribution function
β	Estimated parameters
Y	Dependent variable
X	Independent variable

Model I: Nominal Accrual Ratios

The results of the restriction test for model I are presented in Table 4.1. The significance level of the LR test for the joint test of restrictions is .999 thus, we cannot reject the hull hypothesis that the following variables do not belong in the model: WC3, EB3, IQ2, IQ3.

The marginal effects for model I are not reported due to a calculation problem caused by the strong effect the variable WC1 has on the model. Since the condition number is 21.2, multicollinearity among the factors does not to create a sever problem.

Model II: Nominal Cash Flow Ratios

The restriction test for model II is presented in Table 4.2. The significance level of the LR test for a joint test of restrictions is .789; thus we cannot reject the null hypothesis that the following variables do not belong in the model: CI1, CI2, CI3, CD1, CL1, and CL2.

The marginal effects for model II are also presented in the table. The condition number is 3.79, suggesting that multicollinearity does not pose any problem.

Model III: Real Accrual Ratios

The restriction test for model III is presented in table 4.3. The significance level for the joint test of restrictions is .827; thus we cannot reject the null hypothesis that the following variables do not belong in the model: WCr2, WCr3, REr1, EBr3, DQr1, DQr2, IQr1, and IQr3.

The condition number for model III is 17.6; thus, multicollinearity among the independent variables does not seem to pose a problem. Marginal effects of the independent variables are also reported.

Model IV: Real Cash Flow Ratios

The restriction test for model IV is presented in Table 4.4. The significance level for the LR test for the joint test of restrictions is .443; thus we cannot reject the null hypothesis that the following variables do not belong in the model: CSr3, CIr1, CIr2, CIr3, CAr1, CDr1, CLr1, and CIr2. The marginal effects and a condition number of 3.8 are also presented.

Model V: Real Accrual Ratios with Economic Variables

Model V uses the same real accrual ratios used in model III but it adds two economic factors: the interest rate and the price of oil. The purpose of including these variables in the model is to test their importance as predictors of bankruptcy in the oil and gas industry.

The restriction test for model V is presented in table 4.5. The significance level for the LR test for the joint test of restrictions is .390; thus we cannot reject the hull hypothesis that the following variables do not belong in the model: WCr2, WCr3, REr1, EBr3, DBr1, DBr3, DQr1, DQr2, IQr1, and IQr2.

Two significant changes noticed because of including the interest rate and the oil price as independent variables, are that the count R^2 of the model improved form 83.95 percent to 95.68 percent. This suggests that the interest rate and the oil price are important variables in classifying bankrupt and nonbankrupt firms in the oil and gas industry.

The other significant change is that the condition number went up from 17.6 to 30.49. This increase in the condition number is due to the presence of interest rate and oil price as deflators in the other independent variables.

Model VI: Real Cash Flow Ratios with Economic Variables

Model VI uses the same real cash flow ratios used in model IV but it adds two economic factors, the interest rate and the price of oil. The restriction test for model VI is presented in table 4.6. The significance level for the LR test for the joint test of restrictions is .924; thus we cannot reject the null hypothesis that the following variables do not belong in the model: CSr1, CIr2, CIr3, CDr1, and CLr2.

Again the classification power increased from 75.30 percent to 91.35 percent in model VI with the addition of the interest rate and oil prices. The condition number also went up from 3.84 to 33.73 for the reason explained above under model V.

Since variables used in this study are lagged three years, a meaningful way of interpreting the effect of a unit change in the independent variable on the change in the probability of the dependent variable is to calculate the long run multiplier for each variable. In time series analysis, long-run multipliers are calculated on the assumption that there is a long-run relationship between the dependent variable and the independent variable. This is done by eliminating the lags for the independent variable; thus one can take the independent variable as a common factor and the long-run multiplier is equal to the sum of the independent variable's coefficients. Thus:

$$Y_t = \beta_1 X_{t-1} + \beta_2 X_{t-2} + \beta_3 X_{t-3}$$

lag eliminated: $$Y = \beta_1 X + \beta_2 X + \beta_3 X$$

$$Y = (\beta_1 + \beta_2 + \beta_3)\, X$$

long run multiplier: $$\frac{\partial Y}{\partial X} = \beta_1 + \beta_2 + \beta_3$$

Where:

Y Dependent variable

X Independent variable

β_i Coefficient; $i = 1,2,3....$

In logit, marginal effects are equivalent to the coefficients of a linear regression model. Tables 4.7 and 4.8 present the long run multiplier for each variable.

Table -- 4.1 Model I: Nominal Accrual Ratios

Variable	Coefficient	t-ratios
Constant	5.62	(6.4)
WC1	-497.13	(-27.6)
WC2	-113.73	(-21.9)
RE1	-0.88	(-2.4)
RE2	13.95	(11.1)
RE3	-12.27	(-13.2)
EB1	45.87	(11.0)
EB2	-23.12	(-7.6)
EB3	63.84	(14.8)
DB2	-113.23	(-20.6)
DB3	-11.79	(-2.2)
DQ1	-5.65	(-13.3)
DQ2	4.78	(9.1)
DQ3	11.55	(14.0)
IQ1	-32.05	(-22.6)

Log-Likelihood	-0.00005
Restricted (Slopes=0) Log-L.	-104.44
LR test that all the coefficients = 0	208.89
Significance level	0.000
Significance level for the test of restrictions	.999
Count R^2	100%
Condition number	21.2

Notes: The 1, 2, and 3 in the name of the variables indicate the number of year lags. The numbers in parentheses are t-ratios. Variables are described in Chapter 3.

Table -- 4.2 Model II: Nominal Cash Flow Ratios

Variable	Coefficient	t-ratio	Marginal Effect	t-ratio
Constant	0.03	(0.1)	0.62E-02	(0.1)
CS1	-0.29	(-1.8)	-0.50E-01	(-1.8)
CS2	0.77	(2.0)	0.14	(2.0)
CS3	-0.61	(-1.8)	-0.11	(-1.7)
CA1	-1.41	(-1.5)	-0.27	(-1.5)
CA2	-6.07	(-2.5)	-1.14	(-2.5)
CA3	6.86	(1.9)	1.29	(2.0)
CD2	-13.23	(-2.8)	-2.49	(-3.1)
CD3	4.70	(2.3)	0.88	(2.3)
CL3	-1.40	(-2.7)	-0.26	(-2.7)

Log-Likelihood	-75.71
Restricted (Slopes=0) Log-L.	-104.44
LR test that all the coefficients = 0	57.45
Significance level	0.00
Significance level for the test of restrictions	.789
Count R^2	77.78%
Condition number	3.7

Notes: The 1, 2, and 3 in the name of the variables indicate the number of year lags. The numbers in parentheses are t-ratios. Variables are described in Chapter 3.

Table -- 4.3 Model III: Real Accrual Ratios

Variable	Coefficient	t-ratio	Marginal Effect	t-ratio
Constant	0.92	(1.9)	0.15	(2.0)
WCr1	-12.91	(-4.0)	-2.09	(-6.5)
REr2	-25.64	(-2.5)	-4.15	(-2.5)
REr3	24.90	(2.5)	4.03	(2.4)
EBr1	-1242.90	(-3.9)	-200.94	(-4.6)
EBr2	1545.70	(2.7)	249.90	(2.7)
DBr1	3.42	(-2.8)	-0.55	(-3.1)
DBr2	10.29	(3.1)	1.66	(2.8)
DBr3	-6.95	(-1.8)	-1.12	(-1.6)
DQr3	0.02	(2.0)	0.38E-02	(1.8)
IQr2	-9.63	(-1.9)	-1.56	(-1.8)

Log-Likelihood	-58.19
Restricted (Slopes=0) Log-L	-104.44
LR test that all the coefficients = 0	92.51
Significance Level	0.000
Significance level for the test of restrictions	0.827
Count R2	83.95%
Condition number	17.6

Notes: The 1, 2, and 3 in the name of the variables indicate the number of year lags. The numbers in parentheses are t-ratios. Variables are described in Chapter 3.

Table -- 4.4 Model IV: Real Cash Flow Ratios

Variable	Coefficient	t-ratios	Marginal Effects	t-ratio
Constant	0.12	(0.4)	0.02	(0.4)
CSr1	-0.40	(-1.5)	-0.07	(-1.4)
CSr2	0.70	(2.3)	0.12	(2.3)
CAr2	-2709.70	(-3.2)	-482.99	(-3.2)
CAr3	3256.50	(2.4)	580.46	(2.4)
CDr2	-0.67	(-3.0)	-0.12	(-3.3)
CDr3	0.22	(2.3)	0.04	(2.2)
CLr3	-36.69	(-3.0)	-6.54	(-3.1)

Log-Likelihood	-77.77
Restricted (Slopes=0) Log-L.	-104.44
LR test that all the coefficients = 0	53.34
Significance level	0.000
Significance level for the test of restrictions	0.443
Count R^2	75.30%
Condition number	3.8

Notes: The 1, 2, and 3 in the name of the variables indicate the number of year lags. The numbers in parentheses are t-ratios. Variables are described in Chapter 3.

