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A study of the ability of financial ratios to predict corporate failure and the relationship between bankruptcy model probability assessments and stock market behavior

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A STUDY OF THE ABILITY OF FINANCIAL RATIOS TO PREDICT CORPORATE FAILURE AND THE RELATIONSHIP BETWEEN BANKRUPTCY MODEL PROBABILITY ASSESSMENTS AND STOCK MARKET BEHAVIOR

by

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A DISSERTATION

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CHAPTER I

INTRODUCTION

The incidence of corporate bankruptcy has become increasingly common since 1970, the year in which Penn Central filed for bankruptcy. This trend is evident for large companies as well as small ones. Between 29,500 and 32,500 firms filed for bankruptcy per year during the 1970s. The number of filings grew dramatically during the 1980s (See Table 1-1).

A portion of the increase in bankruptcy filings in the 1980s has been attributed to economic conditions that encouraged firms to take on high levels of debt (e.g., Altman 1983, 41-42; Dimancescu 1983, 10). Another major contributor to the increase in bankruptcies may be the Bankruptcy Reform Act of 1978, effective October 1, 1979, under which debtor firms no longer have to prove to the courts that they are insolvent (Yacos 1983). The substantive changes in bankruptcy law resulting from the Bankruptcy Reform Act of 1978, as it relates to the incidence of corporate bankruptcy, include the following: (1) It is no longer necessary for the debtor (referred to as "bankrupt" under the old law) to have committed an act of bankruptcy (e.g., preferentially paying creditors, fraudulently transferring property, etc.) in order to be subjected to involuntary bankruptcy (Kaplan 1985). Under the new Code, it is sufficient to show that the debtor is generally not paying its debts as such debts become due (Altman 1983). (2) Balance sheet insolvency (where a firm's total assets at fair valuation are less than its total liabilities) is no longer required to initiate a proceeding under the new Code (Kaplan 1985). (3) The new Code allows for firms forced into involuntary bankruptcy proceedings to present a reorganization plan, and in many cases for the firm's management to remain intact during reorganization. Under the old law, the court appointed a disinterested trustee to manage the involuntarily bankrupt firm with debts in excess of $250,000, and the court-appointed trustee proposed the plan of reorganization (Kaplan 1985). As a result of the provisions of the new Code, various authors have argued that bankruptcy has become an effective strategy to manage debt (e.g., Casey et al. 1986; Cifelli 1983; Dimancescu 1983).

Despite the changes in bankruptcy law, bankruptcy remains a costly process. Altman (1983) notes that from the firm's perspective, both direct and indirect costs are associated with bankruptcy. Direct costs include the out-of-pocket expenses of liquidation or reorganization (e.g., legal fees and accountant fees), and may amount to between 1% and 5% of the market value of the firm (Warner 1977; Altman 1983). The indirect costs, which are potentially much more significant, include lost management time, loss of revenue and profit, and increased credit costs (Altman 1983). In addition, there are ramifications to the creditors, who may receive none or only a small portion of their original claims; to the employees, who lose their jobs; and to the government, which suffers a reduction in the tax base.

Dimancescu (1983, 32) suggests that in many cases the market does not perceive that a firm is in distress until long after its failure has become imminent. This statement seems to suggest that accrual-based accounting numbers, as reported in the financial statements, do not provide investors with the information they need to evaluate firms as potential investments. A substantial amount of research has studied the ability of accrual-based accounting numbers to explain/predict bankruptcy or some less drastic form of financial failure. In many cases, researchers have constructed, with some success, models using selected financial ratios to explain/predict bankruptcy (e.g., Beaver 1966; Altman 1968; Blum 1974; Zavgren 1985).

The earliest bankruptcy prediction models were either univariate (Beaver 1966) or multivariate models constructed with the application of multiple discriminant analysis (MDA) (e.g., Altman 1968; Deakin 1972; Edmister 1972; Blum 1974; Altman et al. 1977). The models based on MDA have been quite successful in discriminating between healthy and distressed firms, but have been criticized in at least two ways. First, they have suffered from potential violations of the multivariate normality assumption of MDA (Ohlson 1980; Zavgren 1983). Second, with the exception of Deakin (1972), the MDA models have yielded only a dichotomous classification scheme, based on an arbitrary cutoff point (Ohlson 1980). It is not clear that a dichotomous classification scheme meets the needs of investors, who may be more concerned with the degree of vulnerability to failure as measured along a continuous scale rather than with an "either/or" classification.

More recent bankruptcy prediction models (e.g., Ohlson 1980; Zavgren 1985; Lau 1987) have been constructed using the logit analysis technique. These models represent an improvement over MDA for at least three reasons: 1) they yield a probability assessment of failure rather than a dichotomous classification of non-failing and failing firms, 2) the logit technique does not place as strict a set of distributional assumptions on the predictor variables, and 3) the relative significance of individual predictors can be determined from the magnitude of their standardized coefficients. A drawback to most of the prediction models (constructed using both MDA and logit) is that they have been developed using data from before implementation of the new bankruptcy code.

Recently, researchers in the failure prediction area have begun to study the relationship between market behavior and model predictions. Altman and Brenner (1981); Katz et al. (1985); and Zavgren et al. (1988) studied abnormal stock returns after a change in model prediction occurred. Burgstahler et al. (1989) tested for an association between unexpected annual changes in the probability of bankruptcy (as measured using Ohlson's (1980) bankruptcy model) and abnormal stock returns. These studies have been only marginally successful in demonstrating a link between market behavior and financial model predictions.

Purpose

The purpose of this study is threefold. First, a series of logit bankruptcy prediction models based on financial ratios of firms that have filed for bankruptcy since the implementation of the Bankruptcy Reform Act of 1978 will be constructed. The purpose of these models will be to discriminate between sample firms that have filed for bankruptcy and firms that have not, and to yield probability assessments of each firm's vulnerability to bankruptcy on a zero-to-one scale. While the models to be used in this study are not intended for financial management use, they conceivably could be adapted into a single prediction model for the purpose of yielding predictions of bankruptcy for non-sample firms. Given the increase in bankruptcies and the claims that bankruptcy is being used as a means of reducing debt, a model that yields probability assessments of bankruptcy should be useful to creditors in assessing default risk or the risk of having to make some accommodation with the debtor (It should be noted that if managers are using bankruptcy as a means of reducing debt, the bankruptcy prediction models constructed in this study may not yield a classification accuracy as high as models constructed on data prior to implementation of the Bankruptcy Reform Act of 1978). Such a model also should be useful to auditors, who may be required to include a going concern explanatory paragraph in the audit opinion if circumstances dictate. When evaluating evidence contrary to the going-concern assumption, the auditor may find a bankruptcy prediction model useful in confirming or disconfirming the "contrary" evidence. Managers who are trying to avoid the problems of bankruptcy should benefit from such a model because the model would yield an early warning of financial difficulty.

