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PREDICTING BANKRUPTCY

FOR GOVERNMENT CONTRACTORS

THESIS

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PREDICTING BANKRUPTCY

FOR CONTRACTORS

THESIS

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Table of Contents

List of Figures

List of Tables

List of Ratio Abbreviations

C/CL	CASH/CURRENT LIAB (Net Liquid Balance)
C/S	CASH/SALES
C/TA	CASH/TOT ASSETS
CF/S	CASH FLOW/SALES
CF/TD	CASH FLOW/TOT DEBT
CA/CL	CURRENT ASSETS/CURRENT LIAB
EBIT/TA	EBIT/TOT ASSETS
INC/TC	INC BEF DO&EI/TOT CAPITAL
LTD/TC	LONG-TERM DEBT/TOT CAPITAL
NI/S	NET INCOME/SALES
NI/TA	NET INCOME/TOT ASSETS
NW/TA	NET WORTH/TOT ASSETS
QA/CL	QUICK ASSETS/CURRENT LIAB
RE/TA	RETAINED EARNINGS/TOT ASSETS
S/NP	SALES/NET PLANT
S/R	SALES/RECEIVABLES
S/TA	SALES/TOT ASSETS
S/WC	SALES/WORKING CAPITAL
TD/TA	TOT DEBT/TOT ASSETS
WC/TA	WORKING CAP/TOT ASSETS

Abstract

This study attempted to build a bankruptcy prediction model for evaluating potential and current government contractors. The study addressed two general research questions: (1) What financial distress models have been developed and how reliable are these models for predicting bankruptcy for government contractors? (2) Can new models be built that can reliably forecast bankruptcy for government contractors?

Review of the literature found a multitude of previous research efforts on predicting financial distress. Two of the models developed by other researchers were based on government contractor data; one was developed using discriminant analysis (Dagel and Pepper) and the other using a combination of discriminant analysis and univariate analyses (Moses and Liao).

Inputting the financial information from the samples of bankrupt and nonbankrupt firms into four other models (Altman, Dagel and Pepper, Moses and Liao, and Zavgren) showed that the models were less successful predicting bankruptcy than reported in these studies. None of these four studies appeared to take prior probabilities or differences in misclassification costs into account when reporting their accuracy/error rates. These can have a tremendous impact on a model's reliability.

Two techniques--logistic regression and discriminant analysis--were used to build models based on the sample data. Both yielded a single variable model using cash/total assets as the predictor variable. In both cases the prediction accuracy is about 78%, or a 22% apparent error rate. Using Lachenbruch's holdout procedure showed a 25% error rate. But this

method does not take into consideration prior probabilities and differences in misclassification costs. Another test that allows one to account for these considerations showed that the model provided almost a 100% accuracy rate for predicting nonbankruptcy, but a 0% accuracy for predicting bankruptcy.

Probably a major factor in the poor performance of the model is the fact that the ratio means for the two samples were often very close to each other. Although the samples are from two different groups--bankrupt and nonbankrupt--the categories may not be as exclusive as they first appear to be. A nonbankrupt company may not be any more financially secure than a company filing for bankruptcy.

PREDICTING BANKRUPTCY FOR GOVERNMENT CONTRACTORS

I. Introduction

General Issue

The Air Force has contracts with a myriad of corporations worth billions of dollars. Before a contract is awarded, financial analysts are required to look at the financial health of the bidders "to determine whether they can stay in business long enough to complete the contract" (10:6). Dealing with a company that starts having financial problems can cost the government a substantial amount of money. Government analysts use various methods of assessing a contractor's health, such as ratio analysis of the financial statements (10:16-18) and interviewing the contractor's banker (10:13-14). A useful addition to the analyst's tool kit of analytical techniques would be a model to predict financial distress.

Specific Problem

Although other models have been developed, none have proved reliable enough for the government to use in evaluating potential contractors. Can a model be developed to reliably indicate financial distress for government contractors? How reliable is the model?

Research Questions

1. What financial distress models have been developed?

    a. What sort of data (i.e., number and types of companies, years of data, financial statement items) were used to develop these models?

b. What techniques were used in building the models?

c. What is the reliability of these models when used with government contractor data?

2. Can new models be built applying the statistical techniques used to develop previous models? Which of these new models demonstrates the most reliability for government contractors?

Scope

For this research effort, financial distress models will be developed using financial statements from government contractors. The study data base will include information from (1) companies whose contracts with the government were terminated for financial reasons within the past ten years matched with (2) viable companies with similar characteristics (type of industry and size of assets).

Assumptions

1. The financial statements are accurate reflections of a firm's operations.

2. The accounting methods used for a company's statements are consistent for the years of statements reviewed for this study.

Limitations

1. Models developed using this data will be appropriate for forecasting financial distress for government contractors only.

2. The effecti eness cf any developed models will be affected by the qua!ity of the data shown in the financial statements.

Summary

This chapter explained the goals of this research effort, along with the assumptions and limitations concerning this study. The next chapter, the literature review, will attempt to answer the first two parts of Research Question 1. Chapter 3 will describe the methodology to be used in answering the other questions, while Chapter 4 will discuss the results of the analyses. Chapter 5 will summarize the answers to each of the research questions and suggest areas for future research.

II. Literature Review

Introduction

This chapter reviews the literature concerning the prediction of financial distress. Although the terms financial distress and bankruptcy are not synonymous, bankruptcy is the event upon which most financial distress models are based. Thus, these terms are used interchangeably throughout the literature discussing these models and throughout this document. Defining financial distress will be discussed under the heading "Considerations in Building Prediction Models" at the end of this chapter.

Scope of Research

A search of the literature concerning the prediction of financial distress was performed. The search data bank included the Business Periodicals Index, Accounting Articles Index, Air University Abstracts of Research Reports, Selected Rand Abstracts, and the Defense Technical Information Center's data base.

Organization of Discussion

The discussion will first focus on models using accrual-based financial ratios--ratios developed from income statements and the balance sheets. Next, the focus will be on models based upon the cash flow statements. The discussion ends with an overview of some of the issues researchers should be concerned with when developing bankruptcy prediction models. See Table 1 for a comparison of most of the bankruptcy prediction models discussed in this chapter.

TABLE 1

Comparison of Bankruptcy Prediction Models

RESEARCHERS	TYPES OF COS.	SAMPLE SIZES	MATCHED BY	STATISTICAL METHOD	RATIOS IN MODEL	OVERALL MISCLASSIF	VALIDATION METHOD
Beaver	industrial	79 F 79 NF	industry, assets	univariate	cash flow/tot debt net income/tot assets tot debt/tot assets work cap/tot assets current ratios no cr interval	13%	none
Altman	manufacturing	33 F 33 NF	industry, assets, year	discriminant analysis	work cap/tot assets ret earn/tot assets EBIT/tot assets mkt val equity/ tot debt sales/ tot assets	5%	holdout sample
Deakin	industrial	32 F 32 NF	no matching	probabilistic	cash flow/tot debt net inc/tot assets curr assets/tot debt quick assets/tot assets work cap/tot assets cash/tot assets curr assets/curr liab quick assets/curr liab cash/current liab current assets/sales quick assets/sales work cap/sales cash/sales	3%	holdout sample
Edmister	small businesses	21 F 21 NF	no matching	discriminant analysis	funds flow/curr liab equity/sales work cap/sales current liab/equity inventory/sales quick ratio	7%	bias test
Diamond	manufacturing	75 F 75 NF	industry, assets	discriminant analysis	activity (5 ratios) profitability (4 ") liquidity (5 ") leverage (5 ") cash flow (4 ")	9%	n-1 holdout method

TABLE 1 (continued)

RESEARCHERS	TYPES OF COS.	SAMPLE SIZES	MATCHED BY	STATISTICAL METHOD	RATIOS IN MODEL	OVERALL MISCLASSIF	VALIDATION METHOD
Liao & Moses	govt contractors	26 F 26 NF	assets	univariate & discriminant analysis	net worth/assets work cap/assets sales/assets	19%	split sample
Dagel & Pepper	manufacturing	28 F 28 NF	time period	discriminant analysis	tot debt/tot assets cash flow/tot debt curr assets/curr liab quick assets/tot assets work cap/tot assets net sales/tot assets	3%	n-1 holdout method
Ohlson	industrial	105 F 2000 NF	none	logit	log(tot assets/ GNP price level index) tot liab/tot assets work cap/tot assets curr assets/curr liab dummy var for tot assets > tot liab net inc/tot assets funds from ops/tot liab	17%	none
Zavgren	industrial	45 F 45 NF	industry, assets	logit	tot inc/tot cap sales/net plant inventory/sales debt/tot cap receivables/inventory quick assets/curr liab cash/tot assets	18%	none
Platt & Platt	mixed	57 F 57 NF	industry, assets, year	logit	sales growth cash flow/sales net fixed/tot assets tot debt/tot assets current liab/tot liab output*cash flow/ sales output*tot debt/ tot assets	10%	n-1 holdout method

TABLE 1 (continued)

RESEARCHERS	TYPES OF COS.	SAMPLE SIZES	MATCHED BY	STATISTICAL METHOD	RATIOS IN MODEL	OVERALL MISCLASSIF	VALIDATION METHOD
Casey & Bartczak	industrial	60 F 230 NF	industry	discriminant analysis logit	cash/tot assets curr assets/tot assets curr assets/curr liab sales/current assets net inc/tot assets tot liab/equity cash flow/tot liab	13%	none
Gentry & others	mixed	33 F 33 NF	assets, sales	probit	operations working capital financial fixed coverage exp capital expenditure dividends other assets & liab flows chg in cash & marketable securities	17%	holdout sample
Gahlon & Vigeland	industrial	60 F 204 NF	industry	Mann-Whitney	sales growth rate COGS/net sales S,G,A exp/net sales collection period age of inventory age of accts payable cash coverage cash margin	-	none

Explanation of abbreviations:

F - failed
NF - nonfailed
S,G,A - selling, general, & administrative

Accrual-Based Models

Accrual-based models use ratios developed from the income statements and the balance sheets. The primary types are (1) univariate: one ratio acts as a predictor and (2) multivariate--several ratios are taken into account (in one equation) in making a prediction. Two types of multivariate models are discriminant analysis models and conditional probability models. An example of a univariate model and several of the more significant multivariate models are described in this section. In preparing to discuss the last type of model, multivariate conditional probability models, a statistical technique called factor analysis is described.

Univariate Model.

Beaver. Beaver performed his study in 1966, using a univariate approach, "in which the predictive ability of the ratios was analyzed on a one-by-one basis" (37:3). He took a sample of 79 firms which had failed and matched these with firms in the same industries and with similar sizes of assets (37:3). He calculated ratios from the financial statements for each of the firms up to five years prior to bankruptcy and then calculated the means of these ratios (37:8). He then reduced his original set of 30 ratios to 6 and classified the firms into mutually exclusive groups--failed versus non-failed--by deriving optimal cutoff points. He did this by ranking the ratios and selecting cutoff points so that "firms with ratios lower than the cutoff points would be classified as bankrupt" (19:54).