Table -- 4.5 Model V: Real Accrual Ratios; Economic Variables

Variable	Coefficient	t-ratios	Marginal Effects	t-ratio
Constant	2.72	(0.6)	0.48	(0.6)
WCr1	-39.42	(-4.0)	-7.00	(-2.9)
REr2	-34.90	(-3.4)	-6.19	(-2.6)
REr3	32.11	(3.3)	5.70	(2.5)
EBr1	-2151.70	(-3.1)	-381.62	(-2.5)
EBr2	1641.10	(2.0)	291.06	(2.0)
DBr2	6.23	(2.0)	1.11	(1.7)
IQr3	-142.53	(-3.4)	-25.28	(-2.5)
IT1	1166.10	(3.1)	206.81	(2.0)
OL1	-3.63	(-2.7)	-0.64	(-1.8)

Log-Likelihood	-16.39
Restricted (Slopes=0) Log-L.	-104.4
LR test that all the coefficients = 0	176.09
Significance level	0.000
Significance level for the test of restrictions	0.390
Count R^2	95.68%
Condition number	30.4

Notes: The 1, 2, and 3 in the name of the variables indicate the number of year lags. The numbers in parentheses are t-ratios. IT is interest rate, OL is oil price. Other variables are described in Chapter 3.

Table -- 4.6 Model VI: Real Cash Flow Ratios; Economic Variables

Variable	Coefficient	t-ratios	Marginal Effects	t-ratio
Constant	-0.61	(-0.2)	-0.15	(-0.2)
CSr2	0.70	(2.3)	0.17	(2.3)
CSr3	-1.84	(-3.5)	-0.44	(-3.4)
CIr1	0.01	(1.8)	0.42E-02	(1.9)
CAr1	868.53	(2.5)	208.44	(2.2)
CAr2	3030.20	(-2.9)	-727.23	(-2.9)
CAr3	3934.70	(3.0)	944.29	(3.1)
CDr2	-0.96	(-2.9)	-0.23	(-3.3)
CDr3	0.42	(3.8)	0.09	(4.1)
CLr1	-9.30	(-2.6)	-2.23	(-2.5)
CLr3	-28.93	(-2.1)	-6.94	(-2.2)
IT1	566.33	(3.6)	135.91	(3.1)
OL1	-1.75	(-2.8)	-0.42	(-2.5)

Log-Likelihood	-42.43
Restricted (Slopes=0) Log-L.	-104.44
LR test that all the coefficients = 0	124.02
Significance level	0.000
Significance level for the test of restrictions	0.924
Count R2	91.35%
Condition number	33.7

Notes: The 1, 2, and 3 in the name of the variables indicate the number of year lags. The numbers in parentheses are t-ratios. IT is interest rate, OL is oil price. Other variables are described in Chapter 3.

Table -- 4.7 Long Term Multiplier of Accrual Ratios on the Probability of bankruptcy

Nominal Accrual	Multip.	Real Accrual	Multip.	Real/E Accrual	Multip.	EXP (-/+)
WC	na	WCr	-2.08	WCr	-6.99	-
RE	na	REr	-0.11	REr	-0.49	-
EB	na	EBr	48.96	EBr	-90.56	-
DB	na	DBr	-0.01	DBr	1.1	+
DQ	na	DQr	0.003	DQr	na	+
IQ	na	IQr	-1.56	IQr	-25.28	-
Economic Factors						
IT					206.81	+
OL					-0.64	-

Notes: Multip. is long run multiplier; (na) variable was not estimated; Real/E real ratios with economic variables; EXP(-/+) expected sign; variables are described in Chapter 3.

Table -- 4.8 Long Term Multiplier of Cash Flow Ratios on the Probability of bankruptcy

Nominal Cash	Multip.	Real Cash	Multip.	Real/E Cash	Multip.	EXP (-/+)
CS	-0.0020	CSr	0.053	CSr	-0.27	-
CI	na	CIr	na	CIr	0.0042	-
CA	-0.11	CAr	97.47	CAr	425.5	-
CD	-1.6	CDr	-0.080	CDr	-0.13	-
CL	-0.26	CLr	-6.54	CLr	-9.17	-
Economic Factors						
IT					135.91	+
OL					-0.42	-

Notes: Multip. is long run multiplier; (na) variable was not estimated; Real/E real ratios with economic variables; EXP(-/+) expected sign; variables are described in Chapter 3.

Section 2: Neural Network Models

Building a neural network model starts with defining the number of input, hidden, and output units, based on the problem confronted. In this study, the number of independent variables for each model will determine the number of input units. Thus, for models I and III the number of input units is 18 for both models (six variables with three lagged observations for each). For models II and IV the number of input units is 15 for both models (five variables with three lagged observations for each), for models V and VI the numbers of input units are 20 and 17 respectively.

According to Fletcher and Goss (1993) the number of hidden units for optimal generalization should be tested in a range from approximately ($2\sqrt{n} + m$) to the value (2n+1), where n and m represent the number of input and output units respectively.

The number of output units for all of the models is set to one, since the neural network will be tested to classify the firms either as bankrupt or not. This study uses an advanced neural network simulator called SNNS (Stuttgart Neural Network Simulator) from the University of Stuttgart, Germany. All of the models developed are feed-forward networks which implement an error back-propagation methodology. Back-propagation permits connection weights W_i between units to be modified in a supervised fashion using gradient descent to minimize the error function. In supervised learning models, known pattern pairs of target outputs and neural network outputs are repeatedly presented to the network to adjust the network W_i.

The transfer function for all of the units of the network is set to the logistic function described in chapter three. The output function for all of the units in the model, except the unit in the output layer, is set to an identity function that makes the output of a unit equal to its activation value:

$$O_j(t) = a_j(t)$$

Where:

$O_j(t)$ Output for unit j at step t

$a_j(t)$ Activation value of unit j at step t

The output function for the unit in the output layer is set to a threshold function:

$$O_j(t) = \begin{cases} 0 \text{ if } a_j(t) < .5 \\ 1 \text{ if } a_j(t) > .5 \end{cases}$$

The output function for the models is defined this way to make the results of the neural network models comparable with the results of the logit models.

Neural networks perform best when they are presented with large sets of data. This is not possible in this study, since the total number of observations is 162. A method called *v*-fold cross validation, introduced by Geisser (1975) and

Wahba et al (1975) solves this problem.

The method divides the total data set into v randomly selected disjoint subsets P of roughly equal size. Let N_j denote the number of observations in subset P_j. Let λ be an estimator trained on all data except for the observations in subset P_j. Then, the cross-validation mean square error (MSE) for subset P_j is (Utans and Moody, 1991):

$$CV_{P_j} = \frac{1}{N_j} \cdot \sum (t_k - \lambda(X_k))^2$$

Where:

CV_{P_j}	Cross validation error for subset P_j
t_k	Training output for observation k
$\lambda(X_k)$	Network's output for observation k

and for the whole network the cross validation error is:

$$CV(\lambda) = \frac{1}{v} \cdot \sum CV_{P_j}$$

Where:

$CV(\lambda)$	Cross validation error for the network λ
v	Number of disjoint sets

Thus, the first formula calculates the prediction error for all of the observations in subset P_j and the second formula calculates the prediction error across all of the subsets. This way, a cross-validation error for the whole network can be calculated.

The complete data set (162 observations) is used to find the best architecture for the network. The best architecture is chosen to minimize the mean square error (MSE) for the network defined as:

$$MSE = \frac{1}{N} \cdot \sum (t_k - \lambda(X_k))^2$$

Where:

MSE	Mean squared error
N	Number of observations

After the best architecture is found, the *v*-fold cross validation method is applied. The whole data set is divided into eighteen disjoint sets with nine observations in each set (162=18x9).

Building the Neural Network Models:

First, the whole data set is used to find the best architecture. The simulation begins with specifying the number of input units equal to the number of independent variables. Using the formula (2n+1) the maximum number of hidden units is set for each model. The number of output units for all models is set at one.

The network is then trained to minimize its MSE. Similar to the restriction test aimed at simplifying the model in the logit section, a neural network model can also be simplified by a process called pruning. Pruning algorithms try to make neural networks smaller by pruning unnecessary units. By using a pruning algorithm called *skeletonization* (SNNS 1994) the general models are simplified.