Second, in light of Dimancescu's assertion that the market often does not perceive that a firm is in distress until after its failure has become imminent, the relative success of previous bankruptcy prediction models based on financial information, and the lack of success of previous studies to demonstrate a relationship between market behavior and financial model predictions, the relationship between model predictions and stock market behavior will be tested. Earlier prediction models (e.g., Beaver 1966; Altman et al. 1977; Zavgren 1985) have exhibited the ability to discriminate bankrupt firms from healthy firms for as long as five years before the bankruptcy event. Thus, given a semi-strong efficient market, it would be expected that the information contained in the bankruptcy models (since the models are typically constructed using financial statement information) would be reflected in stock prices. To test this hypothesis, quarterly changes in model predictions and abnormal stock returns will be observed for the sixteen-quarter period leading up to bankruptcy for failed firms and a concurrent period for a matched sample of nonfailed firms. It is expected that changes in abnormal stock returns will be inversely related to changes in the probability of bankruptcy. If such a relationship is observed, the claim by Dimancescu (1983) that the market often does not perceive that a firm is in distress until long after its failure has become imminent would appear to be unfounded. However, the lack of such an observed relationship does not necessarily indicate that capital market agents in the aggregate do not use the information contained in the financial statements. It is likely that capital market agents use financial statement information as well as complementary information from other sources in assessing the value of a firm's securities. Such other information may result in stock price movements that obscure the association between financial statement based bankruptcy probability assessments and stock price behavior.

The third step of the research is exploratory in nature. A statistical technique described by Hillmer and Yu (1979) will be used to determine when major switching points in stock returns (Ramaswami 1987) occur for firms that eventually file for bankruptcy. An "eyeball" test then will be conducted to determine if the switching points occur in close proximity to the period in which the greatest increase in bankruptcy model probability assessments is observed. Because it has been suggested that information other than that contained in the financial statements is used by capital market agents in assessing the value of a firm's securities, the timing of the switching points will be compared to firm-specific news releases in the financial press to determine if non-financial statement information may be obscuring the association between model predictions and stock price behavior.

The study is arranged as follows. Chapter 2 contains a review of previous research related to the prediction of bankruptcy and the association between bankruptcy model predictions and stock return behavior. In chapter 3, the hypotheses to be tested are formulated, and the methods of testing them are discussed. Chapter 4 presents the results of the hypothesis tests. In chapter 5, the contributions and limitations of this research project are discussed, and suggestions for future research are presented.

Table 1-1
Number of Bankruptcy Cases Filed in the U.S.
From 1970 to 1987

Year	Number of Bankruptcy Filings
1970	16,197
1971	19,103
1972	18,132
1973	17,490
1974	20,747
1975	30,130
1976	35,201
1977	32,189
1978	30,528
1979	29,500
1980	45,841
1981	66,006
1982	56,423
1983	69,818
1984	65,520
1985	66,651
1986	76,281
1987	88,278

Source: Administrative Office of the U.S. Bankruptcy Courts

CHAPTER II

REVIEW OF PREVIOUS RESEARCH

The previous research related to the prediction of bankruptcy can be divided into two broad categories (which, in turn, may be further subdivided). The first category of previous research considers simply the construction of models to discriminate between nonfailed and failed or bankrupt companies. The second category attempts to relate the model predictions to the behavior of stock prices.

Bankruptcy prediction models

Univariate Approach

In one of the earliest failure prediction studies, Beaver (1966) applied a univariate approach to analyze the ability of financial ratios to explain/predict failure. Failure was broadly defined as either bankruptcy, default on bond payments, an overdrawn bank account, or nonpayment of a preferred stock dividend. The ultimate purpose of the study was to provide an empirical verification of the usefulness of accounting data.

To test for predictive ability, Beaver selected a sample consisting of 79 failed firms and 79 nonfailed firms, pair-matched on the basis of industry membership and size. The purpose of taking a matched sample was to " . . .

[mitigate] the disruptive influence of the industry and asset-size factors" (Beaver 1966, 76). This approach seems appropriate, but, as Beaver himself notes, it may be problematic if either of these two factors possesses predictive ability (1966, 76).

The ratios included in the study were selected according to three criteria: popularity in the literature, good performance in previous studies, and that the ratio be defined in terms of a cash-flow concept. Thirty ratios were selected and divided into six "common element" groups. Only one ratio from each group was used in the analysis. The final group of ratios included cash flow to total debt, net income to total assets, total debt to total assets, working capital to total assets, current ratio, and the net defensive credit interval (defensive assets minus current liabilities to fund expenditures for operations).

Ratios were computed for the failed firms for five years preceding bankruptcy and for the same period for the nonfailed firms. Beaver expected the mean values of each ratio to be more favorable for the nonfailed firms than for the failed firms. The differences in the mean values were in the predicted direction for all ratios in all five years before failure.

Beaver then conducted a dichotomous classification analysis to predict the failure status of a firm based on the financial ratios. The firms were divided into two subsamples. An optimal cutoff point for each ratio was identified to maximize the correct classification of firms in one subsample. The same cutoff points then were used to predict failure status of the firms in the holdout subsample. Cash flow to total debt was the ratio that best classified firms. The overall error rate was 13% in year 1 and increased to 22% for year five (using the holdout sample). Since a random-prediction model would possess an expected error rate of 50%, the probability that such a model would outperform the ratio classification scheme is very small. Net income to total assets and total debt to total assets also predicted failure status significantly better than 50% of the time for all five years. The other ratios performed well in years one and two before failure, but were less successful in years three, four and five.

Because simply comparing overall classification error rates does not consider the relative costs of Type I errors (misclassifying a failed firm) and Type II errors (misclassifying a nonfailed firm), both types of errors were calculated for each of the ratios. In all cases, Type I errors occurred at a much higher rate than Type II errors.

The cutoff point could be adjusted to minimize the more costly of the two.

Beaver's study is notable in that it demonstrated that a significant correlation exists between accounting numbers and financial health. However, the univariate approach does not capture relationships that exist between or among the predictor variables, and it is possible that different ratios may yield inconsistent classifications for a given firm.

Models Using Multiple Discriminant Analysis

In light of the weaknesses of the univariate approach, Altman (1968) developed a model to assess firms' financial condition using multiple discriminant analysis (MDA). MDA has several advantages over the univariate approach. Perhaps the greatest advantage of MDA is that it considers simultaneously the entire profile of characteristics common to the relevant firms, as well as the interaction among these characteristics, while univariate analysis considers the measurements for group assignments only one at a time. Another advantage of MDA is that it reduces the researcher's space dimensionality from the number of individual independent variables to the number of original a priori groups minus one.