Cash flow/total debt was the best predictor and could predict bankruptcy up to five years before the event. (The other five ratios, in order of best predictive power, were: net income/total assets, total debt/total assets, working capital/total assets, current assets/current liabilities, and no-credit interval.) The predictive ability of the cash flow/total debt ratio can be explained by noting that businesses with low cash flow to total debt ratios have a potential problem of future debt repayment and thus bankruptcy may result. Using this ratio misclassified 13 percent of the sample firms one year before bankruptcy and 22 percent of the sample firms five years before bankruptcy (37:8).

Multivariate Discriminant Analysis.

Altman. Instead of trying to determine which ratios were by themselves good predictors of bankruptcy, Altman chose to use a technique called multivariate discriminant analysis. This statistical technique classifies observations into distinct groups--in this case, those firms that declare bankruptcy and those which were financially healthy (26:15).

> Discriminant analysis chooses ratios and assigns coefficients resulting in a linear combination of ratios that provide an individual score for each firm. An optimal cutoff can be chosen which minimizes misclassifications in a sample. The model and the cutoff score can then be applied to new firms outside the sample. (28:29)

By using this technique, he was able to integrate several ratios into one equation and therefore evaluate their ability to together "assess the financial health of a firm" (37:16-17).

Altman took a sample of 33 manufacturing firms that filed bankruptcy under Chapter X and matched these with firms in the same industries and with the same asset sizes. He then analyzed financial statements filed during the year before bankruptcy (37:16). After evaluating 22 commonly used ratios, he selected five. Below is Altman's Z-score model:

$$Z = 1.2(WC/TA) + 1.4\,(RE/TA) + 3.3\,(EBIT/TA) + .6(MVE/TL) + 1.0(S/TA) \quad (1)$$

WC/TA = working capital/total assets
RE/TA = retained earnings/total assets
EBIT/TA = earnings before interest and taxes/total assets
MVE/TA = market value of common equity/total liabilities
S/TA = sales/total assets
Z=the overall index of corporate health.

If Z-score is less than 1.81, classify as bankrupt.
If Z-score is between 1.81 and 2.99, exercise caution.

(19:54;12:553)

The Z-score misclassified 5 percent of the sample firms one year before bankruptcy and 18 percent the second year before bankruptcy. Accuracy dropped off sharply for any year before these two (37:15-16).

Several models have been developed using the methodology devised by Altman in his Z-score model. Four of these are described below.

Deakin. During 1972, Deakin modified Altman's model. Instead of the five ratios included in Altman's model, he used 14 ratios. Also, he selected his nonfailed firms sample randomly, rather than trying to match them with the failed firms. He developed discriminant functions for each of the five years, but assigned subjective probabilities, rather than finding optimal cutoffs, to determine which class the firms should fall into--failed versus nonfailed. Deakin's methodology turned out to be invalid, as it relied on his variables having a normal distribution when, in fact, they did not (37:19-20).

Edmister. In his analysis of small businesses, Edmister started out with "all ratios found significant in previous empirical studies except the net operating margin ratio" (8:1480). His final model included seven variables: cash flow/current liabilities, current liabilities/equity, inventory/sales, net working capital/sales, equity/sales, quick ratio/industry trend, and quick ratio/industry quick ratio (8:1487-88). Recognizing the problems of multicollinearity, he did not allow any variables in his function that were correlated above a certain percentage (8:1484). Edmister determined the following techniques were useful in predicting failure: (1) comparing a firm's ratios to its industry averages (by dividing), (2) observing three-year trends for its ratios, (3) calculating three-year ratio averages, and (4) analyzing relationships between ratio trends and industry relative levels (8:1490-1491). His seven-variable function classified failure/nonfailure correctly 93 percent of the time for one year prior to failure (8:1480).

Diamond. In 1976, Diamond used a more sophisticated method of multivariate discriminant analysis, but prediction accuracy did not improve significantly. His results indicated that the "benefits to further improvements in the discriminant analysis approach have neared an asymptotic limit" (37:23).

Liao and Moses (Scoring Method). Liao and Moses (1986) developed a scoring model, using a sample of 52 government contractors--26 failed and 26 nonfailed firms (28:28). Applying univariate analysis, these researchers identified seven predictors of failure and determined optimal cutoff points for each of the ratios. They then applied discriminant analysis to determine which combination of these ratios would result in the best prediction equation; test results showed these were equity/assets, working capital/assets, and sales/assets. Next, they developed what they called a failure index: if a firm's ratio exceeded the corresponding ratio's cut-off, it received a score of one; otherwise, it received a score of zero; the three scores of 'ones' or 'zeros' were then added to arrive at the failure index. If a firm scored less than 'two,' it was classified as a failing firm (28:34-35). The index classified failed firms 92 percent of the time and healthy firms 69 percent of the time. In addition, there were no bankrupt firms among those given a score of 'three' (28:36).

Dagel and Pepper. Dagel and Pepper (1990) analyzed statements from 28 bankrupt and 28 nonbankrupt manufacturing firms, one-third of these being defense contractors. They considered 18 financial ratios, and with discriminant analysis, ended up with the following six variables for their model: total debt/total assets, cash flow/total debt, current assets/current liabilities, quick assets/total assets, working capital/total assets, and net sales/total assets. A Z-score below zero indicated bankruptcy. Results showed that the model correctly classified 97% of the original firms. Using a "holdout" model validation procedure, classification accuracy was 93% (5:24).

Factor Analysis. Factor analysis is a statistical tool that can reduce the number of variables while still retaining all of the information given by the whole set. Using factor analysis, Pinches et al. (1975) divided 48 ratios into 7 groups that together described a firm's operations (30:295). They then defined ratios in each group that best represented that group. These ratios did not coincide with those found to have predictive power in former studies. The seven categories and the ratios most representative of these groups are shown below (30:304).

Factors	Ratios
Return on investment	Total income/total capital
Capital turnover	Sales/net plant assets
Inventory turnover	Inventory/sales
Financial leverage	Debt/total capital
Receivables turnover	Receivables/inventory
Short-term liquidity	Quick assets/current liabilities
Cash position	Cash/total assets

> By selecting one ratio from each classification, researchers and analysts can identify a set of ratios which essentially are independent of each other (i.e., have low intercorrelations), but which represent the seven different empirical aspects of a firm's operations identified in the present study. (30:304)

Conditional Probability Models. It is often useful to know not only that a company may go bankrupt, but also the probability that it may do so. While discriminant analysis is a useful method to classify firms into two distinct classes, the conditional probability technique is better suited for determining risk (37:24). (For example, knowing the financial risk associated with a company would be more useful for lending and investing decisions than just a fail/nonfail classification.) In addition, the coefficients developed with a conditional probability model can be used to assess the importance of the associated variables on the outcome (37:25).

Ohlson. Ohlson (1980) applied a conditional probability technique called the logistics (logit) model. (This statistical technique estimates the "probability that an event [for example, bankruptcy] will occur based on a set of predesignated variables" (12:546-547).) He used nine ratios, including firm size. His sample of 105 failed firms was not matched with his sample of 2000 nonfailed firms (37:26-27). Although, theoretically, the type of model Ohlson used should have provided improved prediction accuracy, his model's error rates were no better than those of previous models. Two possible contributing factors to these results are the multicollinearity evident among his variables and the lack of a theoretical justification for the choice of variables (37:28).

Zavgren. Zavgren also used a logit model (36:28). For her sample firms, Zavgren chose 45 failed industrial firms and matched them with 45 nonfailed firms (36:25). For each firm, she reviewed financial statements from five years of operations. She used ratios that had been identified in the factor analysis study by Pinches et al. as the most representative of their seven most important predictive ratio types. Separate sets of coefficients were derived for each of the five years before bankruptcy (38:37).

Zavgren noted that efficiency ratios and long-term debt/equity were significant over all years. Failed companies tended to have poor efficiency ratios, such as large inventory/sales ratios, indicating a pile-up of inventory. And failing companies relied on leverage more than did the nonfailing firms (36:20,40). Liquidity measures were significant in early years; this suggested that failed firms had excess cash, but not enough invested in capital equipment (36:19-20). The acid test ratio was highly significant for the three years prior to failure, indicating that the ability to meet maturing obligations was critical in avoiding bankruptcy (36:20). To test her model, Zavgren used a sample from a later time period. The resulting prediction error rates were 31 percent for each of the five years. While these rates seems high compared to many of the previous models, few of the other researchers had used holdout samples to test their models; those that did used samples from the same period. Taking samples from the same period as the data the model was developed from will bias the error rate downward (36:42). Although Zavgren's model did not show improved prediction accuracy over previous models for the year before bankruptcy, it was reliable for each of the five years prior to bankruptcy (36:20). Her model could also be used to determine the relative importance of the ratios in each year.

Dugan and Zavgren tested the Zavgren model on a firm that went bankrupt in 1982. The model predicted 29 percent failure for the fourth year before bankruptcy, 56.6 percent for the third year, 78.7 percent for the second year, and 99.9 percent for the year before bankruptcy (7:64). As can be seen from these figures, looking at the trend of the model's results each year can also indicate pending trouble.

Industry-Relative Ratios. Platt and Platt (1990) studied the impact of industry-relative ratios on the effectiveness of bankruptcy prediction models. Many models are based on companies from several manufacturing companies; but industry ratios differ, which may affect the prediction ability of the model (31:32). Industry-relative ratios place all companies on the same scale (31:37). Using these ratios makes the model more stable--analogous to single-industry models (31:46).

Also, time periods used in building the model will be different than when forecasting with it. Since conditions not be the same, the accuracy of the model's predictive capability will decrease (31:34-35). For example, a ratio that is high in one time period (above the mean) may be considered low in another time period. "Financial ratios may change across time for a variety of reasons. An industry-relative ratio incorporates both the individual company's response to an event as well as the industry response" (31:35). The model the authors developed using industry-relative ratios improved prediction accuracy and stability vs models using unadjusted ratios (31:45).

Cash Flow-Based Models

Since 1985, several studies have focused on cash flow variables in bankruptcy prediction models. Several models based on cash flow variables are discussed below.

Casey and Bartczak. These researchers concluded that "accrual-based multivariate discriminant models forecasted corporate bankruptcy more accurately than any single operating cash flow ratio" (4:385). In another study, they concluded that using operating cash flow data did not improve the prediction accuracy of multiple discriminant and logit models using accrual-based ratios (4:394).

Gentry, Newbold, and Whitford. During the same time period, Gentry et al. (1985) developed a logit failure-prediction model based on funds flow components. They used the following seven components to measure "major financial decision" areas: net operating funds, working capital, financial funds, fixed coverage expenses, capital expenditures, dividends, and other asset and liability flows. These were expressed relative to total net funds: to "determine the percentage each component contributes to the total net flow of funds in one firm" (15:147). An eighth predictor, total net flows/total assets, was added as a measure of size.