Skeletonization prunes units by estimating the change of the error function when a unit is removed:

$$P_i = \frac{\Delta E}{\Delta \alpha}$$

Where:

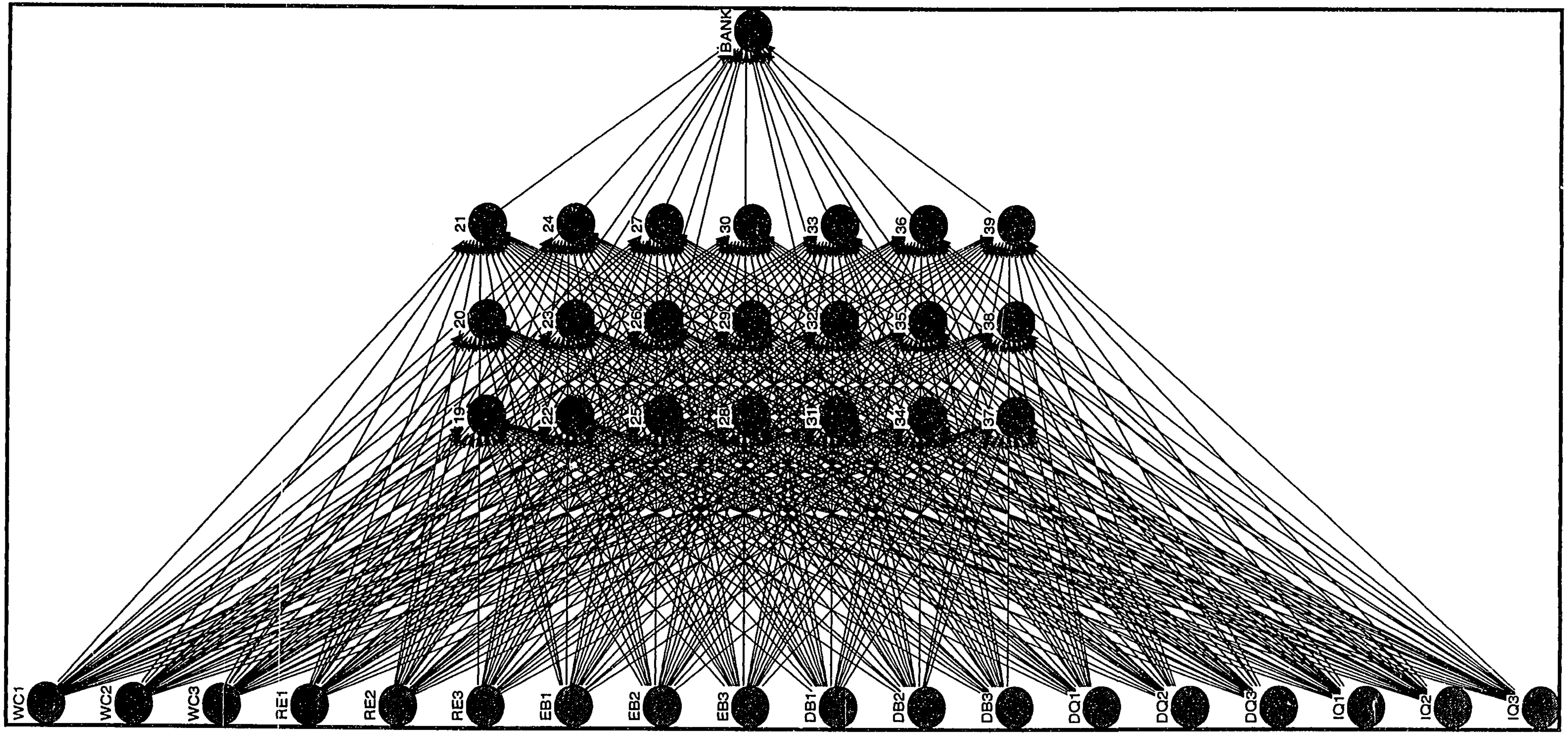
P_i	Change in the error term caused by the removal of unit α_j.
ΔE	Change in the error term.
$\Delta \alpha_j$	Removal of the unit α_j.

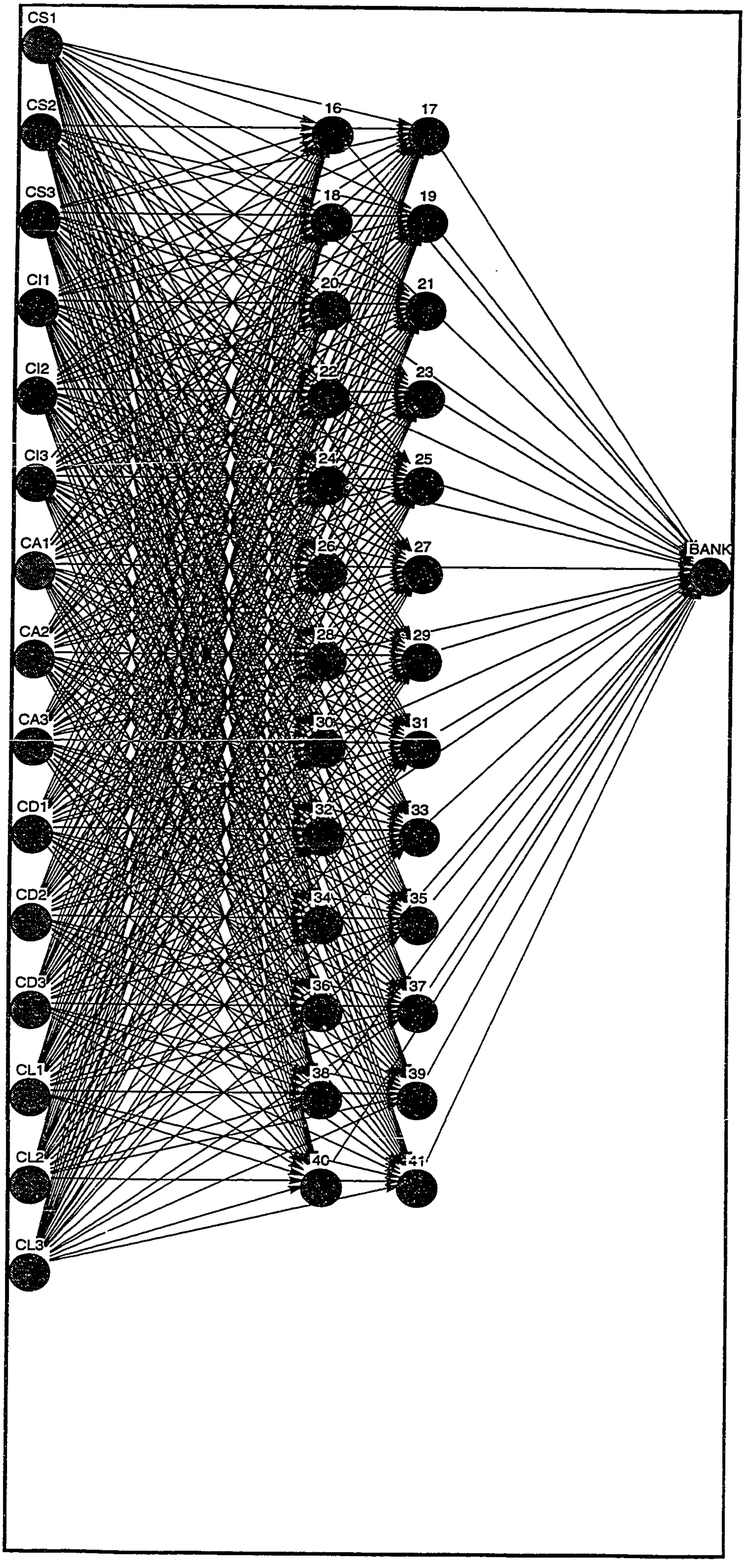
Applying this pruning algorithm to both input and hidden units of the general models, resulted in the elimination of some of the hidden units from each model but none of the input units. Table 4.9 presents a summary of the neural network architecture for all of the models, Figures 4.1 through 4.6 present a graphical presentation of the models.