Altman's sample consisted of 33 matched pairs of bankrupt and nonbankrupt firms. The sample of bankrupt firms included manufacturing firms that had filed for bankruptcy under Chapter X of the National Bankruptcy Act during the period 1946-1965. Thus, Altman defined the bankruptcy event more narrowly than did Beaver. The sample firms were pair-matched on the basis of size and industry. In this respect, Altman's study suffers from the same limitations as Beaver's. Financial information was gathered for one year prior to bankruptcy for the bankrupt firms and for the same period for the matching firms in the nonbankrupt sample. Twenty-two ratios found to be useful in previous studies were chosen for evaluation. These ratios were classified into five standard ratio categories: liquidity, profitability, leverage, solvency, and activity ratios. From the original list of 22 variables, 5 ratios, when combined, were selected as providing the most accurate explanation/prediction of corporate bankruptcy. These ratios were: working capital to total debt, retained earnings to total assets, EBIT to total assets, market value of equity to book value of total debt, and sales to total assets.

An overall index (Z-score) of financial health was calculated as a linear combination of the five ratios. The coefficients were determined by application of MDA. A cutoff point was established to maximize overall classification accuracy for the original sample. Using this cutoff point, 95% of the original 66 firms were correctly classified. The Type I error rate was 6%, while the Type II error rate was 3%.

The model was applied to the same firms using information from the period two years prior to bankruptcy (for the failed firms). The model correctly classified 83% of the firms. The type I error rate was 28%, while the Type II error rate was 6%. The results still were significantly better than chance. When applied to three years and longer prior to bankruptcy, the predictive accuracy of the model was no better than chance. It should be noted that Altman used the same model for all five years prior to bankruptcy. Beaver (1966) and other subsequent researchers used different models or cutoff points for each year prior to the event. An argument could be advanced that if the ultimate objective of developing such models is to provide a decision aid for financial decision-makers, Altman's approach, while not as accurate in the more remote years, is more realistic than the others, because in actuality, the timing of future bankruptcy (if it is to occur) is not known.

Altman's model was validated using a holdout sample of 25 bankrupt firms and 66 nonbankrupt, but below average, firms. Twenty-four of the bankrupt firms were correctly classified (Type I error rate of 4%). The model correctly classified 79% of the nonbankrupt firms.

Perhaps the primary contribution of the Altman study is its introduction of a technique for evaluating firms' health using several ratios simultaneously. This approach is a definite improvement over the univariate method used by Beaver (1966). However, Zavgren (1983) observes that the predictive accuracy of MDA may be affected by nonnormality of the predictor variables. Altman (1968) did not test for normality. Thus, to the extent that the normality assumption was violated, the results of his study may be open to question. Another concern expressed by Zavgren is that the selection of ratios on the basis of popularity in the literature and potential relevancy to the study restricts the theoretical importance of the results (Zavgren 1983, 17).

Citing the high classification accuracy of Beaver's (1966) univariate model and the intuitive appeal of Altman's (1968) discriminant function, Deakin (1972) used the 14 ratios suggested by Beaver to develop a new discriminant function. Deakin's model achieved overall error rates of

3%, 4.5%, 4.5%, 21%, and 17% for the first, second, third, fourth, and fifth years before failure. Deakin did not discuss the relative costs of Type I and Type II errors, and gave no indication of the relative incidence of these two error types. It would appear that Deakin's model is a dramatic improvement over that of Altman (1968) in the third, fourth, and fifth years prior to bankruptcy. However, it is not clear whether Deakin used the same discriminant function with the same coefficients for all five years. If he did not (as Altman did), then comparison with the Altman study is not meaningful.

Unlike Altman, who established an index of financial condition and was forced to select an arbitrary cutoff point, Deakin used a modification of MDA that enabled him to assign probabilities of failure. Because of this innovation, Deakin's model is probably more responsive to the needs of financial decision-makers than Altman's dichotomous scheme. Nonetheless, Deakin's approach is limited if the multivariate normality assumption is violated.

Edmister (1972) applied MDA to the prediction of failure among small firms that had applied for loans from the Small Business Administration. His methodology was basically similar to that of Altman (1968). Probably the most interesting innovation of this study was the inclusion of ratio trends, which provide more dynamic predictors of failure than the static ratios. Two trend variables were used in the study. The first was a three-year trend for each ratio. Regardless of the value of a ratio, if it showed steady improvement, the model treated the improvement as a positive factor that would decrease the likelihood of failure. In comparable fashion, a negative trend was treated as increasing the likelihood of failure. A second trend variable combined the industry relative trend and the industry relative level. For example, if a company's current ratio is below the industry average but is showing steady improvement, the model would not mark the company down badly on the basis of this ratio. Edmister also differed from the previous studies in his use of three-year ratio averages. However, three years' data were available for only 42 of the 282 firms in the sample.

Of the 42 firms for which three years' data were available, the discriminant function that included the trend and average variables correctly classified 39, or 93%. Because of the lack of data, this function was not validated using a holdout sample. A satisfactory function could not be developed to classify the firms for which only one year's data were available.

Edmister set his z-score cutoff point at a level that maximized overall predictive accuracy. He recognized that the relative costs of Type I and Type II errors may vary and be difficult to assess. He therefore suggested that a z-score range be designated as an unclassified zone in which correct classification is difficult. For firms in this range, other information would be necessary to assess their probability of survival.

Blum (1974) used MDA to develop a classificatory model for potential use in anti-trust suits. Variables were selected based on a cash flow framework. Because Blum followed an underlying coherent rationale for variable selection, his study was more theoretically appealing than its predecessors. Another improvement over the Altman (1968) model was the inclusion of various dynamic variables, such as trends, standard deviations, and slopes arising from trend regressions performed on various ratios.

Blum used a matched sample of 115 failed and 115 nonfailed firms to construct his discriminant functions. The firms were matched on the basis of four criteria--industry, sales, number of employees, and fiscal year. The final discriminant functions were used to compute an index score analogous to Altman's (1968) z-score. A cutoff point was established to maximize correct classification of firms as failing or nonfailing. Unlike Altman, who performed only one discriminant analysis for all five years, Blum performed 21 different discriminant analyses by varying the range of years used in calculating trend, standard deviation, and the slope coefficients for the various ratios. The most accurate models for each of the five years before the event of bankruptcy (or continued good health) then were applied to a holdout sample. These models had overall classification accuracy of 93% the first year before failure, 80% the second year, and 70% for years three through five on the holdout sample. Comparison of these results to Altman (1968) is difficult. Blum used a different discriminant function for each of the five years in the prediction period, whereas Altman used only one discriminant function, based on data one year before failure, to predict failure or nonfailure for the five-year period. While not as accurate, Altman's method is more intuitively appealing because in a realistic setting, users would be employing the model ex ante, without the knowledge of the interval before the occurrence of the event (failure or continued health).