Gentry et al. matched 33 failed firms--21 industrial and 12 a mixture of other industries--with healthy firms (in the same industry) having similar asset sizes and sales in the year three years before bankruptcy (15:149). Results of their analysis showed that cash flow from operations was not significant, but the dividends fund flow component was significant in distinguishing between failed and nonfailed companies (15:146). "A typical failing firm will generally experience a shortfall of funds from operations, thereby causing a reduction in its dividend payments" (15:156-157).

To test the predictive ability of their logit model, Gentry et al. collected a sample of 23 financially weak companies and matched these with 23 strong firms. Companies rated as financially weak were rated correctly

70 percent of the time (using data from one year before) and 78 percent (using the three-year means) Nonweak companies were classified correctly 74 percent and 70 percent, respectively (15:158).

In a follow-up study, the authors tested to see which method was more accurate: ratios or funds flow components. They found that adding cash-based funds flow components to traditional ratios improved prediction of financial failure (16:47).

The results of the studies by Casey and Bartzak and Gentry et al. appear to contradict each other. While both research teams agreed that the line item, cash flows from operations, was insignificant, they disagreed on the general usefulness of cash flow information. The key difference is how cash flow is defined and the type of cash flow statement being used. Casey and Bartczak used a different concept of cash flow in their studies than did Gentry et al. in their research. A study using a different type of cash flow statement is described below.

Direct Cash Flow Statements. Gahlon and Vigeland studied how cash flow statement line items and ratios differed between financially distressed and financially healthy firms. Since 1987, the Financial Accounting Standards Board (FASB) has mandated the "inclusion of a statement of cash flows whenever a full set of statements is prepared" (14:6). Two types of cash flow statements are allowed: (1) direct, which, starting with sales, shows cash inflows and outflows; and (2) indirect -- "starts with net income and makes a series of adjustments for depreciation, deferred taxes, gains and losses on sales of equipment and businesses, and changes in working capital" (14:6). The direct method is encouraged by the FASB; also, the indirect method will not provide several of the cash flow line items that the authors found to be significant.

Gahlon and Vigeland took a sample of 60 bankrupt companies that failed between 1973 and 1974 and matched them with financially sound companies in the same or similar industries (14:11). They selected ratios, such as the age of accounts payable ratio, that are "indicative of how well management has managed certain areas of the firm's operating and financial activities that are critical to its cash position" (14:5). Cash flow statements and the selected ratios were calculated for each company over five-year periods (14:11). For each of the five years they analyzed, cash operating income, cash income taxes, and cash flow after mandatory debt retirement were significantly higher for the healthy firms. (Each of these items was scaled by total assets.) The age of accounts payable ratio was higher and cash coverage ratio lower for financially unsound firms. For four of the five years, differences in net cash flow from operations and cash net income were significantly different (14:12). These findings appear to contradict those in the Gentry et al. study done where they determined "cash flow from operations" was not significantly different for bankrupt and nonbankrupt firms.

Gahlon and Vigeland did not attempt to develop a predictive model; this was a descriptive study showing how cash flows and certain ratios differed between financially distressed and healthy firms (14:6).

Net Liquid Balance Measure. Dambolena and Shulman criticized traditional liquidity measures, such as the accrual-based current and quick ratios, because they included assets and liabilities tied up in operations. In searching for a significant cash flow measure, they came up with what they termed the "net liquid balance." This balance is the "difference between all liquid financial assets (essentially cash and marketable securities) and all callable liabilities (essentially short-term notes payable and current maturity due on long-term debt)" (6:74). Dividing the net liquid balance by its total assets or total funds will result in a ratio that "reflects the percentage of net financial assets that a firm has in liquid form" (6:74). A negative net liquid balance indicates that the firm has callable debt greater than its liquid assets. Therefore, the lower this is, the higher the risk of subsequent bankruptcy (6:74-75).

The authors tested the net liquid balance measure by seeing if it improved performance of the Altman and Gentry et al. models. The net liquid balance ratio improved performance of both models and was shown to be the "single best explainer of failure" (6:77).

Considerations in Building Prediction Models.

Defining Financial Distress. Before research is started in developing a model, there must be some understanding of what is meant by 'financial distress.'

> There is a continuum of events that can lead up to liquidations, e.g., declining share of major product markets, deferment of payments to short-term creditors, omission of a preferred dividend, and filing of a Chapter X or XI bankruptcy. Both the legal system and the empirically based classificatory models seek to determine the points on this continuum that can serve as criteria for distinguishing distressed from nondistressed firms. (11:462)

Researchers have used various criteria in defining failure. Beaver defined failure as a business defaulting on its bonds, overdrawing its bank account, not paying a preferred stock dividend or declaring bankruptcy (37:3). Deakin defined failed firms as "those that went bankrupt, were insolvent, or were liquidated" (37:19). Zavgren chose for her sample those firms that had filed for Chapter X or XI bankruptcies (36:25). This last definition is the one used by most researchers because of its ease in application. However, this definition may be too narrow: the percentage of firms filing for bankruptcies is less than three percent (37:9); this restricts the population from which a sample can be drawn for research.

One method to choose the best definition is to determine for what purpose the model will be used. For example, auditors are most concerned whether the firm is a "going concern" (the business will be in existence for an indefinite period); choosing the narrower definition would be appropriate. On the other hand, bankers are most concerned that the firm continues to make prompt payments on its loans; a broader definition is more appropriate in this case in order to predict problems before disaster.

Financial Distress vs. Bankruptcy. Closely related to the above discussion is the difficulty of categorizing financial distress vs. bankruptcy. A nonfinancially distressed company may file for bankruptcy as may a financially distressed company continue operations without filing for bankruptcy. (Options available to a firm in financial distress are: continue operations; merge with another firm; file for bankruptcy and reorganize; and file for bankruptcy and liquidate.)

Gilbert et al. examined this latter issue in their study, "Predicting Bankruptcy for Firms in Financial Distress." They looked at whether a model could discriminate between financially "at risk" firms that survive vs those that file for bankruptcy (in contrast to other studies that discriminated between risky companies that failed vs healthy companies that did not).

They were unable to develop a reliable model to do this (17:162). Although it has been shown in prior bankruptcy studies that financial ratios of bankrupt firms are different from those of healthy firms, they may not be different enough from the ratios of other financially distressed firms to develop a reliable model. In addition, the path that a financially distressed company takes may be influenced by both financial and nonfinancial factors (17:162).

The authors also demonstrated that a bankruptcy model developed using traditional methods couldn't distinguish between firms that fail vs other financially distressed firms (17:162). "If the objective is to identify likely bankruptcies from a pool of problem companies, these bankruptcy models perform poorly" (17:169). Therefore, "bankruptcy model scores sould be interpreted as descriptions of financial distress rather than as predictions of bankruptcy per se" (17:169).

Problems with Ratio Selection. A researcher should consider the following in selecting ratios:

1. Certain financial ratios are highly correlated. Although this means only a small number are needed, it also means this number must be selected carefully (30:295).

2. "Popular ratios are the objects of the attention of analysts and management and hence are subject to 'window dressing.' Thus, the predictive ability of popular ratios may be unreliable" (37:8).

3. There is no theoretical basis for choosing ratios used in many of the proposed models. (37:8). Factor analysis alleviates this problem.

Number of Years Analyzed. In analyzing sample data, researchers have chosen varying time periods--from one to five years. Although it is useful to have a model that can predict bankruptcy five years in advance, requiring sample firms to have five years worth of data will exclude firms in operation less than five years. Yet, young firms have a higher failure rate than more mature ones (26:16).

Sample Selection. Concerns have been raised about sample selection. First, the failure rate used in matched samples studies (50 percent) is much higher than the actual failure rate in the business population, leading to misclassification of nonfailing firms as failing (37:9-10,17). Second, the selection of both the failed and nonfailed firms samples are not truly random samples (37:17). (Because of the small population of failed firms, it is almost impossible to select a random sample.) Results of a study performed by Zmijewski show that while both of these factors contribute to biased samples, neither affects overall classification rates (39:80). An additional concern over the selection of samples is that most researchers selected their ratios after the sample was selected--which may lead to sample-specific results--versus choosing the sample after the selection of ratios (6:77).

Data Base. Each of the models described above relies on information from companies' financial statements. Two problems with using these statements are:

1. Firms may have differing methods of computing statement line items, such as for inventories and depreciation. This can affect studies compiling and comparing information on numerous firms.

2. Firms may change their accounting methods. Research done by Lilien et al. and Schwartz showed that distressed firms were much more likely to make changes in their accounting methods to display increased

income (25:642; 35:41). This could make comparison--between firms and between years for the same firm--less valid.

Costs of Prediction Errors. In using a prediction model, two types of errors may be made: Type I, identifying a failed firm as nonfailed, and Type II, identifying a nonfailed firm as failed (37:8). The importance to the user of the model and the costs of both of these errors needs to be considered in developing a model to classify firms as failed or nonfailed. For example, for an auditor, a Type I error could result in lawsuits because of inadequate disclosure; a Type II error could result in a lost client (2:15,17).

Economic Climate. Different ratios have more predictive power depending on the economic climate. Inflation, interest rates and credit availability, and business cycles (recession/expansion phases) will influence a company's operations and can influence its success or failure (32:31; 27:383). A study conducted by Mensah concluded that "the accuracy and structure of predictive models differ across different economic environments" (27:393). His analysis also indicated different prediction models seem appropriate for companies in different industrial sectors even for the same economic environment" (27:393).

Summary

This chapter answered the first two parts of Research Question 1, i.e., the types of data and techniques used in other bankruptcy models. As was shown in this chapter, numerous models have been proposed over the past 25 years. New techniques have been proposed in an effort to improve prediction accuracy, such as incorporating factor analysis, taking advantage of the new requirement for cash flow statements, and considering the economic climate the companies operate in.

This research effort will focus on developing a new model for evaluating government contractors using:

1. Conditional probability techniques (logistic regression)--incorporating ratios identified by Pinches <u>et al.</u> in their factor analysis study, and

2. Discriminant analysis techniques.

III. Methodology

Overview

The methodology described in this chapter is designed to answer the investigative questions concerning the reliability of other models and whether new, reliable models can be developed to predict bankruptcy for government contractors. This research will survey financial statements from both bankrupt and nonbankrupt companies. Two statistical methods--logistic regression and discriminant analysis--will be used with this financial data to derive models to predict bankruptcy. This chapter discusses how the data will be obtained, describes the two statistical techniques and how to test models developed with these techniques, and then discusses ways to validate new models.

Gathering the Data

In order to survey both bankrupt and nonbankrupt firms, first, financial information from various government contractors must be gathered. The following steps will be accomplished.

1.) Obtain a list from the Air Force Accounting and Finance Center (Denver) of government contractors who filed for bankruptcy.

2.) Gather financial statements for these companies using Moody's, the Q-File, Disclosure Database (PC database), and COMPUSTAT. (Financial statements will be for the three years prior to the bankruptcy filing.)

3.) Match these companies with financially healthy companies of similar size and in the same industries. The search for these companies will be made on COMPUSTAT.

4.) Spreadsheets will be used to calculated ratios from the financial statements of both the bankrupt and nonbankrupt firms.