Table 4.9 -- Neural Network Architecture for the Models

MODEL	INPUT	HIDDEN	OUTPUT
I	18	21	1
II	15	26	1
III	18	36	1
IV	15	28	1
V	20	36	1
VI	17	33	1

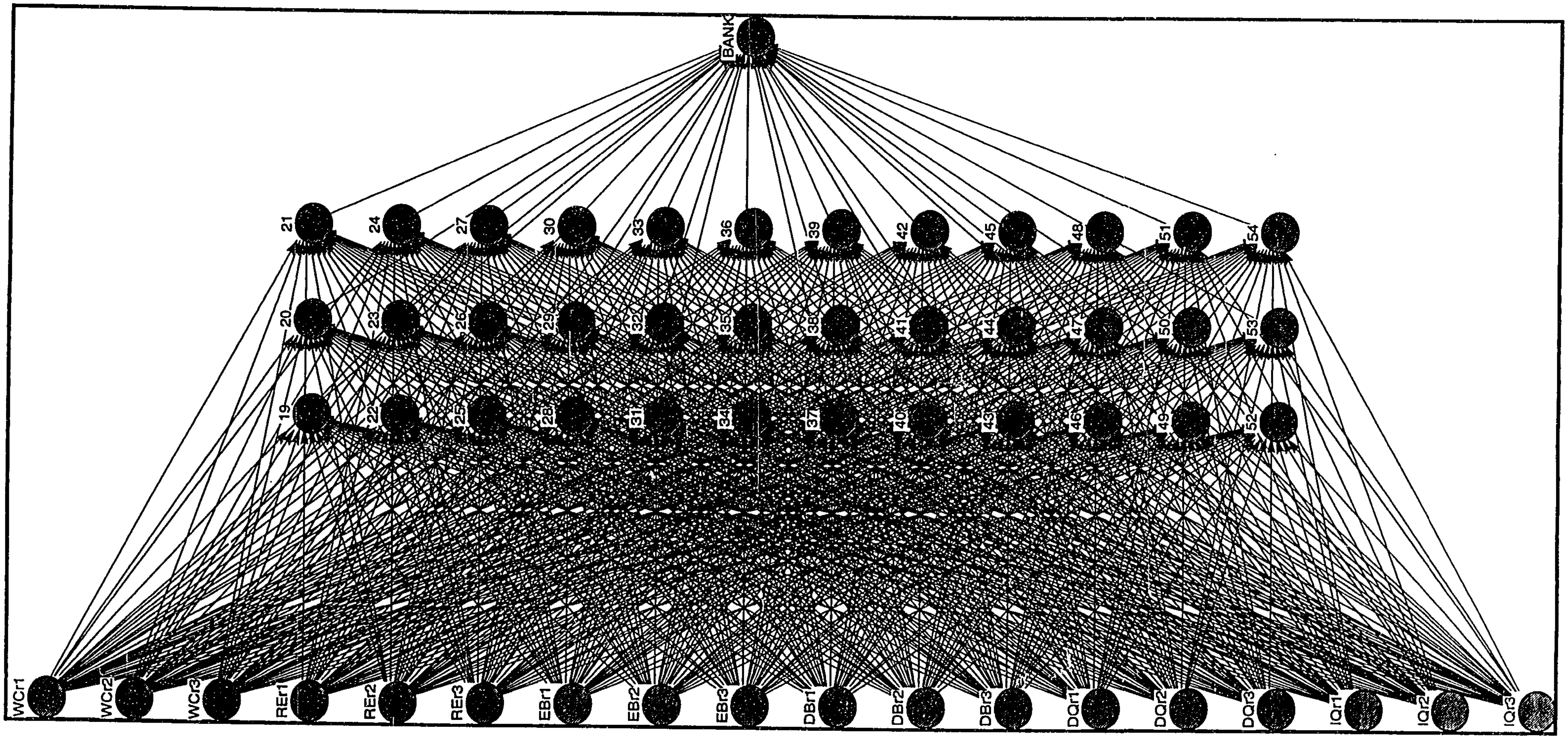
Model I: Nominal Accrual Ratios (Neural Network Architecture)



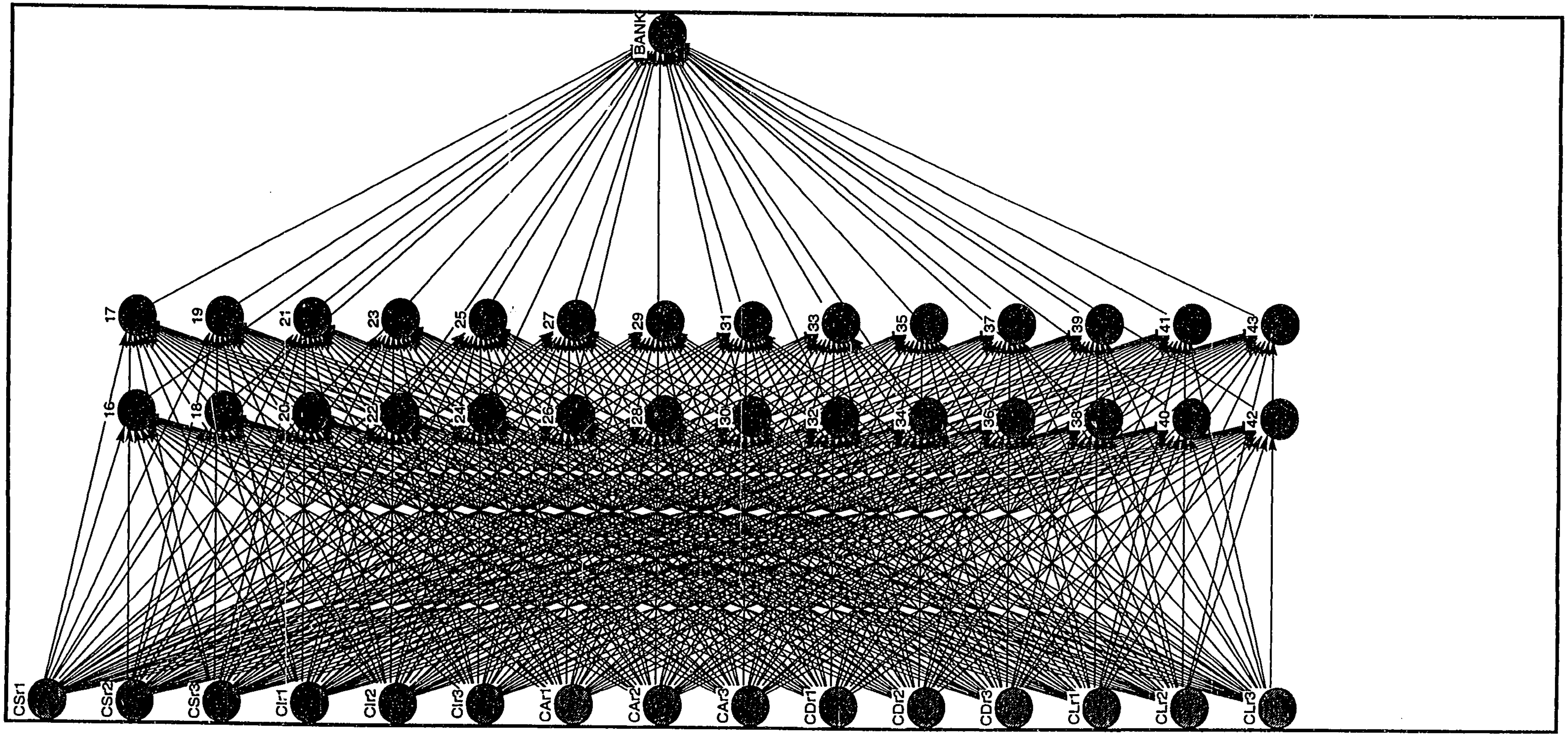


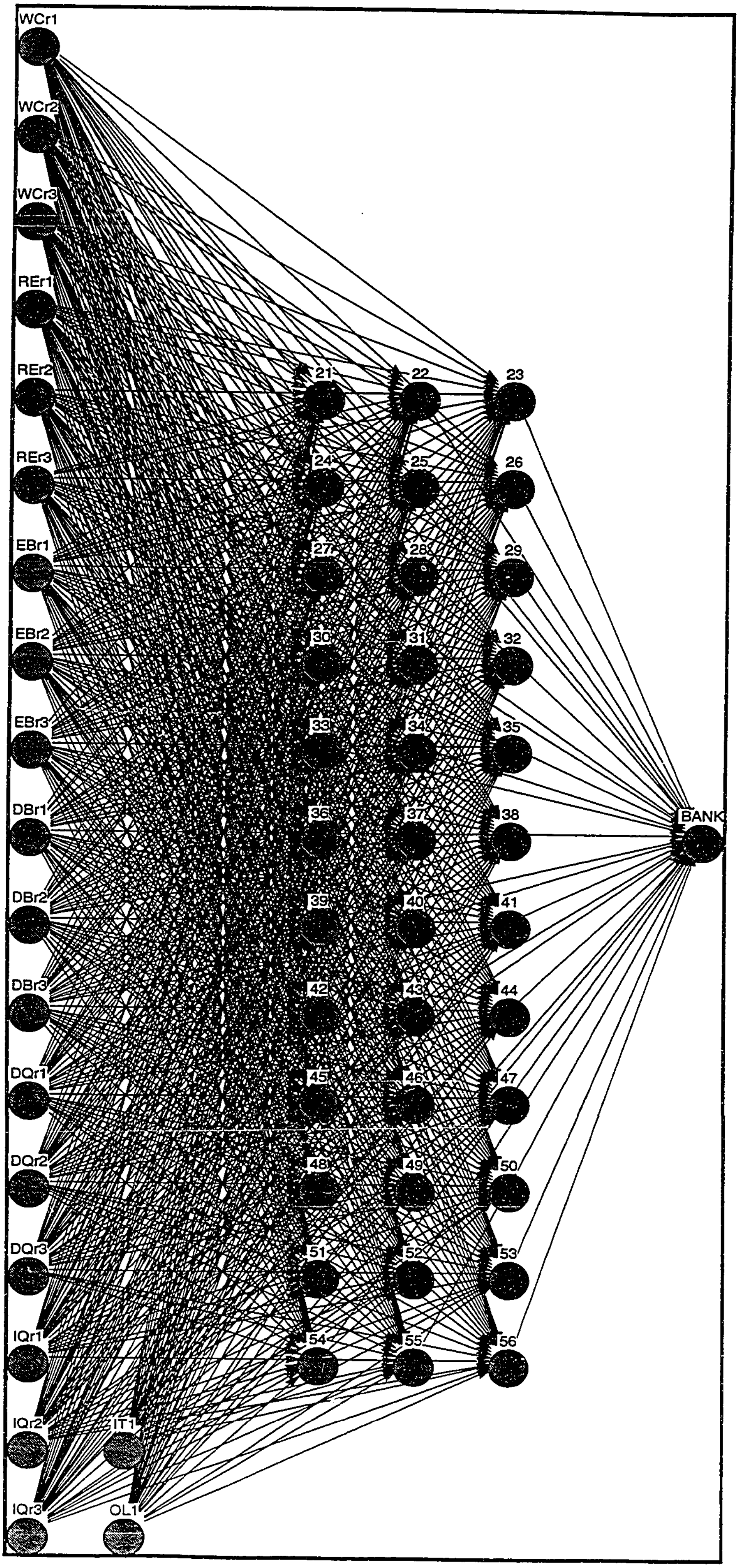
Model II: Nominal Cash Flow Ratios (Neural Network Architecture)