Altman et al. (1977) constructed a revised version of the Altman (1968) model. The model was constructed using data from a matched sample of 53 failed and 58 nonfailed firms (five of the original 58 failed firms were not useable because of insufficient data). The basic sample data were adjusted to allow uniform treatment of items such as leases (all leases were capitalized for the purposes of the study), reserves, minority interests, captive finance companies and other unconsolidated subsidiaries, and capitalized research and development costs. The adjustments were made to facilitate comparison among companies.

Using MDA, Altman et al. reduced the number of variables from an original list of twenty-eight to seven. Dynamic measures found useful by other researchers (Edmister 1972; Blum 1974), as well as static ratios, were included. The dynamic measures included stability of earnings and cumulative profitability. The static measures were return on assets, debt coverage ratio, current ratio, common equity to total capital, and size.

Based on tests for equality of dispersion matrices, it was determined that a quadratic function was more appropriate for model development than a linear function. Both a quadratic and a linear model were constructed. Despite statistical considerations, the linear model was selected over the quadratic model because of greater classification accuracy over a five-year period.

The linear model, constructed with the financial information for only one year prior to failure, achieved an overall classification accuracy rate of 93% for the first year before failure, 89% for year 2, 85% for year 3, 80% for year 4, and 77% for the fifth year before failure. However, because the model was not validated on a holdout sample, it is difficult to assess the accuracy of the model relative to other models. The authors mentioned that the classification accuracy of the model may be affected by changing the cutoff point to consider individual users' assessments of the relative costs of Type I and Type II errors.

The new model is significantly more accurate in the more remote years than Altman's (1968) earlier model. As with the earlier model, it is appealing in that only one model, with one set of coefficient parameter estimates, is involved. However, like its predecessor (Altman 1968), it does not provide probabilities of failure. Such information probably would be more useful to financial decision-makers than the dichotomous classification scheme.

Other empirical studies of bankruptcy prediction using MDA (e.g., Sinkey 1975; Deakin 1976; Moyer 1977) have had success comparable to that of the studies described above. All of these studies have suffered from potential violations of the assumptions of multivariate normality and equal covariances (Zavgren 1983).

Models Using Multivariate Conditional Probability Techniques

Ohlson (1980) used the technique of logit analysis to construct a bankruptcy prediction model. Logit is an improvement over multiple discriminant analysis for several reasons. First, a logit model results in a probability assessment of the event under study. To most decision-makers, this information probably is of greater value than the MDA dichotomous classification scheme. Second, logit does not place as strict a set of distributional assumptions on the predictor variables. Third, if multicollinearity is not a problem, the variable coefficients of a logit model are interpretable. Specifically, based on an analysis of the coefficients, it is possible to determine which variables are the most important predictors.

Ohlson's model differed from its predecessors because it was not constructed using the matched sample approach. Instead, it was based on a sample of 105 bankrupt firms and 2,058 nonbankrupt firms. The bankrupt firms represented all the useable bankrupt firms during the period 1970 to 1976, and the nonbankrupt firms represented all the useable nonbankrupt firms on the Compustat tape during the same period.

Ohlson included size as a predictor variable in his model. This approach represents a potential improvement over previous multivariate studies. Beaver (1966, 80) concluded that the " . . . larger the reservoir [of liquid assets], the smaller the probability of failure." Researchers have used this assumption to justify matching on the basis of size. However, if a model is to yield an accurate assessment of the probability of failure for a given firm, then it is more valuable to use size as a predictor variable than as a matching attribute. All the previous studies reviewed here matched firms on the basis of industry membership as well as size. Apparently, these earlier researchers believed that industry must be systematically related to the probability of bankruptcy. Thus, it was disappointing that Ohlson did not incorporate industry membership as a potential explanatory influence in his study.

Despite the more appealing methodology, both in sample selection and the use of logit, the model's classification accuracy for the first year before failure was disappointing. Assuming that the relative costs of Type I and Type II errors are equal, Ohlson selected a probability cutoff rate of .038. If a firm's probability of nonfailure as assessed by the model was less than .038, then the firm was classified as failing. Using this criterion, the model correctly classified 83.6% of the nonfailing firms and 87.6% of the failing firms in the first year before bankruptcy. These correct classification rates are substantially lower than the classification accuracy of the previously reviewed models. Classification accuracy rates for years two and three before bankruptcy were not reported. At least two reasons have been advanced as having attenuated the classificatory success of Ohlson's model. First, no theoretical basis existed for his selection of predictors (Zavgren 1983, 28). Second, three of the predictor variables related to net income (net income/total assets, a categorical variable based on whether net income was negative or otherwise for the prior two years, and a variable that measures change in net income for the most recent period), which indicates that the model potentially suffered from problems of multicollinearity (Zavgren 1983, 28). Ohlson did not directly address the issue of collinearity. A third reason may be that industry was not included, either as a predictor variable or as a matching attribute.

Using the maximum likelihood logit technique, Zavgren (1985) sought to improve Ohlson's classification accuracy by employing ratios identified in two previous studies (Pinches et al. 1973; Pinches et al. 1975) as constituting the principal independent dimensions of financial statement data. Thus, Zavgren was able to reduce any problems attributable to multicollinearity.

Zavgren developed five bankruptcy prediction models, one for each of five years before bankruptcy. The models were constructed on a matched sample of 45 failed and 45 nonfailed firms. The failed and nonfailed firms were matched on industry membership and size (as measured by total assets), because both had previously been found to be related to the occurrence of bankruptcy. Matching nonfailing firms with failing firms on these attributes certainly facilitates the data collection process, but as stated earlier, it prevents the model from using the information contained in these variables in assessing the probability of bankruptcy.

The models were evaluated for classification accuracy using the firms in the original sample, and then on a holdout sample of 16 failed and 16 nonfailed firms. On the original sample, the models had total classification error rates of 18%, 17%, 28%, 27%, and 20%, respectively, for years one to five. On the holdout sample, the total error rate was 31% for each of the five years studied, which is inferior to those of the previous models (Altman 1968; Deakin 1972; Edmister 1972; Blum 1974; Altman et al. 1977). Thus, it appears that opportunity still exists for further refinement of the logit model approach.

Lau (1987) used the technique of multinomial logit analysis to develop a five-state financial distress prediction model. The five financial states used in the study were: state 0 (financial stability), state 1 (omitting or reducing dividend payments), state 2 (technical default and default on loan payments), state 3 (protection under Chapter X or XI of the Bankruptcy Act), and state 4 (bankruptcy and liquidation). The predictive ability of the model was not very high when tested on a holdout sample. Further, it is not apparent that it is necessary to define five states of financial health. A logit model with a dichotomous response variable yields a probability (of failure) assessment that can be used to assess the relative health of a firm without forcing the results into categories.