Testing Other Models

The calculated financial ratios will be run through models developed by Altman, Dagel and Pepper, Moses and Liao, and Zavgren. The results will serve as points of comparison between those models and any new models developed.

Building New Models

New models will be built based on the calculated financial ratios by using two different statistical techniques used by other researchers: logistic regression and discriminant analysis. (The SAS statistical package will be used to perform most of the statistical analyses; LIMDEP will be used for developing a model using logistic regression.) The prediction accuracy of these models will be tested in two ways: (1) comparing accuracy to that of four models developed by other researchers, and (2) using several error rate validation tests. The rest of this chapter discusses these two statistical techniques and describes ways to validate models.

Statistical Techniques Used in Model Building

In predicting bankruptcy, we are interested in two responses: bankruptcy vs nonbankruptcy. Since the dependent variable is binary, it can be considered an indicator variable. But, having an indicator variable as the dependent variable raises certain problems: (1) nonnormal error terms, (2) nonconstant error variances, and a constraint of zero to one for the response function (29:580-581). Because of these problems, a linear regression model is not optimal. Two techniques that can handle binary dependent variables--logistic regression and discriminant analysis --will be discussed in this section.

Logistic Regression. A logistic model with a binary dependent variable will estimate the probability that an observation will fall into one or the other class.

The logistic regression function is (29:596):

$$P\{B\} = [1 + \exp(-\beta'X)]^{-1}, \tag{2}$$

where P{B} is the probability of bankruptcy, and

$\beta'X = \beta_0 + \beta_1 X_1 + \ldots \beta_{p-1} X_{p-1}$; the ßs are the unknown parameters and the Xs are the independent variables.

The method of maximum likelihood is used to estimate the model parameters. Because the parameters β_i are nonlinear, numerical search methods must be used to find a solution (29:591). LIMDEP uses Newton's method of iteration (18:153). Once the maximum likelihood estimates β_i are found, they can be substituted in the logistic regression function shown above. Substituting the variable observations for the X_i in this function provides the fitted response for each case.

Model Tests. Several tests can be made for developed models to determine the performance of the models. These tests are described below.

1. T-Ratio Test: A standard T-ratio test can be used in evaluating the significance of individual coefficients in the response function, i.e., if

$$\begin{aligned} H_0&: \beta_i = 0 \\ H_a&: \beta_i \neq 0 \end{aligned} \tag{3}$$

and the test statistic is

$$t^* = \frac{b_1}{s\{b_1\}} \tag{4}$$

where s = the standard deviation of the corresponding coefficient, then the decision rule is:

$$\begin{aligned} &\text{If } |t^*| \le t(1-\alpha/2;\ n-p), \text{ conclude } H_0 \\ &\text{If } |t^*| > t(1-\alpha/2;\ n-p), \text{ conclude } H_a \end{aligned} \tag{5}$$

where α = significance level, n = sample size, and p = number of parameters (29:243, 603).

2. Likelihood Ratio Test: Another test of the model is to determine whether a subset of the parameters can be dropped without significantly affecting the performance of the model. The test of whether the associated β_i can be omitted is called the likelihood ratio test (29:604). The maximum likelihood estimates, β_i, are estimated and the response function evaluated for both the full [denoted as L(F)] and reduced [denoted as L(R)] models. The hypothesis to be tested is whether the coefficients of the variables considered for omission equal zero. The closer L(R) is to L(F), the more likely that this hypothesis is true. i.e., that the additional parameters do not increase the likelihood function very much.

To evaluate how close L(R) is to L(F), the test statistic, denoted by X^2, is:

$$X^2 = -2[\log L(R) - \log L(F)] \quad (29:605) \tag{6}$$

A small X^2 would lead to the conclusion that the additional variables are unnecessary.

This statistic "follows a chi-square distribution with K degrees of freedom under the null hypothesis that all K coefficients (not counting the intercept) are zero" (1:143).

The decision rule is:

$$\text{If } X^2 \le X^2(1-\alpha;\ p-q), \text{ conclude } H_0 \qquad (7)$$
$$\text{If } X^2 > X^2(1-\alpha;\ p-q), \text{ conclude } H_a, \text{ where}$$

q = number of variables remaining after the test variables are dropped

LIMDEP reports the overall chi-square statistic (X^2). This statistic is actually the result of performing the likelihood ratio test comparing the log-likelihood of the full model and the log-likelihood based only on the intercept. It is a good indicator of the overall fit of the model (1:143).

3. Pseudo R^2: The pseudo R^2 purports to measure the goodness-of-fit of the model. Various formulas for calculating a pseudo R^2 have been proposed, but according to Aldrich and Nelson, they "suffer serious disadvantages. There is no consensus on which of the several measures to use, and . . . interpretation is difficult" (1:143). The measure used for testing in this study is: 1 - (log-likelihood at convergence/restricted log-likelihood) (3:591).

Using the Model for Prediction. If, when substituting a new observation into the model likelihood function, the resulting probability is large, one can predict that the outcome is 1. Likewise, if the probability is low, one may predict that the outcome is 0. The difficulty arises when trying to determine the proper cutoff point to use in classifying the result as 1 or 0. The simplest method is to use .5 as the cutoff point, where if the fitted value is ≥ .5, classify as 1; otherwise classify as 0. This method is only appropriate if the likelihood of 1s and 0s in the population is equal and if the costs of making prediction errors are the same for each of the two cases (29:609).

Discriminant Analysis. The discriminant function uses a weighted linear combination of variables, $Z = \beta_1 X_1 + \beta_2 X_2 + \ldots \beta_p$, to classify an observation into one of several groups (e.g., bankrupt vs. nonbankrupt), based on the Z score (23:415). The discriminant function "maximizes group differences while minimizing variation within the groups" (22:43). If the groups differ more on one variable than on another, that variable should have more weight in the discriminant function (20:365).

Assumptions. (1) The data come from two or more mutually exclusive groups (22:8); (2) the variance of a given variable in both of the samples is the same as that of the variance in the population; (3) the correlation between any two predictor variables in both samples is the same as the correlation between the variables in the population (20:360); (4) the variables come from normal populations; (5) the means of the same variable in the two populations are different (12:517). "The smaller the difference between the two groups on the predictor variable--i.e., the greater the overlap--the more errors of classification we are destined to make" (20:360).

> For the researcher whose main interest is in a mathematical model which can predict well or serve as a reasonable description of the real world, the best guide is the percentage of correct classifications. If this percentage is high, the violation of assumptions was not very harmful. (22:62)

Although presence of multicollinearity among the variables does not violate any of the assumptions, a model will be a more reliable predictor when there is little multicollinearity. Variables will have to have the same relationships in the future as in the sample data in order for the model to be effective; this condition cannot be counted on to happen, since relationships among variables are likely to change over time (27:392).

Distance Measure. One method that can be used to classify observations is to minimize the distances from each observation to each of the "group centroids and classify the case into the closest group" (22:44). This distance measure is called D^2. The formulas shown below are those used by the SAS program in computing this measure (34:318):

$$D_a^{\,2} = g_1(\mathbf{x},a) \text{ where} \tag{8}$$

$D_a^{\,2}$ = the generalized squared distance from 1 to group a

$g_1(\mathbf{x},a) = (\mathbf{x} - \mathbf{m}_a)'S^{-1}(\mathbf{x} - \mathbf{m}_a)$

a = subscript to distinguish the groups

S = the pooled covariance matrix

$\mathbf{x}$ = a vector containing the variables of an observation

$\mathbf{m}_a$ = the vector containing means of the variables in the group a

An observation will be classified into the group with the lowest corresponding D^2.

Linear Discriminant Function. SAS also provides the linear discriminant function that can be used to make predictions. Substituting observations into the equation will result in individual Z-scores for each case. Observations are classified into groups based on their Z-scores: observations with scores greater than or equal to zero are classified into group one, while observations with scores less than zero are classified into group two (23:427). Classification results for the above two methods are the same.

Statistical Interpretation. The coefficients cannot be tested for significance ($b_i = 0$) as they can be in regression analysis because they are not unique (9:883). Several measures have been proposed to "determine the relative importance of individual variables, but none of these has proven to be particularly successful (9:883).

Validation of Error Rates. Several methods can be used to determine what the model prediction error rate is. The most direct method is to take the sample data and run it through the model developed from this data and note how it classifies each observation. Divide the misclassified observations by the sample size to calculate the error rate. This is the method used initially to report the error rates in most studies. (In bankruptcy studies, accuracy rates (1 - error rate = accuracy rate) are most often reported). But this apparent error rate is biased; testing the model by inputting the same observations that the model was built with will tend to make the model predict better than would be the case when testing the model with new observations. Three other methods that can be used to validate a model's accuracy are described below.

Holdout Sample. (A common method used to validate a model requires a holdout sample: a portion of the data is set aside from the observations used to build the model. The model is then tested using this set aside data. Although this is a commonly used method, there are several disadvantages in using procedure (24:2-3):

1) Large samples are often unavailable.

2) There are problems in selecting the size of the holdout sample. "If it is large, a good estimate of the performance of the discriminant function will be obtained, but the function is likely to be poor. If the holdout sample is small, the discriminant function will be better, but the estimate of its performance will be highly variable" (24:2-3).

3) It is "uneconomical with data" (24:2-3); more data than is necessary to build the model must be collected.

Because of the relatively small sample size, this validation method is not used for this research.

Using D^2 (Discriminant Analysis). With a discriminant function, the following equations may be used to calculate a more realistic classification rate (23:429):

$$P_1 = F[(\text{cutoff point} - D^2/2)/D] \tag{9}$$

$$P_2 = F[-(\text{cutoff point} + D^2/2)/D]$$

where P_1 = probability of incorrectly classifying a member of population 1 as a member of population 2, P_2 = probability of incorrectly classifying a member of population 2, D_2 is the Mahalanobis' distance, and F represents the standard normal distribution function. If the cutoff point = 0, then $P_1 = P_2 = F(-D/2)$.

To adjust for a small sample size the following equation may be substituted for D^2 in the above two equations (23:429; 24:4):

$$[(m - p - 3)/(m - 2)]*(D^2), \text{ where } m = \text{total sample size and} \tag{10}$$

p = number of parameters in the discriminant model.

Lachenbruch's Holdout Procedure. This method successively omits observations one at a time, calculates a new discriminant function with the remaining observations, and then classifies the holdout observation using each new function (24:4; 9:895). "The estimates of the probabilities of misclassification are then computed by summing the number of cases that were misclassified from each group and dividing by the number in each group" (24:4-5). This method provides a good estimate of error rates, better than the D^2 method described above and with similar results to the holdout sample method discussed previously. It is especially recommended if the distance measurement, D^2, is less than one (24:9).

Summary

This chapter described data collection methods, the types of statistical methods to be used in building the new models (logistic regression and discriminant analysis) and ways to validate models. The next chapter will discuss the results of the procedures described in the current chapter.

IV. Data Analysis and Findings

This chapter discusses the data used in building the bankruptcy models, the types of analyses performed, and the results.