Model III: Real Accrual Ratios (Neural Network Architecture)



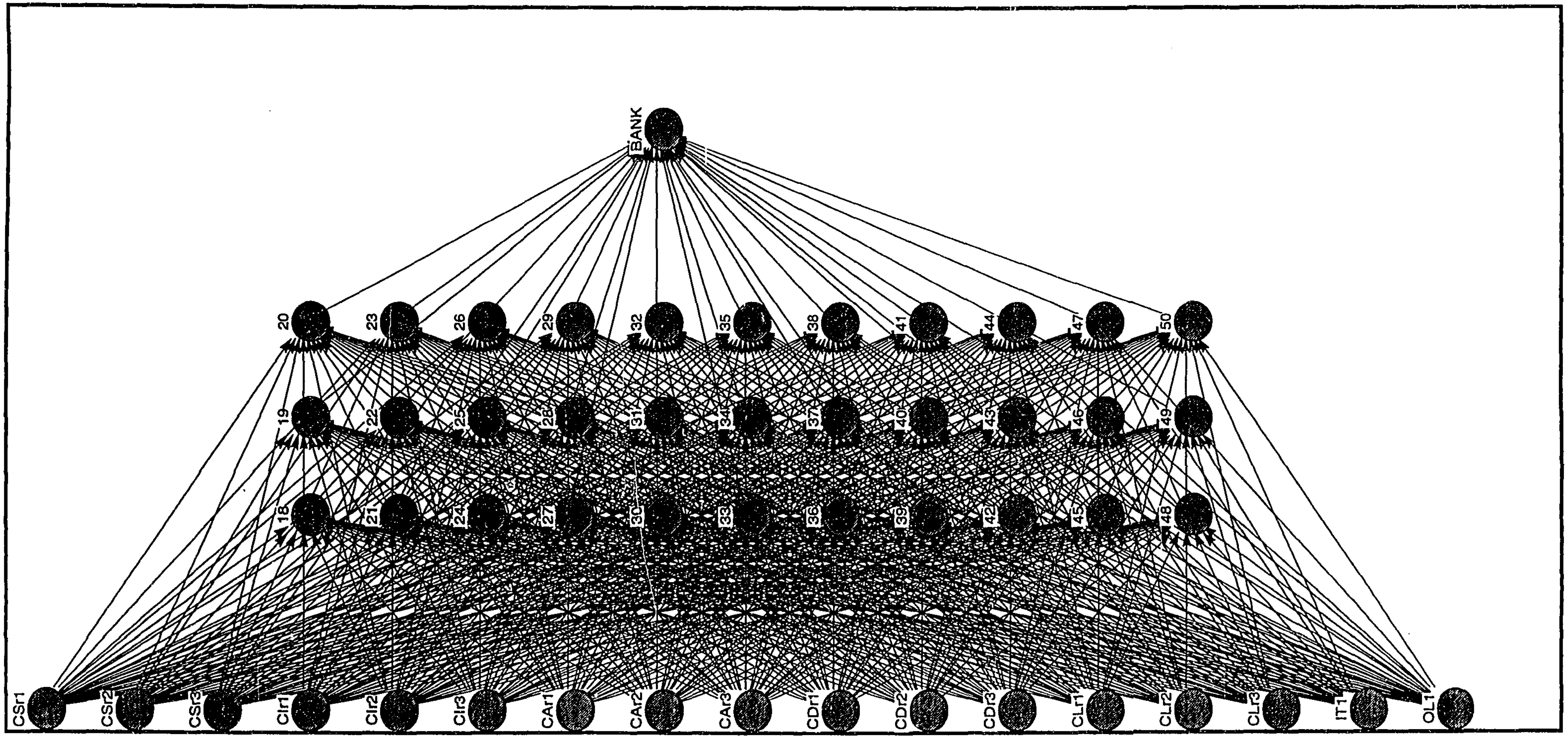
Model IV: Real Cash Flow Ratios (Neural Network Architecture)





Model V: Real Accrual Ratios with Economic Variables
(Neural Network Architecture)

Model VI: Real Cash Flow Ratios with Economic Variables
(Neural Network Architecture)



Section 3: Evaluation of the Models

As stated earlier, this study will use the *v*-fold cross validation method to evaluate the predictive accuracy of the different models. Each logit model is estimated 18 times using a different set of 153 observations, then the estimated model is used to classify the remaining nine observations. This method tests the classification power of the estimated model on a set of observations that were not used in its estimation. An error rate is calculated for each of the 18 runs and then a cumulative error rate is calculated for the whole model. The end result of the v-fold cross validation method is that each model is tested to classify all of the 162 observations using disjoint sets of observations to estimate and then test the model. Similarly, the neural network models were evaluated in the same manner described above for the logit models. Tables 4.10 though 4.15 present the performance results for all the models. Models are then ranked based on their cross validation error, where the best model is the one with the smallest cross validation error rate.

Table 4.10 -- Model I Nominal Accrual Based Ratios

EVALUATION	METHOD	
CRITERIA	LOGIT	NEURAL NETWORK
Total Missed	7	0
Total Accuracy	95.68%	100%
Bankrupt %	94.64%	100%
Nonbankrupt %	96.23%	100%
CV Error	0.043	0.00

Notes: CV cross validation error. Total sample is 162, with 56 and 106 bankrupt and nonbankrupt firms, respectively.

Table 4.11 -- Model II Nominal Cash Flow Based Ratios

EVALUATION	METHOD	
CRITERIA	LOGIT	NEURAL NETWORK
Total Missed	50	14
Total Accuracy	69.14%	91.36%
Bankrupt %	69.64%	85.71%
Nonbankrupt %	68.87%	94.34%
CV Error	0.386	0.086

Notes: CV cross validation error. Total sample is 162, with 56 and 106 bankrupt and nonbankrupt firms, respectively.

Table 4.12 -- Model III Real Accrual Based Ratios

EVALUATION CRITERIA	METHOD LOGIT	NEURAL NETWORK
Total Missed	43	5
Total Accuracy	73.46%	96.91%
Bankrupt %	76.79%	98.21%
Nonbankrupt %	71.70%	96.23%
CV Error	0.265	0.030

Notes: CV cross validation error. Total sample is 162, with 56 and 106 bankrupt and nonbankrupt firms, respectively.

Table 4.13 -- Model IV Real Cash Flow Based Ratios

EVALUATION CRITERIA	METHOD LOGIT	NEURAL NETWORK
Total Missed	43	28
Total Accuracy	73.46%	82.72%
Bankrupt %	71.43%	66.07%
Nonbankrupt %	74.53%	91.51%
CV Error	0.265	0.172

Notes: CV cross validation error. Total sample is 162, with 56 and 106 bankrupt and nonbankrupt firms, respectively.

Table 4.14 -- Model V Real Accrual Ratios with Economic variables

EVALUATION	METHOD	
CRITERIA	LOGIT	NEURAL NETWORK
Total Missed	14	8
Total Accuracy	91.36%	95.06%
Bankrupt %	85.71%	91.07%
Nonbankrupt %	94.34%	97.17%
CV Error	0.086	0.049

Notes: CV cross validation error. Total sample is 162, with 56 and 106 bankrupt and nonbankrupt firms, respectively.

Table 4.15 -- Model VI Real Cash Flow Ratios with Economic Variables

EVALUATION	METHOD	
CRITERIA	LOGIT	NEURAL NETWORK
Total Missed	25	23
Total Accuracy	84.57%	85.80%
Bankrupt %	76.79%	71.43%
Nonbankrupt %	88.68%	93.40%
CV Error	0.154	0.141

Notes: CV cross validation error. Total sample is 162, with 56 and 106 bankrupt and nonbankrupt firms, respectively.

Section 4: Analysis of the Results

One of the purposes of this study is to find which of the following four methods provides the best forecasts.

1. Nominal accrual ratios vs. nominal cash flow ratios.
2. Real accrual based ratios vs. nominal accrual ratios.
3. Real cash flow based ratios vs. nominal cash flow ratios.
4. Real accrual based ratios vs. real cash flow ratios.

The study also tests if the inclusion of the interest rate and the oil price in models that use real variables improve their prediction accuracy. Finally, the predictive power of neural networks and logit is compared.

Table 4.16 can answer the above questions. The table first ranks the models within each method of estimation, then it ranks the models on their general performance based on the model's cross validation error (CV). In both estimation methods, models that used nominal accrual ratios outperformed models that used nominal cash flow ratios. For models I and II estimated with logit, the CV errors were .043 and .386 respectively. The models had CV errors of 0.00 and .086 respectively when they were estimated with the neural network. The difference between the CV error within each method demonstrates the superiority of the neural network models over the logit models.