The evidence presented above clearly indicates that financial ratios provide a signal about the financial condition of a firm. Some of the models performed better than others in discriminating between failed and nonfailed firms, but all the studies found that the failed firms had significantly worse ratios than nonfailed firms. As a result, some researchers have taken an additional step and have examined whether the market uses the information contained in the ratios in assessing firm health. These studies are reviewed in the next section.

Studies linking model signals and market behavior

Beaver (1968) tested for a relation between stock returns and changes in financial ratios. Using the data from a previous study (Beaver 1966), stock returns and ratio changes were tracked over a five-year period. For failed firms, the period represented the five years immediately preceding failure. Rates of return and ratios for the nonfailed firms were computed for the same years as their failed counterparts. Beaver found that the market, as measured by stock returns, predicts failure before the ratios. This is not too surprising since the ratios were analyzed on a univariate basis. Perhaps a multivariate model, which should capture to a greater degree the complexity of the financial decision process, would perform better than the univariate models. Another limitation of this study is that raw ratios were used as opposed to probabilities of failure. Presumably, the assumption was that changes in the univariate ratios were equivalent to changes in probability of failure. A multivariate model, which indicates probabilities of failure based on the sample data, probably would correspond more closely to market returns than would the univariate ratios.

Altman and Brenner (1981) tested market response to information about firms whose future had been assessed as problematic. The study was designed to be an explicit test for market efficiency. If it was found that there were " . . . excess negative returns indicating that the information provided by the model is new, and that these returns are slow in their manifestation, then we may have evidence that the market has not efficiently digested the information when it was first available" (Altman and Brenner 1981, 36). The sample consisted of companies for which new financial information had indicated a change in status from a going concern to one of potential bankruptcy, according to the Altman (1968) bankruptcy prediction model. Altman and Brenner tested for the speed of the market response to the new information.

Using a sample of firms listed on the Annual Compustat Tape (ACT) during the years 1960 to 1963, companies were selected for inclusion in the final sample if they were classified by the Altman (1968) MDA model in one year as nonfailing but reclassified the following year as failing (i.e., their calculated z-score was above the cutoff point one year, but below it the next). Using the two-factor capital asset pricing model (CAPM) to calculate abnormal returns, negative abnormal returns were detected for as long as twelve months after the reporting of the new information. This result possibly indicates some evidence of market inefficiency.

This study raises several unresolved issues. The model employed to classify the firms was constructed on a sample of firms from 1945 to 1963. The sample of firms to be classified came from the years 1960 to 1963. Thus, structural changes in the economy might lessen the applicability of the model. Another weakness is that the model could offer only a dichotomous classification of firms. It is very possible that some firms' z-scores changed significantly without crossing the classification threshold, while other firms' z-scores changed only slightly, but the slight change resulted in their being reclassified as failing since the change crossed the threshold. The underlying assumption must have been that if the model classified a firm as nonfailing, then the distance of the z-score from the cutoff point was not important. Likewise, if a firm was classified as failing, the market could not consider degrees of vulnerability to failure based on the z-score. In other words, the study is based on the assumption that the market classifies a firm as either failing or nonfailing without assessing probabilities of failure, which appears to be highly unlikely. Even if such an assumption were acceptable, then another issue arises. Given the possibility that the relative costs of Type I and Type II errors are not equal, then it is possible that (if the model is a valid surrogate for the decision processes of capital market agents in the aggregate) the cutoff threshold selected by Altman and Brenner is not the cutoff threshold used by the market. An inappropriate cutoff point would render the results of the study inconclusive, especially for firms whose z-scores are close to Altman and Brenner's cutoff point.

Katz et al. (1985) examined stock market behavior for the 12-month period immediately preceding and immediately following the release of financial information for firms that were deteriorating and for firms that were recovering as classified by the Altman (1968) model and by Wilcox's (1976) gambler's ruin model. Because these models do not provide probability assessments of failure, and the cutoff points are arbitrarily set by the researchers, this study suffers from the same limitations as those noted for the

Altman and Brenner (1981) study. During the period preceding the release of new information that changed the signal from distressed to healthy, Katz et al. found that abnormal securities returns were significant and positive. This indicates that the market uses information received before the release of financial statements. However, in the case of firms whose status changed from healthy to distressed (as indicated by the prediction models), significant negative abnormal stock returns were observed throughout the nine month period subsequent to the release of the new information. Thus, the study provides evidence that the models (especially Altman 1968) have information content and that the market is not entirely efficient in impounding the information contained in the models. This latter finding supports Altman and Brenner's (1981) results. Once again, because of arbitrary selection of cutoff points, possible structural changes in the economy between the model construction period (1945 - 1961) and the period from which the sample was drawn (1968 - 1976), and sensitivity to the particular market expectation model selected, the results of the Katz et al. study are somewhat difficult to interpret.

Zavgren et al. (1988) examined the association between model-derived probabilities of failure and market reactions for a group of failed and nonfailed firms for a period of one year prior to bankruptcy for the failed firms and a concurrent period for the nonfailed firms. The objective of the study was to determine the relationship between unanticipated financial failure or survival and market reaction (as measured by both abnormal market returns and trading volume).

The model used to classify firms was the logit model developed by Zavgren (1985). The sample was a subset of the sample of 45 failed and 45 nonfailed firms from the 1985 study. In the Zavgren et al. study, focus was placed on both failed and nonfailed firms that were erroneously classified by the model. The period of interest was the twelve-month period between the model prediction of failure or nonfailure and the unexpected result (recognized survival for the nonfailed firms or failure for the failed firms). It was posited that if the model prediction had information content, a dramatic market reaction would be detected when it became apparent that the model had made an erroneous classification. Nonfailed firms that had been predicted to fail would be expected to exhibit abnormal positive returns upon recognized survival. Failed firms predicted to survive would be expected to exhibit abnormal negative returns.

As expected, the results indicated that firms that were predicted by the model to fail, but which did not (Type II error), exhibited dramatic market returns in the year subsequent to the prediction. In other words, as it became apparent that the firm's health was improving, the market reacted positively. However, firms that were predicted by the model to survive, but which actually failed (Type I error), experienced no dramatic market reaction in the year prior to failure. One reason for this finding posited by the authors was that these firms failed for reasons anticipated by the market but not captured within the model. If this is so, then it is plausible that with a refined model, fewer firms would be misclassified, and thus, less noise would confound the results.