Data Gathering

A list of 150 government contractors who filed for bankruptcy was compiled from Air Force Accounting and Finance Center records. A search through Moody's manuals, the Q-File, Disclosure Database, and COMPUSTAT revealed financial information for only five of the companies. In order to develop a larger sample, names of bankrupt companies likely to do business with the government were obtained from the 1988 Securities and Exchange Commission's annual report and the Wall Street Journal Index. COMPUSTAT provided information for 13 of these companies, bringing the total bankrupt sample to 18 companies. (See Table 2 for a list of the industries these companies are in.) Financial statements for these

TABLE 2

Industries
AIR TRANSPORT, SCHEDULED (2)
CMP INTEGRATED SYS DESIGN
COMPUTER STORAGE DEVICES
ELECTRONIC COMPONENTS, NEC
FABRICATED PLATE WORK
GLASS PD, MADE OF PURCH GLASS
JEWELRY, SILVERWR, PLATED WARE
MOBILE HOME DEALERS
MOTOR VEHICLE PART, ACCESSORY
MOTORS & GENERATORS
NONSTORE RETAILERS
PETROLEUM BULK STATIONS-WHSL
RADIO, TV BROADCAST, COMM EQ (2)
RETAIL STORES, NEC
TRUCKING, EXCEPT LOCAL
VARIETY STORES
X-RAY & RELATED APPARATUS

companies were available for at least two years before the dates of bankruptcy filing. In order to match the bankrupt companies to 18 healthy companies, a search by SIC and size of assets of the 18 bankrupt companies was performed on COMPUSTAT. Table 3 lists the companies in the two samples, along with the total assets, sales, and net income for the year before bankruptcy filing for each firm.

Information from the balance sheets and income statements was input into spreadsheets in order to calculate the ratios used in this research and to calculate the scores for the models developed by Altman, Dagel and Pepper, Moses and Liao, and Zavgren.

Ratio Selection

Initially 40 ratios were compiled from Dagel and Pepper (5:10), Dambolena (6:74), Fulmer (13:34-35), and Pinches et al. (30:303-304). These were then pruned down to 20 ratios and placed into the seven categories described by Pinches et al. in their factor analysis study of business ratios. Presumably, by choosing one ratio from each of these categories, the fullest descriptive capability will by maintained as well as the independence of the ratios (30:304). The categories and ratios used in this research are listed in Table 4.

The ratio, Cash & Equivalents/Current Liabilities, is based on Dambolena's Net Liquid Balance measure. Dambolena states that one way to calculate this measure is to subtract current liabilities from cash and equivalents. He asserts that, "the higher the level of the net liquid balance, . . . the lower the risk of impending liquidity problems and, presumably, the lower the risk of subsequent bankruptcy" (6:74). If used as a ratio, lower risk would be indicated as the number increased over one.

TABLE 3

Bankrupt/Nonbankrupt Companies

Bankrupt Companies	Assets	Sales	Net Income
AIR FLORIDA	172.942	218.126	-39.229
BIRDVIEW SATELLITE	23.709	58.922	-9.456
BRANCH INDS	52.458	134.838	-3.541
CAPITOL AIR	36.494	176.164	-11.147
CASTLE INDS	16.226	6.764	-7.864
COLONIAL X-RAY	1.504	1.604	-0.551
COOK UNITED	95.066	244.630	-30.848
ENTERPRISE TECHNOLOGIES	33.301	90.427	-3.588
HELIONETICS	27.890	12.194	-22.448
KELLETT CORP	0.635	2.896	-1.482
LA POINTE INDS	6.361	4.583	0.112
NATL BUSINESS COMM	5.549	3.116	-3.445
SERVAMATIC SYSTEMS	28.717	91.135	0.556
SHATTERPROOF GLASS	24.186	24.838	-4.430
SYKES DATATRONICS	32.687	20.235	-14.015
SYMETRICS INDS	2.942	5.788	0.021
TOWLE MANUFACTURING	134.525	221.762	-67.240
WEDTECH CORP	188.607	117.514	9.667
Mean	49.0999	79.7520	-11.6071
Max	188.6070	244.6300	9.6670
Min	0.6350	1.6040	-67.2400
Nonbankrupt Companies			
AIR WIS SVCS	130.570	54.772	4.031
HERLEY INDS	20.670	15.599	2.127
PAM TRANSPORTATION SVCS	68.003	68.739	2.554
AIR MIDWEST	26.930	33.301	1.815
HUGHES HOMES	23.396	67.625	1.026
XSIRIUS	1.822	0.021	-1.129
SPROUSE-REITZ	93.172	205.652	2.477
SUMMIT OILFIELD	33.729	32.050	-2.109
FRANKLIN ELECTRIC	52.434	179.327	-7.170
NO ATLANTIC TECH	2.114	2.760	-1.379
DECOM SYSTEMS	4.557	6.589	-2.247
HEARX LTD	3.682	1.026	-3.422
OLD FASHION FOODS	13.404	14.082	0.882
TELEPHONE EXPRESS	11.060	9.424	-0.175
CREATIVE COMPUTER APPL	5.339	4.538	-0.658
BUNTING INC	3.102	5.811	-0.611
LAZARE KAPLAN INTL	29.658	29.808	-1.724
SUPERIOR INDS	75.055	130.836	7.249
Mean	33.2609	47.8867	0.0854
Max	130.5700	205.6520	7.2490
Min	1.8220	0.0210	-7.1700

TABLE 4

Ratios Used in the Analysis

Profitability
Cash Flow/Tot Debt
EBIT/Total Assets
Income Before Discontinued Operations & Extraordinary Items/Total Capital
Net Income/Sales
Net Income/Tot Assets
Capital Turnover
Cash Flow/Sales
Sales/Net Plant
Sales/Total Assets
Inventory Turnover
Sales/Working Capital
Financial Leverage
Long-Term Debt/Tot Capital
Net Worth/Total Assets
Retained Earnings/Total Assets
Total Debt/Total Assets
Receivables Turnover
Sales/Receivables
Liquidity
Current Assets/Current Liabilities
Quick Assets/Current Liabilities
Working Capital/Total Assets
Cash Position
Cash & Equivalents/Current Liabilities
Cash & Equivalents/Sales
Cash & Equivalents/Total Assets

Cash Flow = Net Income + Depreciation/Depletion/Amortization
EBIT = Earnings before Interest + Taxes
Net Worth = Assets - Liabilities
Quick Assets = Cash & Equivalents - Receivables
Total Capital = Total Equities - Current Liabilities
Working Capital = Current Assets - Current Liabilities

Two companies had zero inventories; therefore the three ratios with inventory in the denominator gave errors in the spreadsheet calculations. Because the sample size was already small and no other study has ever shown any of the inventory ratios to be significant in bankruptcy prediction, these ratios were not considered for inclusion in a model.

Ratio Statistics. Statistics for each ratio for both bankrupt and nonbankrupt companies are presented in Table 5. Of special interest in this table is the column looking at the difference in the means between the bankrupt and nonbankrupt sample. The means of seven ratios--CF/S, CF/TD, INC/TC, LTD/TC, NI/S, S/TA, and TD/TA--are higher for the bankrupt sample than for the nonbankrupt sample. (Higher means would be expected only for the LTD/TC and TD/TA ratios.) Figure 1 graphically compares the means of each of the ratios for the bankrupt and nonbankrupt firms. A model using these ratios may discriminate for this sample, but would likely give misleading results in making future predictions. These ratios were still considered for model inclusion, because for future samples, some of these ratios may still be higher for nonbankrupt vs bankrupt firms.

Also, in this table are the results of the "paired-t tests," which tested whether the difference between the individual ratio means of the two samples are significant. This test divides the mean of the differences for each ratio by the standard deviation for the differences over the square root of the sample size (21:158). The resulting statistic is then compared to t-table values to test for significance. As can be seen from the last column in the table, even at the 20% significance level, only 11 of the 20 ratios have means that are significantly different.

TABLE 5

Ratio Statistics for Bankrupt & Nonbankrupt Companies

Ratios	Bankrupt Companies: Mean	Max	Min	Std Dev	Nonbankrupt Companies: Mean	Max	Min	Std Dev	Diff Between Means *	Difference Significant at: ** 5%	10%	20%
C/CL	0.09	0.37	0.00	0.11	1.22	14.94	0.01	3.44	1.14			x
C/S	0.05	0.41	0.00	0.10	4.22	74.00	0.00	17.41	4.18			
C/TA	0.04	0.23	0.00	0.06	0.15	0.85	0.01	0.19	0.11	x	x	x
CF/S	-0.33	0.13	-1.69	0.50	-3.12	0.18	-52.95	12.46	-2.79			
CF/TD	-0.30	0.10	-0.95	0.34	-0.70	0.31	-10.69	2.55	-0.40			
CA/CL	1.20	3.06	0.19	0.83	2.59	15.21	0.57	3.35	1.39		x	x
EBIT/TA	-0.30	0.12	-2.23	0.52	-0.11	0.16	-0.94	0.32	0.19			x
INC/TC	0.63	7.79	-2.92	2.06	-0.51	1.24	-6.66	1.77	-1.14		x	x
LTD/TC	3.60	79.64	-10.41	19.14	2.78	66.37	-18.96	16.5[illegible]	-0.82			
NI/S	-0.37	0.08	-1.84	0.52	-3.22	0.14	-53.76	12.64	-2.85			
NI/TA	-0.39	0.05	-2.33	0.54	-0.15	0.10	-0.93	0.31	0.24		x	x
NW/TA	-0.01	0.56	-1.35	0.53	0.32	0.94	-1.31	0.47	0.33	x	x	x
QA/CL	0.60	2.12	0.08	0.60	1.75	15.08	0.34	3.38	1.15			x
RE/TA	-0.41	0.48	-2.00	0.60	-0.24	0.48	-2.59	0.75	0.17			
S/NP	7.15	22.93	0.80	5.60	7.87	37.50	0.29	9.93	0.71			
S/R	13.46	72.12	1.24	16.91	26.92	333.85	1.50	77.43	13.45			
S/TA	1.86	5.07	0.42	1.40	1.22	2.89	0.01	0.72	-0.64			x
S/WC	-23.63	52.89	-471.46	113.42	5.74	95.67	-41.30	25.93	29.36			
TD/TA	1.01	2.35	0.44	0.53	0.68	2.31	0.06	0.47	-0.33	x	x	x
WC/TA	-0.18	0.41	-1.74	0.62	0.23	0.81	-0.30	0.31	0.41	x	x	x