Methods two and three evaluate whether real financial ratios, accrual or cash flow, are better than nominal financial ratios. The results indicate that nominal financial ratios outperform real ratios except for the case of cash flow ratios in the logit model. For accrual ratios, the CV errors for models I and III are 0.043 and 0.265, respectively, for the logit estimation. The models have a CV error of 0.00 and 0.030, respectively, when they are estimated with the neural network. For cash flow ratios, the CV errors for models II and IV are 0.386 and 0.265, respectively, for the logit estimation. The models have a CV error of 0.08642 and 0.17284, respectively, when they are estimated with neural network.

These results suggest that nominal ratios have more information than real ratios. This extra information improves their classification rate. Nominal ratios, as Platt et al. suggest, incorporate both their own dynamics and the effects of external economic factors, while deflated ratios do not contain the effect of inflation.

As to whether real accrual ratios are better predictors than real cash flow ratios? The answer is different for the two methods. For the logit method, models III and IV have an equal CV error of 0.265 suggesting equal performance. But the models have a CV error of 0.030 and 0.172 respectively under neural networks. Real accrual ratios outperformed real cash flow ratios. This result could be due to two things: first, real accrual ratios have more information than real cash flow ratios. Accrual ratios that provide long term performance and financial structure information such as retained earnings to total assets and total debt to total assets do not have a counterpart in cash flow ratios. Second, this could be due to estimation bias toward the model that uses real accrual ratios. The neural network model for accrual ratios has eighteen inputs while the real cash flow model has only fifteen inputs.

The inclusion of economic factors improved the performance of all models that use real financial ratios except the neural network model that uses real accrual ratios. Models III and V for real accrual ratios, have a CV error of 0.265 and 0.086, respectively, for the logit method, suggesting a big improvement. Under the neural network method the models have a CV error of 0.030 and 0.049, respectively. Models IV and VI using real cash flow ratios, have CV errors of 0.265 and 0.154, respectively, also suggesting an improvement. Under the neural network method models IV and VI have a CV error of 0.172 and 0.141, respectively. These results suggest that, after deflating financial ratios, economic variables made significant contributions to the models.

As to whether neural network models are better predictors of bankruptcy than logit models: in this study, the answer is "yes" for all of the models. This finding conforms with the findings of other studies that compared neural networks with the other traditional estimating techniques mentioned in chapter II.

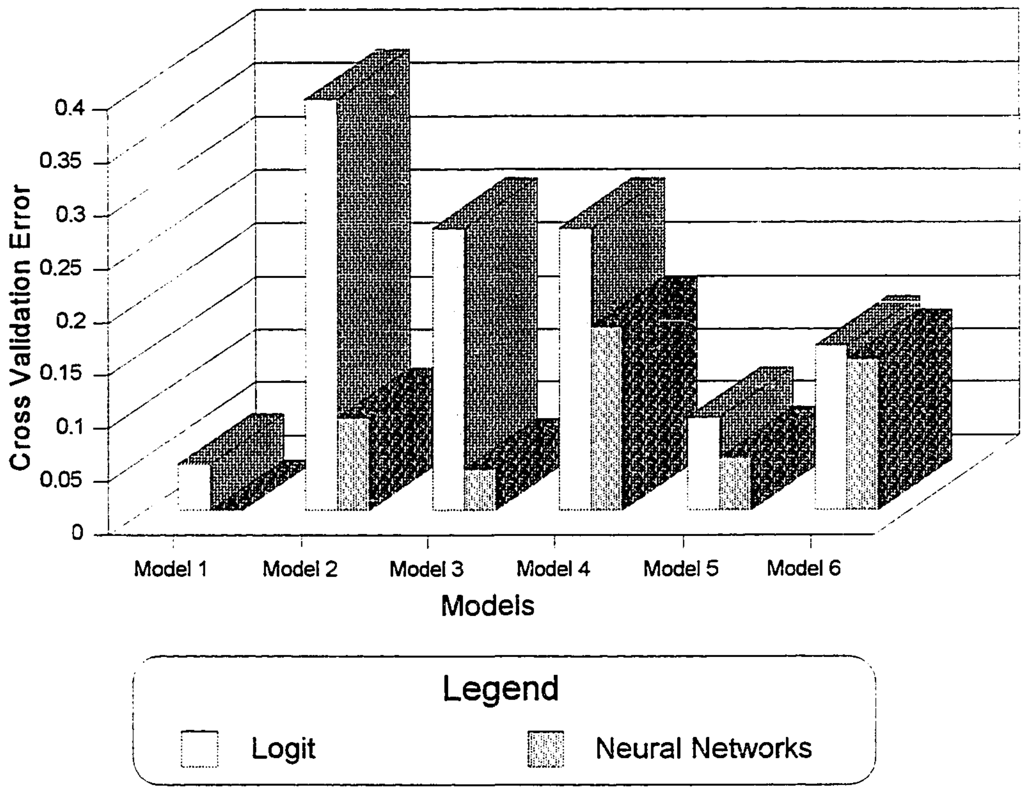
Table 4.16 -- The Rank of Each Model Within Each Method and its General Performance

METHOD		RANK	
LOGIT	CV ERROR	WITHIN/M	OVERALL
Model I	0.043	1	3
Model II	0.386	5	10
Model III	0.265	4	9
Model IV	0.265	4	9
Model V	0.086	2	5
Model VI	0.154	3	7
NEURAL NETWORK			
Model I	0.000	1	1
Model II	0.086	4	5
Model III	0.038	2	2
Model IV	0.172	6	8
Model V	0.049	3	4
Model VI	0.141	5	6

Notes:
Model I: nominal accrual ratios;
Model II: nominal cash flow ratios;
Model III: real accrual ratios;
Model IV: real cash flow ratios;
Model V: real accrual ratios with economic variables;
Model VI: real cash flow ratios with economic variables.
CV cross validation. Within/M: within each method. Overall: over the twelve models.

Figure 4.7 presents the results graphically

Figure -- 4.7 Comparison of Cross Validation Error Between the Estimation Methods.



CHAPTER V

EDUCATIONAL ASPECTS

Among the objectives of this study is to compare logit and neural networks as estimation methods. The results indicate that neural networks perform better than logit in predicting bankruptcy in all of the six models that were estimated. Bankruptcy prediction is only one of the tasks that neural networks have been shown to perform well. Neural networks have been used in financial forecasting and other business and nonbusiness applications. In a competitive business environment, managers should be familiar with any tool that can help them make critical decisions. Students graduating from business schools should, at a minimum, have some knowledge of available estimation and quantitative methods that are used in decision making. Since neural network methodology is still in its infancy, there is not enough simple educational material that can be used to introduce neural network fundamentals to students.

The purpose of this chapter is to help instructors introduce the concept of neural networks to students. The chapter starts with a list of objectives put in question format. These objectives need to be achieved in order to introduce neural networks to students. There follows a list of steps and exercises that an instructor could use to achieve those objectives. Finally, the chapter presents a testing strategy that could be used to determine the effectiveness of the teaching steps and exercises.

Objectives:

1. What are neural networks?
2. What does a neural network model look like?
3. What are the names and functions of its components?
4. How does one train a neural network?
5. How does one know whether to use supervised, graded, or unsupervised training when building a neural network?
6. How does one determine the size of the input layer of a neural network?
7. How does one determine the size of the output layer of a neural network?
8. How does a neural network modify its weights to classify patterns correctly?
9. How are neural networks used in real life applications?
10. How do neural networks compare with traditional estimation techniques?

Steps and Exercises:

The instructor should use both in-class lectures and hands-on exercises using a neural network simulator to achieve his or her objectives. Class lectures should be used mainly to introduce students to the concept of neural networks. Using the section on neural networks from Chapter III, class discussions, and visual aids, the instructor could achieve objectives one, two, and three.

Objectives four through seven could be achieved by introducing students to a neural network simulator. Taking the students to the computer lab, and dividing them in groups of two or three, the instructor could use a completely built neural network model to demonstrate a neural network in operation.

For objective eight the instructor could ask the students to do an exercise that shows how weights are modified in a neural network. Although training a neural network is done mainly by a computer simulator, doing an exercise on how to modify the weights by hand can give students a good understanding of the workings of a neural network.

Weight Modification Exercise:

Using the delta rule defined below, find the weight that a neural network could use to classify correctly the data points A and B as +1 and -1, respectively (Caudill and Bulter, 1992).

Data Patterns (A = +1, B = -1)

A1 = (.3, .7)	B1 = (-.6, .3)
A2 = (.4, .9)	B2 = (-.4, -.2)
A3 = (.5, .5)	B3 = (.3, -.4)
A4 = (.7, .3)	B4 = (-.2, -.8)

The output function for the output unit is set to the following rule:

$$O_i(t) = \begin{cases} +1 , & \text{if } I_i > 0 \\ -1 , & \text{if } I_i \leq 0 \end{cases}$$

and the delta rule is:

$$\Delta \ Rule: \quad W^{New} = W^{Old} + \frac{\beta E X}{| X |^2}$$

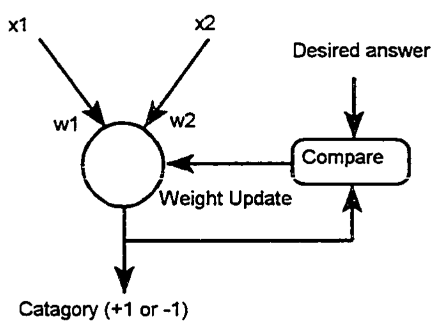
where:

$O_i(t)$	Output of unit i at step t
I_i	Input of unit i equal to $I_i = \sum w_i x_i$
β	Learning constant between 0 and 1
E	Error = desired output - actual output
X	Input vector with components (x_1, x_2)
W	Weight vector with components (w_1, w_2)

The initial weight vector is $w_0 = (-.6, .8)$, and $\beta = 0.5$.