Ramaswami (1987) attempted to determine when the market first perceives the impending bankruptcy of a potentially bankrupt firm. Stock market perception is defined in the study to have occurred in the month in which the mean (μ) and/or variance (σ^2) of stock returns changes. Since under the semi-strong version of the efficient market hypothesis (EMH), values of μ and σ^2 reflect all public information pertinent to the firm available at time t, the parameters μ and σ^2 should change only when new information becomes available. Ramaswami used a statistical method developed by Hillmer and Yu (1979) to measure the market perception time of bankrupt firms. Ramaswami found that market lead times (the interval between market perception of impending bankruptcy and occurrence of bankruptcy) differed from firm to firm, but he was unable to explain conclusively why the observed differences occurred. Ramaswami suggested that the stronger the signal of potential bankruptcy, the more quickly the market adjusted to the new information. However, this suggestion could not be tested, because Ramaswami had no exogenously determinable measure of the strength of the bankruptcy signals for the sample of firms in his study.

Burgstahler et al. (1989) tested for an inverse relationship between unexpected annual changes in the probability of bankruptcy as measured by Ohlson's (1980) bankruptcy prediction model and unexpected changes in the abnormal returns of firms' securities. Unexpected changes in the variables of interest were used as opposed to raw changes in these variables, because it was assumed that any expected component of changes in the predictor variables would be reflected in securities prices before the release of financial information. To test for the effect of unexpected changes in bankruptcy model probability assessments on securities returns, the authors separated the information effect of changes in earnings on firms' securities from the incremental effects of changes in bankruptcy prediction model probability assessments on securities returns by including both predictors in the multiple regression model. Despite acknowledged collinearity between the two predictors (earnings is a separate predictor variable as well as a component of certain predictors in the model bankruptcy probability assessment), both were found to be significantly correlated, in the expected directions, with changes in securities returns. It should be noted that in order to maximize the effects of the variables of interest, the authors included in the study only firms with model bankruptcy probability assessments of at least .3 (i.e., 30% probability of bankruptcy) in at least one year during the period of interest (1977-1986).

The findings of the Burgstahler et al. (1989) study are noteworthy because they are not consistent with the results of related prior studies (e.g., Katz et al. 1985; Zavgren et al. 1988). Perhaps the primary reason for more conclusive results is that Burgstahler et al. had a sample size of over 1,800 firms. With such a large sample, even a very small effect, if it exists, should be detected. Indeed, when changes in bankruptcy probability assessments are regressed against the cumulative abnormal returns adjusted for earnings effects, although the significance level on the coefficient of the bankruptcy model changes variable is less than .0001, the model R^2 is only .014. This indicates that any correlation between changes in the annual bankruptcy prediction model probability assessments and abnormal securities returns is very small, which is consistent with the previous studies.

Summary of Previous Research

Of the bankruptcy prediction models constructed to date, the models based on multiple discriminant analysis appear to discriminate between failed and nonfailed firms at least as well as, if not better than, univariate models or models developed based the logit technique. However, the logit models are more appealing in that the logit technique yields a bankruptcy probability assessment which allows the user of such a model to determine the relative vulnerability of a firm to failure.

A related stream of research has attempted to link bankruptcy model scores to stock market behavior. These studies generally have been based on the assumption that capital agents in the aggregate use financial statement information as though it were filtered through a multivariate bankruptcy prediction model. Such an assumption is consistent with the efficient markets hypothesis. Despite the demonstrated ability of all the bankruptcy models described above to discriminate between bankrupt firms and nonbankrupt firms, none of the market-related studies has found a strong association between model bankruptcy predictions and stock returns. Although Burgstahler et al. (1989) found unexpected changes in bankruptcy model probability assessments to be a significant predictor variable in explaining cumulative abnormal returns, the explanatory power of the changes in model scores was only .014. This suggests that some other explanatory variable(s) is (are) omitted. Perhaps stock market reaction to information contained in quarterly financial reports as well as information from sources other than financial statements have confounded the results of these previous studies.

CHAPTER III

HYPOTHESIS FORMULATION AND DATA ANALYSIS

The results of the studies discussed in the previous chapter suggest that the role annual financial statement information (as filtered through a particular multivariate bankruptcy prediction model) plays in the valuation of securities prices is still not well understood. The success of bankruptcy prediction models in discriminating between failed and nonfailed firms suggests that the models possess validity. Therefore, it seems reasonable in an efficient market to expect that a change in the probability of bankruptcy as assessed by a successful prediction model would be a signal that the expected present value of a firm's future cash flows has changed. Although Burgstahler et al. (1989) found an association between unexpected changes in model bankruptcy probability assessments on an annual basis and annual cumulative abnormal stock returns, the low explanatory power of the unexpected changes in bankruptcy model probabilities indicates that variables other than financial ratios from the annual financial statements exert a considerable influence on securities prices. In this research, factors other than annual bankruptcy model predictions are studied for an association with securities prices.

One factor omitted in the previous studies of association between bankruptcy model predictions and securities prices is the effect of quarterly financial information. Accordingly, this study examines the relationship between changes in model predictions and abnormal stock returns on a quarterly basis over a sixteen-quarter period. Because information from sources other than financial statements is expected to impact securities returns, exploratory analysis then is performed to assess the impact of non-financial statement information on securities returns.

This research is a three-part study. First, to test for an association between quarterly bankruptcy model probability assessments and abnormal securities returns, a suitable quarterly bankruptcy model (or series of models) must be constructed. Zavgren (1985) developed five different annual bankruptcy prediction models, one for each of the five years before bankruptcy. The variables included in the Zavgren bankruptcy prediction models are used as the basis for the variables to be included in this study, because they were identified as constituting the principal independent dimensions of financial statement data (Pinches et al. 1973; Pinches et al. 1975), and thus, minimize multicollinearity among the predictor variables. A series of sixteen bankruptcy prediction models, one for each quarter over the four-year period before bankruptcy for failing firms and a concurrent period for matching non-failing firms, is developed. For the purposes of this study, bankruptcy is defined as either the suspension of trading of the firm's securities or filing for bankruptcy, whichever event is earlier.

Second, the work of Katz et al. (1985), Zavgren et al. (1988), and Burgstahler et al. (1989) is extended. These studies provided some evidence that the information contained in bankruptcy prediction models is used by investors. This study examines the relationship between stock market behavior and changes in bankruptcy model signals on a quarterly basis over a four-year period. If the bankruptcy model probability assessments possess information content, then abnormal returns would be expected to decrease as bankruptcy probability assessments rise and to increase as bankruptcy probability assessments fall. To the extent that information from sources other than quarterly financial statements impacts stock price behavior, the association between bankruptcy model assessments and abnormal stock returns will be confounded.