* Nonbankrupt means - bankrupt means

** Based on paired t-tests.

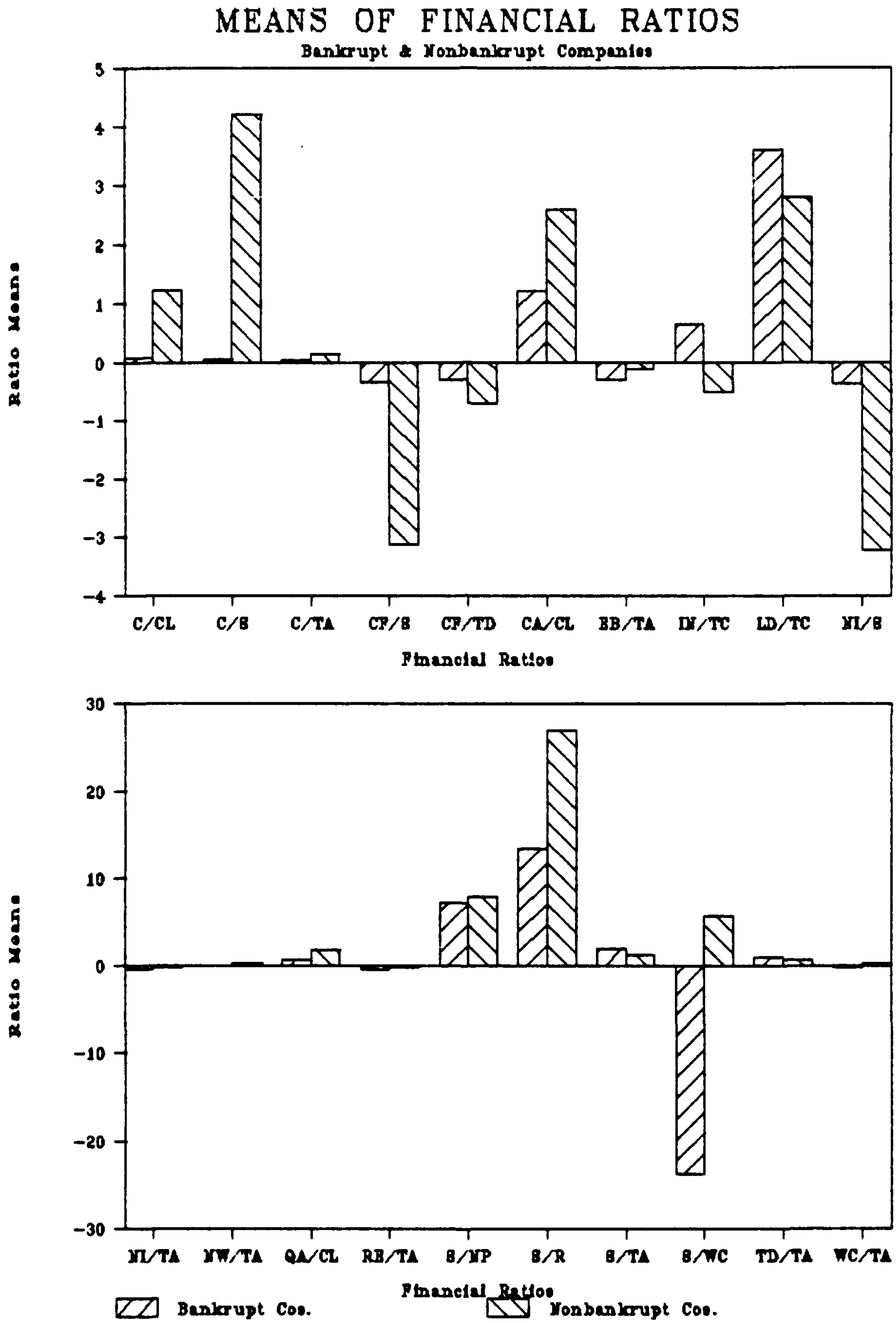

Figure 1. Means of Financial Ratios

Test for Normalcy. Both the paired t-test described above and the discriminant analysis procedure assume that the populations are normally distributed (21:157; 34:41). Therefore, the ratios were analyzed with the SAS PROC UNIVARIATE procedure to determine which exhibited a normal distribution. "This procedure produces a test statistic for the null hypothesis that the input data values are a random sample from a normal distribution" (33:1187). This statistic, the Shapiro-Wilk statistic, is the "ratio of the best estimator of the variance (based on the square of a linear combination of the order statistics) to the usual corrected sum of squares estimator of the variance" (33:1187). Small values would lead to rejection of the null hypothesis.

In this analysis, any value less than .50 led to the assumption that financial ratio in question does not come from a normal distribution. Ratios falling into this category are: LTD/TC and S/WC for the bankrupt sample and CS, C/FS, CF/TD, LTD/TC, NI/S, QA/CL, and S/R for the nonbankrupt sample.

Correlation Matrices. SAS produces two types of correlation matrices, one using Pearson correlation coefficients and the other using Spearman correlation coefficients. (The Spearman correlation statistic does not rely on the distribution of the two ratios being studied to be normal (12:114).) These matrices show the relationship between each of the ratio variables and the amount of collinearity present. It was found that partitioning the ratios into the seven categories described by Pinches et al. did not prevent some major collinearity problems between ratios of different categories. For example, the C/CL ratio was highly correlated (over 98%) with CF/S (capital turnover) and NI/S (profitability).

Results of Other Models

As mentioned previously, financial data for both the bankrupt and nonbankrupt companies was input into the four models developed by Altman, Dagel and Pepper, Moses and Liao, and Zavgren. See Table 6 for a list by company of each models' predictions.

Altman. In Altman's model, the probability of bankruptcy depends on a company's Z-score; these possibilities are shown below (12:553):

1.81 or less	assign to bankrupt group
1.81 to 2.99	gray area
2.99 or higher	assign to bankrupt group

For the 18 bankrupt companies, Altman's model would have predicted possible bankruptcy for 72% of the firms one year before filing bankruptcy. Of the 18 nonbankrupt companies, this model would have predicted 39% nonbankrupt.

Dagel and Pepper. The model developed by these two researchers is:

$$Z = 1.54 - 6.48X_1 + 4.61X_2 - 0.41X_3 + 9.31X_4 - 5.40X_5 + 1.63X_6 \tag{11}$$

where

X_1 = Total Debt/Total Assets
X_2 = Cash Flow/Total Debt
X_3 = Current Assets/Current Liabilities
X_4 = Quick Assets/Total Assets
X_5 = Working Capital/Total Assets
X_6 = Net Sales/Total Assets

For this model, a Z-score of less than zero indicates bankruptcy (5:15). Of the bankrupt companies, this model would predict bankruptcy for 44% of them one year prior to bankruptcy. For the nonbankrupt companies, the model would predict 56% and 72% for the two study years.

Moses and Liao. If the three ratios--equity/assets, working capital/assets, and sales/assets--are above their cutoff points

TABLE 6

Results of Other Models

The charts below and on the next page show results of four different models using the financial statements for one year prior to bankruptcy for the bankrupt companies and comparable time periods for the nonbankrupt companies.

Bankrupt Companies	Altman	Dagel & Pepper	Moses & Liao	Zavgren
	B	NB	IB	0.00
BIRDVIEW SATELLITE	B	NB	IB	0.33
BRANCH INDS	NB	NB	IB	0.00
CAPITOL AIR	B	NB	IB	0.00
CASTLE INDS	B	B	IB	1.00
COLONIAL X-RAY	B	NB	PH	0.00
COOK UNITED	B	B	PH	0.85
ENTERPRISE TECHNOLOGIES	NB	NB	IB	1.00
HELIONETICS	B	B	IB	0.26
KELLETT CORP	B	NB	IB	0.42
LA POINTE INDS	G	B	PH	0.03
NATL BUSINESS COMM	B	B	IB	0.03
SERVAMATIC SYSTEMS	NB	NB	IB	1.00
SHATTERPROOF GLASS	B	B	IB	0.94
SYKES DATATRONICS	B	B	PH	0.02
SYMETRICS INDS	NB	NB	PH	0.14
TOWLE MANUFACTURING	B	B	IB	0.81
WEDTECH CORP	NB	NB	IB	0.00

Predicted possible bankruptcy or higher	Predicted bankruptcy:	Predicted impending bankruptcy:	Probability of bankruptcy 50% or more:
72%	44%	72%	33%

B - Bankrupt
G - Gray Area
NB - Nonbankrupt

IB - Impending Bankruptcy
PH - Financially Healthy

TABLE 6 (continued)

Nonbankrupt Companies	Altman	Dagel & Pepper	Moses & Liao	Zavgren
AIR WIS SVCS	G	B	IB	0.00
HERLEY INDS	G	NB	FH	0.04
PAM TRANSPORTATION SVCS	G	NB	IB	*
AIR MIDWEST	G	NB	IB	0.00
HUGHES HOMES	NB	NB	FH	0.88
XSIRIUS	B	B	FH	*
SPROUSE-REITZ	NB	B	FH	0.56
SUMMIT OILFIELD	NB	B	IB	1.00
FRANKLIN ELECTRIC	NB	NB	FH	0.01
NO ATLANTIC TECH	B	B	IB	0.70
DECOM SYSTEMS	G	B	IB	0.94
HEARX LTD	B	B	IB	0.02
OLD FASHION FOODS	G	NB	IB	0.00
TELEPHONE EXPRESS	B	NB	IB	0.26
CREATIVE COMPUTER APPL	B	NB	FH	0.75
BUNTING INC	NB	NB	IB	0.46
LAZARE KAPLAN INTL	NB	B	IB	0.00
SUPERIOR INDS	NB	NB	FH	0.03
	Predicted not bankrupt:	Predicted not bankrupt:	Predicted not bankrupt:	Probability of bankruptcy less than 50%:
	39%	56%	39%	62%

B - Bankrupt
G - Gray Area
NB - Nonbankrupt

IB - Impending Bankruptcy
FH - Financially Healthy

* - Model could not be calculated because it includes a ratio with inventory as a denominator; this company had 'zero' inventory.

(.391, .191, and 2.51, respectively), then they are given scores of 'one.' Otherwise, their scores will be 'zero.' These scores are then summed. If the sum is two or greater, the company can be considered to be financially healthy; a score of less than two signals impending bankruptcy (28:35).

For the bankrupt companies, this model would predict 72% for the first year prior to bankruptcy. For the nonbankrupt companies, 39% would be predicted to be bankrupt.

Zavgren. A 'y' is calculated by first multiplying the coefficients below with the appropriate ratio and by 100, then adding the products to -.23883.

Inventory turnover	.00108
Receivables turnover	.01583
Cash position	.10780
Short-term liquidity	-.03074
Return on investment	-.00486
Financial leverage	.04350
Capital turnover	-.00110

This 'y' is then plugged into the equation $1/(1 + e^{-y})$ to arrive at the probability of failure (7:64-65).

Zavgren's model would predict 33% of the bankrupt sample, for the first year prior to bankruptcy, would become bankrupt. Of the nonbankrupt sample, her model would predict 62% to be nonbankrupt.

Developing New Models

Two different statistical techniques were used to build two different models.

Logistic Regression. The statistical package LIMDEP was used to develop a bankruptcy prediction model using logistic regression. Over 200 models were run. The first 130 models consisted of one ratio from each of the seven categories described by Pinches et al. in their factor analysis study (30:304). Based on a 50% cutoff point, four of these models could predict 33 out of 36 cases correctly (92% accuracy). But each of these models had three or four coefficients with the "wrong sign." (Bankrupt companies were coded as 1, while surviving companies were coded as 0. Since these models predict the probability of bankruptcy, one would expect the coefficients of most of the ratio variables to have negative signs, indicating an inverse relationship, except for LTD/TC and TD/TA.) Coefficients with the wrong sign were a problem in almost every model. Also, all of these models had five or six variables (out of seven) that were insignificant at the 10% significance level (using the T-ratio test). The cash position ratios-- C/CL, C/TA, and C/S--were significant at less than the 5% significant level for almost every model. Other ratios that came in at relatively low (10%) significant levels for many models were CF/TD and NI/TA, (profitability ratios), CF/S (capital turnover) and QA/CL (liquidity).