Figure 5.1 presents how the delta rule works.

Figure 5.1 -- The delta rule compares the actual output with the desired output; this information is used to adjust the weights.



Solution:

a. Apply A1 to the network and compute I;

$I = (.3)(-.6) + (.7)(.8) = .38$

since $I > 0$, the output = +1

The desired output for this point is +1; thus $E = 0$ and no weights are changed.

b. Apply B1 to the network and compute I:

$I = (-.6)(-.6) + (.3)(.8) = .60$

Since $I > 0$, the output = +1

The desired output for this point is -1, thus, $E = -1-(+1) = -2$. The weights must be adjusted.

Step 1: Square the length of B1 is $.36+.09 = .45$

Step 2: Change in $w_i = [(.5)(-2)(-.6)]/(.45) = 1.3$

Change in $w_2 = [(.5)(-2)(.3)]/(.45) = -.7$

Thus the delta vector is (1.3, -.7)

Step 3: The new weight W_1 (.7,.1) gives $w_1 = -.6 + 1.3 = .7$

and $w_2 = .8 + (-.7) = .1$

c. To confirm that the new weight vector correctly categorizes B1:

$I = (-.6)(.7) + (.3)(.1) = -.39$

The output for B1 is now -1, which is correct.

Important:

Once a weight vector has been changed in neural networks , it must be confirmed that all the correctly classified points could be correctly reclassified with the new weight vector. Thus, point A1 must be reintroduced to the network. Applying A1 to the network:

$I = (.3)(.7) + (.7)(.1) = .28$

since $.28 > 0$, the output for A1 is +1, which is still correct. No further weight changes are needed at this time.

Students should be able to train the network with a total of three weight changes, including the one above.

The solution is: $W_2 = (-.5, 1.7)$ after B3

$W_3 = (.8, 1.0)$ after B1

With a weight vector equal to (.8, 1.0), all of the data points could be classified correctly.

Finally, the instructor could assign some articles that compare neural networks with traditional estimation techniques Listed below are some of these articles:

Bill C. Hardgrare, Rick L. Wilson, and Kent Walstrom, "Predicting Graduate Students Success: A Comparison of Neural Networks and Traditional Techniques"; *Computers and Operations Research*, Vol 21, No 3, March 1994, pg 249-263.

Desmond Fletcher and Ernie Goss, "Applications Forecasting with Neural Networks", *Information and Management*, Vol 24, 1993, pg 159-167.

Joachim Utans and John Moody, "Selecting Neural Network Architecture via the Prediction Risk: Application to Corporate Bond Rating Prediction", *Proceedings: First International Conferences on Artificial Intelligence Applications on Wall Street, IEEE*, Computer Society Press, Los Alamitos, CA, 1991.

Testing and Evaluation:

Students could be provided with a data set and asked to design a neural network that can classify data observations. This data set could be one of the data sets used in this dissertation. The data set is made up of financial ratios for oil and gas firms. Since the data sets indicate whether the firms are bankrupt or nonbankrupt, the students could be asked to build a neural network that could classify the firms correctly.

If students manage to do this assignment without major difficulties, then the objectives of introducing neural networks to the student would have been met. The most important part of making students understand neural networks is for the instructor to require as many hands-on exercises as possible in the available time.

CHAPTER VI

SUMMARY AND CONCLUSION

The purpose of this study is to find the best variables and estimating method to predict bankruptcy in the oil and gas industry. This is attempted by using nominal and real accrual and cash flow ratios in combination with logit models and neural networks to predict bankruptcy. The best variables and estimating technique are chosen according to their ability to classify firms correctly in out-of-sample tests.

Logit Models:

The best predictors of bankruptcy were models that used accrual ratios, whether real or nominal. These models generally outperformed models that used cash flow ratios.

Model I, which used nominal accrual ratios, outperformed model II, which used nominal cash flow ratios. On the other hand, models III and IV, which used real accrual and real cash flow ratios, respectively, had an equal predictive performance. When the interest rate and the oil price were added as extra independent variables on models III and IV, which used real financial ratios, the model that used real accrual ratios also outperformed the model that used real cash flow ratios.

The inclusion of the interest rate and the oil price improved the performance of both models that used real financial ratios. Model III's cross validation error dropped from 0.265 to 0.08 in model V. Also, model IV's cross validation error dropped from 0.265 to 0.154 in model VI. These results suggest that, after deflating the financial ratios, economic variables made significant contributions to the models.

Neural Network Models:

Models that were estimated with neural networks were also dominated by models that used accrual ratios. Model I, which used nominal accrual ratios, outperformed model II, which used nominal cash flow ratios. Model III, which used real accrual ratios, also outperformed model IV, which used real cash flow ratios.

In neural network models, the addition of the interest rate and the oil price as extra inputs improved the performance of only model IV, which used real cash flow ratios. Its cross validation error decreased from 0.173 in model IV to 0.142 in model VI. However, model III, which used only real cash flow ratios, still outperformed model V, which used real cash flow ratios and the interest rate and the oil price as extra independent variables.

The main finding of this study is that all of the models that were estimated with neural networks outperformed all of the models that were estimated with logit. This finding agrees with the findings of other studies that compared the two methods. The ability of neural networks to generalize and their freedom from the data characteristic and estimation assumptions that must be present for other estimation techniques to perform well, are the main reasons why neural networks outperformed logit models.

Conclusions and Implications

It is important to note that bankruptcy prediction research indicates that the findings of one study for a particular industry should not be applied to other industries. So it will be misleading to say that models that use nominal accrual ratios and are estimated with neural networks are the best predictors of bankruptcy for all industries. This happened to be true for the sample of oil and gas firms that were used in this study.

When a model needs to be developed to predict bankruptcy, a researcher must consider all of the relevant variables. If there is doubt about the importance of a variable, that variable should be included in the model, then tested for its importance. The researcher should also try to find macroeconomic variables that might have a strong impact on the industry which the bankruptcy prediction model is being developed for. In this study the oil and gas industry were affected by the interest rate and the price of oil.

Once all the relevant factors have been collected, all estimation methods available to the researcher should be used to develop the model. As Altman and Varetto (1994) suggest, estimation methods should be used in a combined approach for predictive reinforcement. The process of building a neural network model for every industry will be very expensive considering the scarcity of research resources, but for a big investment or accounting firm with an in-house research staff, economies of scale might justify the development of a model that can be used repetitively in the course of their business.

Recommendations for Future Studies

Based on the results of this study some recommendations for future studies could be suggested:

1. An attempt should be made to explain why some of the signs of the long-run multipliers for some of the variables did not match the expected sign. Since the purpose of this study was mainly to predict bankruptcy no attempt was made to investigate the long-run multipliers.
2. The practice of dropping variables from the general model because they are not significant should be investigated, especially when the

purpose of developing the model is to be used for prediction purposes. In this study, in the process of choosing the preferred model, some variables were dropped because they were not significant, and this caused the count R^2 to drop. A future study could investigate what will happen to the model's cross validation prediction error if these variables were left in the model despite their insignificance.

3. An attempt should be made to build a bankruptcy prediction model that uses both accrual and cash flow ratios. The hypothesis of whether to use real or nominal financial ratios for this model should also be investigated.

4. An attempt should be made to test the predictive accuracy of the neural network model that was developed in this study by seeing how far in time it can classify firms. This could be done by applying the model to a cutoff point in time, such as five years, and seeing if the model can classify the firm correctly. If it could, the same process should be repeated but this time the cutoff point should be increased until the maximum cutoff point could be found.

5. The hypothesis of whether neural networks are better predictors of bankruptcy than logit in bankruptcy prediction models should be investigated for other industries.

BIBLIOGRAPHY

BIBLIOGRAPHY

Altman, E., and Levallee, M., "Business Failure Classification in Canada," *Journal of Business Administration*, Vol: 12, Iss: 1, Fall 1980, pp. 147-164.

________, Marco, G., and Varetto, F., "Corporate Distress Diagnosis: Comparisons Using Linear Discriminant Analysis and Neural Networks (the Italian Experience)," *Journal of Business & Finance*, Vol: 18, Iss: 3, May 1994, pp. 505-529.

________, "A Reply," *Journal of Finance*, Vol: 25, December 1970, pp. 1169-72.

________, "Financial Ratios, Discriminant analysis and the Prediction of Corporate Bankruptcy," *Journal of Finance*, Vol: 23, September 1968, pp. 589-610.