The third part of the research draws upon the Ramaswami (1987) study. Ramaswami observed that the interval between the time of stock market perception of impending bankruptcy (switching point in a firm's securities returns) of a potentially bankrupt firm and the eventual date of bankruptcy differs across firms. He suggested that the timing of the switching point may be related to the strength of the bankruptcy signal. Ramaswami utilized a cumulative sum technique described in Hillmer and Yu (1979) to identify the switching point in a firm's securities returns. This study employs the same technique to determine the switching point in the securities returns of firms that later enter bankruptcy. An "eyeball" test is conducted to determine if sufficient evidence exists to support the existence of an association between the switching point and the timing of the greatest increase in the bankruptcy model probability assessments. Because information from sources other than the financial statements may be used by the market in assessing the value of a firm's securities, a second "eyeball" test for association between the switching point and the release of information in the financial press (e.g., The Wall Street Journal) other than financial statement information also is conducted.

Bankruptcy Prediction Model Construction

Logit analysis is used to construct the bankruptcy prediction models. Logit is preferable to multiple discriminant analysis (MDA) for several reasons. Unlike MDA, logit does not require that the independent variables be multivariate normal or that groups have equal covariance matrices (Jones 1987). The relative importance of the predictor variables can be ascertained using logit, but not with MDA (Zavgren 1985). Moreover, logit yields a probability assessment of failure rather than a dichotomous classification scheme.

Variable Selection

The quarterly bankruptcy models developed in this study employ the same set of predictor variables as the Zavgren (1985) models where possible. Zavgren (1985) based variable selection on two factor analysis studies (Pinches et al. 1973; Pinches et al. 1975). Both studies found seven sets of orthogonal factors or classifications of financial ratios which, for industrial firms, explained about 90% of the information contained in the original data matrix of 48 financial ratios. This finding was supported by Chen and Shimerda (1981). Additionally, it was found that the importance of these factors was relatively stable over time (from 1951 to 1969). Zavgren used the ratios which loaded highest on their respective factors, with the exception of the current ratio, which is a measure of short-term liquidity. The current ratio was excluded because as a firm deteriorates, its inventories often accumulate, yielding a misleading signal of liquidity. In its place, the acid test ratio was used. The annual models employed by Zavgren were defined as follows:

$$P(B)_t = f(X_1, X_2, X_3, X_4, X_5, X_6, X_7)$$

where:

$P(B)_t$ = Probability of bankruptcy for year t

X_1 = Total Income/Total Capital (Return on Investment),

X_2 = Sales/Net Plant (Capital Turnover),

X_3 = Inventory/Sales (Inventory Turnover),

X_4 = Debt/Total Capital (Financial Leverage),

X_5 = Receivables/Inventory (Receivables Turnover),

X_6 = Quick Assets/Current Liabilities (S/T Liquidity),

X_7 = Cash/Total Assets (Cash Position).

Three of the predictor variables used in the Zavgren study are not useable, as defined, in the current study. Return on investment (X_1 = total income/total capital) as defined by Zavgren cannot be applied to the current analysis because for some of the ultimately bankrupt firms, capital becomes negative. As capital approaches zero, the ratio is magnified in periods in which total income is reported because of the small denominator. Once a company's capital becomes negative, a net loss results in a positive return on investment ratio, and the larger the loss, the larger the return on investment. Clearly, this phenomenon distorts the difference between failed and nonfailed firms. In its place, return on investment is defined as total income divided by total assets. For similar reasons, Zavgren's proxy for leverage (X_4 = debt/total capital) is replaced by debt divided by total assets. Both of the above "replacement" ratios are commonly used in financial texts as proxies for return on investment and leverage, respectively. A third change is necessary for receivables turnover (X_5 = receivables/inventory), because some of the sampled companies have no inventories in some periods. This situation results in "undefined" values for receivables turnover in some cases. The current study instead defines receivables turnover as receivables divided by sales. This method of calculating receivables turnover is commonly employed in traditional financial statement analysis. Accordingly, the sixteen quarterly bankruptcy prediction models to be constructed are defined as follows:

$$P(B)_t = f(X_1,X_2,X_3,X_4,X_5,X_6,X_7)$$

where:

$p(B)_t$ = Probability of bankruptcy for quarter t,

X_1 = Total income/Total Assets (Return on Investment),

X_2 = Sales/Net Plant (Capital Turnover),

X_3 = Inventory/Sales (Inventory Turnover),

X_4 = Debt/Total Assets (Financial Leverage),

X_5 = Receivables/Sales (Receivables Turnover),

X_6 = Quick Assets/Current Liabilities (S/T Liquidity),

X_7 = Cash/Total Assets (Cash Position).

No attempt is made to assess the relative costs of Type I and Type II errors, as these are considered to be user-specific. Accordingly, the probability cutoff point is set at .50. Thus, the decision rule is to classify as bankrupt those firms whose model bankruptcy probability prediction is .50 or higher. Firms whose model probability predictions are less than .50 are classified as healthy.

Sample

The majority of distress prediction models have been constructed using choice-based samples. In most cases, the samples have included both all the bankrupt/failed firms in the population for which the required information was available over a specified period and an equal number of matching nonfailed firms (e.g., Beaver 1966; Altman 1968; Blum 1974; Dambolena and Khoury 1980; Zavgren 1985). This method of sample selection violates the random sampling and design assumption and results in a bias when unadjusted conditional probability models are used (Zmijewski 1984; Palepu 1986). According to Zmijewski (1984, 60), the ". . . observed result of this bias is that a dependent variable group having a sample probability larger than the population probability is oversampled, with the oversampled group having understated classification and error rates." As the sample composition approaches the population composition, the bias decreases. The bias is eliminated when adjustment procedures such as weighted exogenous sample maximum likelihood (WESML) are employed. However, the bias does not generally affect statistical inferences or overall classification rates (Zmijewski 1984, 77-80). In addition, Palepu (1986) notes that if the purpose of the model is to rank probabilities of the event of interest, the bias is unimportant.

Other researchers (e.g., White and Turnbull 1975; Ohlson 1980) have attempted to use samples that reflect population proportions as closely as possible. These researchers have had to gather data for a very large number of nonfailed firms in order to achieve sample proportions reasonably close to population proportions of failed and nonfailed firms. In most cases, firms without complete data have been eliminated from the studies. If incomplete data observations are nonrandomly distributed in the population, then the estimated parameters and the probabilities will be biased. Bankrupt firms are probably more likely to have incomplete data than healthy firms (Zmijewski 1984, 62-63). Hence, it is possible that these sample selection biases might occur. Once again, it does not appear that such biases affect the statistical inferences or overall classification rates of the model (Zmijewski 1984, 80).

Based on the evidence provided in the previous cited studies, statistical inferences and classification rates do not appear to be significantly affected by the use of a choice-based matched sample. Because the purpose of the model predictions in this study is to indicate a change in financial health rather than to predict precisely a firm's probability of bankruptcy, a sample of failed and nonfailed firms matched on the basis of size and industry membership is employed. Both size and industry are widely believed to be intervening variables in the relationship between financial ratios and failure status. Indeed, Ohlson (1980) found size to be the most important independent variable in his failure prediction model. Given Ohlson's findings, an argument could be advanced that size should be included in the model as a predictor variable and not used as a matching attribute for sample selection. However, the purpose of the current study is not to construct a model for ex ante use by decision-makers. Rather, its goal is to determine, ex post, the ability of certain ratios to discriminate between healthy and failed firms. Accordingly, size is employed as a matching attribute for sample selection. Unlike previous studies, firms that have failed since the implementation of the Bankruptcy Code of 1978 comprise the sample for the current study.