More models were run by dropping the most insignificant variable(s) and/or dropping variables with the wrong sign. This never improved the prediction accuracy nor the log-likelihood and chi-squared statistics reported by LIMDEP. But some of the resulting models were more meaningful (signs and significance of the coefficients).

The two best resulting models included CF/TD, S/WC, and C/TA in one case; and CF/TD, S/WC, and C/CL in the other. The coefficients of the two models had the correct signs and had moderately successful overall prediction rates--83% for the first above model and 75% for the second. But there is a high degree of correlation between CF/TD and C/TA and between CF/TD and C/CL. Performing the likelihood ratio test showed that dropping S/WC and CF/TD did not significantly affect the models' performances at the 5% significance level. Therefore the best models are univariate models containing either C/TA or C/CL. These are shown below:

UNIVARIATE MODEL: C/TA

Variable	Coefficient	Std. Error	T-ratio (Sig.Lvl)	Std.Dev.of X
ONE	1.23147	.5741	2.145 (.03196)	.00000
C/TA	-17.6537	7.242	-2.438 (.01478)	.14793

The probability equation is:

$$\text{Prob(bankruptcy)} = [1 + \exp(1.23147 - 17.6537\ C/TA)]^{-1}$$

Log-Likelihood.............	-19.885
Restricted (Slopes=0) Log-L.	-24.953
Chi-Squared (1)...........	10.136
Significance Level..........	.14537E-02

		Predicted	
Actual	TOTAL	0	1
TOTAL	36	16	20
0	18	13	5
1	18	3	15

UNIVARIATE MODEL: C/CL

Variable	Coefficient	Std. Error	T-ratio (Sig.Lvl)	Std.Dev.of X
ONE	1.40799	.5705	2.468 (.01359)	.0000
C/CL	-7.12484	2.744	-2.596 (.00943)	2.4693

The probability equation is:

$$\text{Prob(bankruptcy)} = [1 + \exp(1.40799 - 7.12484\ C/TA)]^{-1}$$

Log-Likelihood.............	-17.250
Restricted (Slopes=0) Log-L.	-24.953
Chi-Squared (1)...........	15.406
Significance Level..........	.26740E-05

		Predicted	
Actual	TOTAL	0	1
TOTAL	36	14	22
0	18	11	7
1	18	3	15

As can be seen by the above statistics:

1) the t-tests indicate that both C/TA and C/CL are significant--at the 1.5% and .9% levels, respectively.

2) the chi-squares indicate the models are significant (the model chi-square must be greater than 3.84 for the model to be considered significant at the 5% level).

3) Although the two statistical tests discussed above indicate that the univariate model with C/CL is better than the one with C/TA, the second model appears to be a better predictor: it predicts correctly 26 out of 36 times, or 72%, while the first model predicts correctly 28 out of 36 cases, or 78%. A model that possesses the best explanatory power (more statistical significance) is not necessarily the best predictor (4:394).

The pseudo R^2 for the first model is $1 - (-19.885/-24.953) = .20$: for the second model it is $1 - (-17.25/-24.953) = .31$. These statistics do not appear to be unusually low for a non-linear logit model. In addition, as indicated in the previous chapter, the R^2 statistic is not as reliable a test of a model's strength as the likelihood ratio test.

<u>Discriminant Analysis</u>. The SAS statistical package was used to perform the discriminant analysis of the data. Since the procedure assumes a "multivariate normal distribution within each class" (34:41),

variables that were shown as not being from a normal population could not be used in the analyses.

Stepwise Discriminant Analysis. Initially, three different stepwise discriminant analysis procedures were done--forward, backward, and stepwise selection. Only variables with normal distributions were considered. (Variables deleted because of nonnormal distributions are CF/S, C/S, LTD/TC, NI/S, QA/CL, S/R, and S/WC.) For both the forward and stepwise selection processes, three variables remained in the model: CF/TD, EBIT/TA, and NW/TA. The linear discriminant function using just these variables resulted in a model with a prediction accuracy of only 69.4%. For the backward selection process, the following variables remained: CA/CL, CF/TD, EBIT/TA, NW/TA, and S/NP. All of these cannot be included together in one model, as several ratios are from one of the seven categories. (For example, CF/TD and EBIT/TA are both profitability ratios.) The accuracy rates for models with various combinations of these variables ranged from 61.1 to 63.9%.

Subsequently, ratios that were shown to be unexpectedly larger for the bankrupt sample vs the nonbankrupt sample were deleted. (See Table 5; these additional ratios are CF/TD, INC/TC, and S/TA.) Variables remaining in the model after forward and stepwise selection are CA/CL, NI/TA, and S/NP. Variables remaining after backward selection are CA/CL, EBIT/TA, NI/TA, S/NP, and WC/TA. Models developed using combinations of these ratios had accuracy rates ranging from 55.6 to 69.4%. Although one might expect that using the variables found by the stepwise methods will yield the best prediction models, according to Eisenbeis, variables found by these methods do not necessarily provide the best classification results (9:885).

Model. Because of the success of the C/CL and C/TA ratios in the logistic regression model, these ratios were examined in the discriminant analysis models. The best models were C/TA with NI/TA and C/TA alone; both of these had a prediction accuracy of 77.8%. (This is the same accuracy rate reported for the logistic model with C/TA alone. This is not surprising, as other studies using logistic regression and discriminant analysis have reported similar results (4:394).) The one variable model with C/TA was chosen as the final model; the linear discriminant function is shown below:

$$Z = -.51464 + 5.49922 \ C/TA$$

The higher the C/TA ratio, the higher the Z score. (SAS did not report any statistics to enable inference testing.)

Cutoff Points. Assuming a 50% prior probability for being chosen from either the bankrupt or nonbankrupt population, the cutoff point will be zero. Any observation with a Z-score below zero will be considered as bankrupt; any score above zero will be classified as nonbankrupt. Table 7 shows the Z-scores for the 36 companies and shows how they are classified assuming 50% prior probabilities. As can be seen from the first Z-Score Classification column in this table, the prediction accuracy rates are 88.9% for bankrupt firms, and 66.7% for nonbankrupt firms.

But the actual bankrupt to nonbankrupt proportion in the population is quite different from 50/50. The percentage of bankrupt companies is much lower than the percentage of nonbankrupt firms; one estimate places the ratio at .03/.97 (37:9). Therefore, a different cutoff point should be selected. The $\ln(p_1/p_2)$ can be used to derive a new cutoff point

TABLE 7

Z-Score Classification Error Rates

STATUS	C/TA	Z-SCORE	Z-SCORE CLASSIFICATION (50% prior prob/ equal costs)	Z-SCORE CLASSIFICATION (.03/.97 prior prob/ equal costs)	Z-SCORE CLASSIFICATION (.03/.97 prior prob/ unequal costs)
1	0.024	-0.382	1	0	0
1	0.034	-0.330	1	0	0
1	0.029	-0.356	1	0	0
1	0.017	-0.423	1	0	0
1	0.010	-0.462	1	0	0
1	0.142	0.264	0	0	0
1	0.017	-0.418	1	0	0
1	0.035	-0.321	1	0	0
1	0.010	-0.457	1	0	0
1	0.000	-0.515	1	0	0
1	0.044	-0.271	1	0	0
1	0.228	0.741	0	0	0
1	0.006	-0.484	1	0	0
1	0.004	-0.494	1	0	0
1	0.072	-0.121	1	0	0
1	0.023	-0.386	1	0	0
1	0.014	-0.436	1	0	0
1	0.011	-0.455	1	0	0
STATUS '1' ERROR RATES:			88.89%	0.00%	0.00%
0	0.120	0.146	0	0	0
0	0.271	0.977	0	0	0
0	0.027	-0.366	1	0	0
0	0.157	0.346	0	0	0
0	0.097	0.017	0	0	0
0	0.853	4.176	0	0	0
0	0.098	0.023	0	0	0
0	0.015	-0.433	1	0	0
0	0.036	-0.315	1	0	0
0	0.096	0.013	0	0	0
0	0.154	0.334	0	0	0
0	0.100	0.038	0	0	0
0	0.100	0.036	0	0	0
0	0.079	-0.081	1	0	0
0	0.169	0.416	0	0	0
0	0.005	-0.486	1	0	0
0	0.064	-0.164	1	0	0
0	0.208	0.629	0	0	0
STATUS '0' ERROR RATES:			66.67%	100.00%	100.00%
OVERALL ERROR RATES:			77.78%	50.00%	50.00%

taking the different probabilities into consideration, where p_1 is the probability of being in the bankrupt population and p_2 the probability of being in the nonbankrupt population. If $p_2 > p_1$, then the natural log of p_1/p_2 will be some negative number; thus, an observation would be more likely to be classified as being from the nonbankrupt population (since the cutoff number is lower than zero). If, on the other hand, $p_2 < p_1$, then the cutoff point will be some positive number, lowering the chance of an observation being placed in nonbankrupt population (23:427). The $\ln(.03/.97) = -3.476$ is used as the cutoff point in this study when taking just the prior probabilities into consideration. As can be seen in the second Z-Score Classification column in Table 7, using this rule classifies 0% of the companies as bankrupt and 100% as nonbankrupt, for an overall accuracy rate of 50%. It is obvious that the model is no longer any better than a naive model that predicts all companies as being nonbankrupt. If 3% of the companies in the population undergo bankruptcy, then either model would be correct 97% of the time. Klecka notes that if the two groups are very distinct, then taking into consideration prior probabilities is unlikely to have much effect, "because very few cases will be near the borderlines between the groups" (22:47).

In addition to considering prior probabilities in deciding a cutoff point, the costs of misclassification should be considered. It would be more costly to the government to misclassify a bankrupt company as nonbankrupt than vice versa. In adjusting the classification cutoff point to take this into consideration, the same methodology as described above can be used. The new cutoff point is $\ln(c_{12}/c_{21})$, where c_{12} = the cost of misclassifying a bankrupt firm as nonbankrupt, and c_{21} = the cost of misclassifying a nonbankrupt company as bankrupt. (23:428). The difference in costs to the government of misclassification is unknown; the ratio of c_{12}/c_{21} was arbitrarily chosen as 5/1, so that the cost of misclassifying a bankrupt firm as nonbankrupt is five times more expensive than vice versa.

The two ratios described above--prior probabilities and misclassification costs--can be combined in one calculation to determine a cutoff point (23:428):

$$\ln(p_1/p_2) + \ln(p_{12}/c_{21}) = \ln(p_1/p_2)(c_{12}/c_{21}) = -1.867$$

Although this cutoff point is higher than before, the accuracy for the companies in this sample is still 0% for the bankrupt sample and 100% for the nonbankrupt sample. (See the third Z-Score Classification column in Table 7.)