________, Haldman A., and Naraganan B., "Zeta Analysis: A New Model to Identify Bankruptcy Risk of Corporations," *Journal of Banking and Finance*, Vol: 1, Spring 1977, pp. 29-51.

Aly, I., Barlow, H., and Jones, R., "The Usefulness of SFAS No. 82 (Current Cost) Information in Discriminant Business Failure: An Empirical Study," *Journal of Accounting Auditing & Finance*, Vol: 7, Iss: 2, Spring 1992, pp. 217-229.

Aziz, A., Emanuel, D., and Lawson, G., "Bankruptcy Prediction: An Investigation of Cash Flow Based Models," *Journal of Management Studies,* Vol: 25, pp. 419-37.

Bates, T., "An Econometric Analysis of Lending to Black Businessmen," *Review of Economics and Statistics*, Vol: 55, August 1973, pp. 272-83.

Beaver, W. H., "Financial Ratios as Predictors of Failure," *Journal of Accounting Research,* Vol: 4, 1966, pp. 71-127.

Belsley, David E., Edwin Kuh, and R. Welsch, Regression Diagnostics, Identifying Influential Data and Sources of Collinearity, New York: Weley, 1980.

Bill C. Hardgrare, Rick L. Wilson, and Kent Walstrom, "Predicting Graduate Students Success: A Comparison of Neural Networks and Traditional Techniques"; *Computers and Operations Research,* Vol 21, No 3, March 1994, pg 249-263.

Blum, M., "Failing Company Discriminant Analysis," *Journal of Accounting Research,* Vol: 12, 1974, pp. 1-25.

Casey, C. and Bartczak, N., " Using Operating Cash Flow Data to Predict Financial Distress: Some Extensions," *Journal of Accounting Research,* Vol: 23, Iss: 1, Spring 1985, pp. 384-401.

Caudill, Maureen and Butler, Charles, Understanding Neural Networks, The MIT press, Cambridge, Mass. 1992.

Crandall, R., "Inaccuracies in a Bankruptcy Classification Equation," *Journal of Commercial Bank Lending,* Vol: 67, Iss: 8, April 1985, pp. 44-48.

Dambolena, I., and Khoury S., "Ratio Stability and Corporate Failure," *Journal of Finance,* Vol: 35, September 1980, pp. 1017-26.

Deakin, E., "A Discriminant Analysis of Predictors of Business Failure," *Journal of Accounting Research,* Vol: 10, Spring 1972, pp. 167-79.

________, "A Discriminant Analysis of Predictors of Business Failure," *Journal of Accounting Research,* Vol: 10, 1972, pp. 167-179.

________, "An Analysis of Differences Between Non-Major Oil Firms Using Successful Efforts and Full Cost methods," *The Accounting Review,* Vol: 54, October 1979, pp. 722-734.

Eisenbeis, R. and Avery, R., Discriminant Analysis and Classification Procedures, (Lexington, Mass.: Lexington Books, D.C. Health and Co., 1972).

Elam, R., "The Effect of Lease Data on the Predictive Ability of Financial Ratios," *The Accounting Review,* Vol: 50, Jan 1975, pp. 25-43.

Finney, D., Probit Analysis, Second Edition, (Cambridge University Press, New York, 1952).

Fisher, R., The Use of Multiple Measurement in Taxonomic Problems, Annals of Eugenics, VII: 179-188.

Fletcher, D. and Goss, E., "Forecasting With Neural Networks: An Application Using Bankrupt Data," *Information & Management*, Vol: 24, Iss: 3, March 1993, pp. 159-167.

Fulmer, J., Moon, J., Gavin, T., and Erwin, M., "A Bankruptcy Classification Model For Small Firms," *Journal of Commercial Banking Lending*, Vol: 66, Iss: 11, July 1984, pp. 25-3

Geisser, Seymour, "The Predictive Sample Reuse Method with Applications," *Journal of The American Statistical Association*, Vol: 70, Iss: 350, June 1975.

Gentry, J., Newblod, P., and Whitford, D., "Classifying Bankrupt Firms With Funds Flow Components," *Journal of Accounting Research*, Spring 1985, pp. 146-160.

__________, __________, __________, "Funds Flow Components, Financial Ratios, and Bankruptcy," *Journal of Business Finance & Accounting*, Winter 1987, pp. 595-606.

__________, __________, __________, "Predicting Bankruptcy: If Cash Flow's Not the Bottom Line, What Is?," *Financial Analyst Journal*, Vol: 41, Iss: 5, Sep/Oct 1985, pp. 4

Giacomino, Don and Mielke, David, "Cash Flow: Another Approach to Risk Analysis," *Journal of Accountancy*, Vol: 175, Iss: 3, March 1993, pg.55-58.

Greene, William, Econometric Analysis, 2nd edition, MacMillan Publishing Company, New York, 1993.

Hendry, D. F., "Predictive Failure and Econometric Modeling in Macroeconomics: The Transactions Demand For Money." Edited by Paul, Economic Modeling, London, Heinemann, 1979: 217-242.

Maddala, G. S., Econometrics, McGraw-Hill, New York, 1977.

__________, Introduction to Econometrics, 2nd edition, MacMillan Publishing Company, New York, 1992.

McAuliffe, R., "Responsibilities of the Repetition Creditor: Early Detection of Corporate Financial Distress," *Credit & Financial Management*, Vol: 89, Iss: 3, March 1987, pp. 14-17.

Mensah, Y. M., "An Examination of the Stationarity of Multivariate Bankruptcy Prediction Models: A Methodological Study," *Journal of Accounting Research*, Vol: 22, 1984, pp. 380-395.

Mensah, Y. M., "The Differential Bankruptcy Predictive Ability of Specific Price level Adjustments: Some Empirical Evidence," *The Accounting Review*, Vol: 63, 1983, pg. 228.

Moyer, R. C., "Forecasting Financial Failure: A Reexamination," *Financial Management*, Vol: 6, Iss: 1, Spring 1977, pp. 11-17.

Ohlson, J., "Financial Ratios and the probalistic Prediction of Bankruptcy," *Journal of Accounting Research*, Spring 1980, pp. 109-131.

Platt, H., Platt, M., and Pedersen, J., "Bankruptcy Discrimination With Real Variables," *Journal of Business Finance & Accounting*, Vol: 21, Iss: 4, 1994, pp. 491-510.

Richardson, F. and Davidson, L., "On Linear Discrimination with Accounting Ratios," *Journal of Business finance and Accounting*, Vol: 11, Iss: 4, Winter 1984, pp. 511-525.

Royston, J. P., "An Extension of Shapiro and Wilk's W Test for Normality to Large Samples," *Applied Statistics*, 31, pg. 115-124

Santomero, A. M., and vinso, J. D., "Estimating the probability of Failure for Commercial banks and the Banking System," *Journal of Banking and Finance*, Vol: 1, November 1977, pp. 249-76.

Scaggs, M., and Crawford, P., "Altman's Bankruptcy Model Revisited: Can Airline Bankruptcy Be Predicted?" *Review of Regional Economics and Business*, Vol: 11, Iss: 2, Oct 1986, pp. 11-16.

Sharma, J., "Credit Union Solvency: A Discriminant Analysis," *Review of Business and Economics Research*, Vol: 20, Iss: 2, Spring 1985, pp. 54-65.

Sheppard, J., "The Dilemma of Matching Pairs and Diversified Firms in Bankruptcy Prediction Models," *The Mid-Atlantic Journal of Business,* Vol: 30, Iss: 1, March 1994, pp. 9-25.

Statements on Auditing Standards (SAS) No. 59, Auditing (AU) No. 341, *American Institute of Certified Public Accountants*, Commerce Clearing House, Inc. 1992.

Stuttgart Neural Network Simulator (SNNS), Institute for Parallel and Distributed High Performance Systems, Germany, Users Manual, Version 3.3, 1994.

Taksuoka, M. M., "Discriminant Analysis," Data Analysis Strategies and Designs for Substance Abuse Research, edited by P. M. Bentler, D. J. Lettieri, and G. A. Austin (Rockville, MD: National Institute of Drug Abuse, 1976) pp. 201-20.

Udo, G., "Neural Network Performance on the Bankruptcy Problem," *Computers & Industrial Engineering,* Vol: 25, Iss: 1-4, September 1993, pp. 377-380.

Utans, Joachim and Moody, John, "Selecting Neural Network Architecture via the Prediction Risk: Application to Corporate Bond Rating Prediction", *Proceedings: First International Conferences on Artificial Intelligence Applications on Wall Street, IEEE*, Computer Society Press, Los Alamitos, CA, 1991.

Wahba, G. and Wold, S., "A Completely Automatic French Curve: Fitting Spline Functions by Cross-validation," Communications in Statistics, Vol: 4, Iss: 1, pg.1-17, 1975.

Ward, T., "Cash Flow Information and the Prediction of Financially Distressed Mining, Oil, and Gas Firms: A Comparative Study," *Journal of Applied Business Research,* Vol: 10, Iss: 3, Summer 1994, pp. 78-86.

Zavgren, C., "Assessing the Vulnerability of Failure of American Industrial Firms: A logistic analysis," *Journal of Business Finance and Accounting,* Vol: 12, Iss: 1, Spring 1985