Validation of Error Rates. Several different methods were used to determine the model's prediction error. The apparent error rates have already been indirectly reported in the discussions above as accuracy rates (1 - error rates). But, as mentioned in the previous chapter, these error rates are biased. The results of two other methods--the D^2 method (used for discriminant analysis models) and Lachenbruch's holdout procedure--are shown below.

D^2 Method. The estimated error rate assuming

1) 50% prior probabilities and equal costs is:

$$P_1 = P_2 = F(-\sqrt{.58933}/2) = F(-.3838) = .352 = 35.2\%$$

2) prior probability of bankruptcy = 3%, prior probability of nonbankruptcy is 97%, and equal costs is:

$$P_1 = F[-(3.476 + (31/34 * .58933/2))]/\sqrt{.58933} = F(4.178) = 100\%$$

$$P_2 = F[(3.476 - (31/34 * .58933/2))]/\sqrt{.58933} = F(-4.878) = 0\%$$

Prior probability of bankruptcy as in 2) above and unequal costs (the cost of identifying a bankrupt company as nonbankrupt is presumed to cost fives times more than vice versa:

$$P_1 = F[-1.867 + (31/34 * .58933/2))]/\sqrt{.58933} = F(2.082) = 98.12\%$$

$$P_2 = F[1.867 - (31/34 * .58933/2))]/\sqrt{.58933} = F(-2.782) = .27\%$$

(P_1 = probability of incorrectly classifying a member of population 1 as a member of population 2 and P_1 = probability of incorrectly classifying a member of population 2. See Chapter 3 for further explanation of these formulas.)

Lachenbruch's Holdout Procedure. To perform this test, one observation at a time was deleted, and new discriminant funtions were calculated based on each of these m-1 data sets. These new functions were then fitted with the appropriate deleted observations to arrive at the predicted outcomes for those observations. Table 8 shows the 36 new functions along with the Z-scores and classifications when substituting in the deleted C/TA values. (Companies with Z-scores < 0 are classified as bankrupt.) The overall error rate--number of errors divided by the total sample size, m--is 25%. This is slightly worse than the apparent error rate reported in previous sections of 22.2%. Although Lachenbruch has shown this method to provide a better idea of future prediction error rates, and this result appears much better than the results in the sections directly above, this method does not show the true picture for this analysis. Lachenbruch did not compare methods taking prior probabilities and differences in misclassification costs into consideration; the result using the Lachenbruch holdout procedure is probably too optimistic for this data, primarily due to differences of prior probabilities for the bankrupt and nonbankrupt populations.

TABLE 8

Error Rates: Lachenbruch's Holdout Procedure

			COEFFICIENTS			
OBS#	ACTUAL STATUS	C/TA (x)	INTERCEPT (b0)	C/TA (b1)	Z-SCORE	CLASSIFICATION
1	1	0.024	-0.498	5.2928	-0.371	1
2	1	0.034	-0.499	5.3202	-0.318	1
3	1	0.029	-0.498	5.3063	-0.344	1
4	1	0.017	-0.497	5.2746	-0.408	1
5	1	0.010	-0.497	5.2572	-0.444	0
6	1	0.142	-0.519	5.7316	0.295	1
7	1	0.017	-0.497	5.2746	-0.408	1
8	1	0.035	-0.499	5.3230	-0.313	1
9	1	0.010	-0.497	5.2572	-0.444	1
10	1	0.000	-0.496	5.2337	-0.496	1
11	1	0.044	-0.500	5.3493	-0.265	0
12	1	0.228	-0.550	6.2408	0.873	1
13	1	0.006	-0.496	5.2476	-0.465	1
14	1	0.004	-0.496	5.2429	-0.475	1
15	1	0.072	-0.504	5.4401	-0.112	1
16	1	0.023	-0.498	5.2901	-0.376	1
17	1	0.014	-0.497	5.2670	-0.423	1
18	1	0.011	-0.497	5.2596	-0.439	0
19	0	0.120	-0.512	5.4235	0.139	0
20	0	0.271	-0.459	5.0997	0.923	1
21	0	0.027	-0.566	5.8239	-0.408	0
22	0	0.157	-0.495	5.3095	0.338	0
23	0	0.097	-0.523	5.5066	0.011	0
24	0	0.853	-1.168	16.0385	12.513	0
25	0	0.098	-0.523	5.5028	0.016	1
26	0	0.015	-0.574	5.8891	-0.486	1
27	0	0.036	-0.560	5.7773	-0.352	0
28	0	0.096	-0.524	5.5104	0.005	0
29	0	0.154	-0.524	5.3179	0.295	0
30	0	0.100	-0.522	5.4952	0.028	0
31	0	0.100	-0.522	5.4952	0.028	1
32	0	0.079	-0.534	5.5786	-0.093	0
33	0	0.169	-0.491	5.2775	0.401	1
34	0	0.005	-0.581	5.9460	-0.552	1
35	0	0.064	-0.542	5.6435	-0.181	0
36	0	0.208	-0.476	5.1900	0.603	0

OVERALL ERROR RATE: 25.00%

Summary

Although 20 ratios were considered in the model-building process, both logistic regression and discriminant analysis yielded the same "best" model: C/TA. Using this one-variable model in each case resulted in an apparent error rate of about 22%. But this error rate is biased upwards because it is based on the same data that was used in building the model. Several alternate ways of finding the true error rate were calculated; the most reliable method, Lachenbruch's holdout procedure, yielded an error rate of 25%.

Financial information for both the bankrupt and nonbankrupt companies was run through four models developed by Altman, Dagel and Pepper, Moses and Liao, and Zavgren. Altman's model and Moses and Liao's model both predicted bankruptcy correctly 72% of the time. Zavgren's model was the best predictor--62% accuracy--of nonbankruptcy.

Conclusions concerning these findings and recommendations for further research are covered in the next chapter.

V. Conclusion

Introduction

Previous chapters provided an overview of this research effort, a review of the literature concerning bankruptcy models, a description of the methodology used, and results of the subsequent analyses. The primary objective of this research was develop a bankruptcy prediction model for government contractors. Based on this objective, the following research questions were posed:

1. What financial distress models have been developed?

a. What sort of data (i.e., number and types of companies, years of data, financial statement items) were used to develop these models?

b. What techniques were used in building the models?

c. What is the reliability of these models when used with government contractor data?

2. Can new models be built applying the statistical techniques used to develop previous models? Which of these new models demonstrates the most reliability for government contractors? Are any of them reliable enough (i.e., what is their prediction accuracy)?

This chapter will address each of these questions in turn and discuss the results of this research as it pertains to each. A final section of this chapter will provide recommendations for future research.

Discussion of Results

Research Question 1. A review of the literature found a multitude of previous research efforts on this subject. Most of the studies had a minimum of at least 25 bankrupt companies and matched these to nonbankrupt companies by industry and size of total assets. While most models are based on balance sheets and income statements, several recent studies have looked at including cash flow measures. Most of the models are multivariate models that were developed using discriminant analysis. Recently there has been more interest in the logistic regression technique. Two of the models developed by other researchers were based on government contractor data; one was developed using discriminant analysis (Dagel and Pepper) and the other using a combination of discriminant analysis and univariate analyses (Moses and Liao).

Inputting the financial information from the samples of bankrupt and nonbankrupt firms into four other models (Altman, Dagel and Pepper, Moses and Liao, and Zavgren) showed that the models were less successful predicting bankruptcy than reported in these studies. The models that performed the best were those developed by Altman and Moses/Liao--both predicting bankruptcy with 72% accuracy one year before the companies filed for bankruptcy. Two reasons that these models do not show prediction accuracy rates as impressive as reported by the researchers are:

1) Collinearity - This becomes a problem when using the model to predict over a different time period than that used to build the model. Ratios do not stay related to each other in the same say over time, which is what needs to happen for a model with collinear variables to remain a good predictor. (One of the models contained variables highly correlated .pawith each other--enough so that a model coefficient that one would expect to have a positive sign had a negative sign instead.)

2) Prior probabilities and misclassification costs - None of these four studies appeared to take prior probabilities or differences in misclassification costs into account when reporting their accuracy/error rates. These can have a tremendous impact on a model's reliability.

Research Question 2. Two techniques--logistic regression and discriminant analysis--were used to build models based on the sample data. Both yielded a single variable model using C/TA as the predictor variable. In both cases the prediction accuracy is about 78%, or a 22% apparent error rate. Using Lachenbruch's holdout procedure showed a 25% error rate. But this method does not take into consideration prior probabilities and differences in misclassification costs. Another test that is not as reliable as Lachenbruch's method, but allows one to account for these considerations, is the D^2 method. This test showed that the model provided almost a 100% accuracy rate for predicting nonbankruptcy, but a 0% accuracy for predicting bankruptcy.

Probably a major factor in the poor performance of the model is the fact that the ratio means for the two samples were often very close to each other (see Figure 1). Although the samples are from two different groups--bankrupt and nonbankrupt--the categories may not be as exclusive as they first appear to be. A nonbankrupt company may not be any more financially secure than a company filing for bankruptcy.

Recommendations for Future Research

Because this research used companies from several industries, it may be more useful to use industry-relative ratios, i.e., divide a firm's ratios by the mean of the same ratios for its industry. (See the section discussing this topic in the Chapter 2 - Literature Review.)

As of 1988, companies filing financial reports are required to issue statements of cash flows. A study using ratios based on these statements may provide useful information for the prediction of bankruptcy. It may be a few years before data from these statements can be gathered from enough companies to perform an analysis.

This study, and others, have divided their ratios among the seven categories devised by Pinches et al. using factor analysis. These categories may have changed since the time of their study (1975). A new factor analysis could provide interesting results.

In this study, prior probabilities of 97% nonbankrupt and 3% bankrupt were used. Also, it was arbitrarily postulated that the costs of misclassifying a bankrupt company as nonbankrupt is five times more costly than the reverse situation. Research could be done in order to find the true ratios of prior probabilities and misclassification costs for government contractors.

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13. ABSTRACT *(Maximum 200 words)*
This study attempted to build a bankruptcy prediction model for evaluating potential and current government contractors. This research showed that other bankruptcy prediction models were less successful than reported. Many did not appear to take prior probabilities or differences in misclassification costs into account when reporting their error rates. Two techniques--logistic regression and discriminant analysis--were used to build new models. Both yielded a single variable model using cash/total assets as the predictor variable. In both cases, the apparent error rate is about 22%. Using Lachenbruch's holdout procedure showed a 25% error rate. But this does not take into consideration prior probabilities and differences in misclassification costs. Another test that accounts for these considerations showed that the model provided almost 100% accuracy for predicting nonbankruptcy, but 0% accuracy for predicting bankruptcy. Probably a major factor in the poor performance is the fact that the ratio means for the two samples were often very close to each other. Although the samples are from two different groups--bankrupt and nonbankrupt--the categories may not be as exclusive as they first appear to be. A nonbankrupt company may not be any more financially secure than a company filing for bankruptcy.

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