The sample of bankrupt firms is drawn from firms whose financial information is available on Compustat and that were identified in the F & S Index of Corporate Changes and in the The Wall Street Journal Index as having filed for bankruptcy between 1980 and the first quarter of 1988, inclusive. One-hundred-eighty-four such firms were identified. Of these, 152 were eliminated because of lack of data--either because they had not been in existence during the entire 16-quarter event window, or because they apparently had not filed SEC 10-Q reports for all quarters during the event window. Of the 32 firms in the final sample, 30 have data for all 16 quarters in the event window, 1 for 15 quarters before bankruptcy, and 1 for 14 quarters before bankruptcy. The 32 bankrupt firms were matched on the basis of industry membership and size (as proxied by total assets) with nonbankrupt firms (a listing of firms in the sample is provided in Table 3-1). Thus, the sample consists of 32 bankrupt and 32 pair-matched nonbankrupt firms.

The construction of bankruptcy prediction models containing seven predictor variables based on such a small sample potentially results in models that are overfitted to the sample. A potential limitation of overfitted models is that they may not be useful if applied to firms not included in the sample. This limitation is somewhat mitigated in this study because the bankruptcy prediction models constructed are applied only to firms included in the sample. A second issue related to overfitted logit models is that the overfitting may result in correlated parameter estimates, which, in turn, may result in unstable model coefficients and unstable model probability assessments from quarter to quarter. This issue will be discussed in more detail in Chapter 4.

As reported earlier, for a bankrupt firm to be included in the sample, financial information about the firm must be available for at least 16 quarters before bankruptcy (as noted previously, there were two firms included in the sample for which information was available for fewer than the required 16 quarters). In additon to this requirement, for a firm to be included in the second part of the study, security price and dividend information must be available on the Compustat Price-Dividends-Earnings (PDE) files for 48 months prior to the 16-quarter bankruptcy-model construction period. Thus, all the sample firms in this study have been in existence for at least four years before filing for bankruptcy, and most have been in existence for at least eight years before filing for bankruptcy. Altman (1983, 40) reports that in a given year, about 28% of the firms that fail have been in existence for three years or fewer, and over 50% of all failures occur during the first five years of existence. If the predictors of bankruptcy for firms that fail during the first three to five years of existence are different from those of firms that fail in subsequent years, the sampling process introduces a potential survivorship bias. Such a bias would limit making inferences from the results of this study to firms that have been in existence for three to five years or fewer. However, Altman (1983, 40) states that young firms usually fail as a result of inability to repay debt. It can be inferred from this observation that variables that proxy for leverage and liquidity may be important predictors of bankruptcy for young firms. If these same variables are most important in predicting bankruptcy among older firms, then the survivorship bias may not be especially problematic.

Annual Models

Because previous bankruptcy prediction models have been constructed using annual data, usually for each of the five years immediately preceding bankruptcy, the seven financial ratios described earlier are used to construct five annual bankruptcy prediction models. These models can be compared with previous models relative to classification accuracy and significance of individual predictor variables. The sample for the annual models consists of the same 64 firms whose financial ratios were used in the construction of the quarterly bankruptcy prediction models.

Association Between Changes in Bankruptcy Model Probability Assessments and Market Behavior

As indicated earlier, some researchers have gone beyond the development of prediction models to study the association between model signals and market behavior (e.g., Altman and Brenner 1981; Katz et al. 1985; Zavgren et al. 1988; Burgstahler et al. 1989). Zavgren et al. (1988) studied the association between market reaction and unanticipated firm performance (i.e., firm survival when predicted by the model to fail, or firm failure when predicted to survive). Their analysis covered the twelve-month period prior to the "event," and their results were mixed. Although their results were not entirely conclusive, the study provided some evidence that the Zavgren bankruptcy prediction model had information content during the twelve-month event window. Most of the models reviewed in this paper, including Beaver's (1966) univariate models, have exhibited the ability to discriminate between failed and nonfailed firms for as long as five years (twenty quarters) before bankruptcy. Given these results, it would be interesting to measure the relationship between changes in the models' assessments of bankruptcy probability and abnormal market returns on a quarterly basis over a five-year period. If the models represent a valid surrogate for the decision processes of capital market agents in the aggregate, then it would be expected that changes in the probability of bankruptcy as assessed by the models are inversely correlated with abnormal stock returns for a given company. If the association is low, such a result may help explain the somewhat inconclusive results of Zavgren et al. (1988).

Thus, the second part of the project is to examine the association between the quarterly changes in model bankruptcy predictions and abnormal securities returns. Because of the data limitations discussed above, the event window includes 16 quarters before bankruptcy rather than 20. Previous studies (e.g., Katz et al. 1985; Zavgren et al. 1988; Burgstahler et al. 1989) used yearly financial information in their analyses. Because most publicly-traded firms report earnings quarterly, the interim announcements may have confounded the results of these three studies. This study tests for a negative correlation between changes in probabilities of bankruptcy and abnormal stock returns on a quarterly basis. Thus, the correlation study covers fifteen "change periods," the change from quarter 16 to quarter 15 before the event date, from quarter 15 to quarter 14 before the event, from quarter 14 to quarter 13, and so on to the period from quarter 2 to quarter 1 before the event. The event date for failed firms is defined as either the suspension of trading of the firm's securities or filing for bankruptcy, whichever comes first. For matching nonfailed firms, data are gathered for a concurrent period. Thus, the event date for nonfailed firms is the last date for which financial data and stock return information are collected. In alternative form, the hypothesis under consideration is:

> H_{1A}: A negative correlation exists between the changes in failure probability signals from quarter to quarter and abnormal securities returns.

Based on a simulation study to compare various methods of computing abnormal returns, Brown and Warner (1980, 249) concluded that "beyond the simple, one-factor market model, there is no evidence that more complicated models convey any benefit." Accordingly, the one-factor market model,

$$R_{jt} = \alpha_j + \beta_j R_{mt} + \mu_{jt},$$

where R_{jt} = return of firm j in month t adjusted for dividends and splits,

R_{mt} = market return in month t,

α_j, β_j = estimates of the intercept and slope of the linear relationship between R_{jt} and R_{mt}, and

μ_{jt} = stochastic portion of the individualistic factor reflecting that portion of security j's return which varies independently of R_{mt},

is used to determine abnormal returns. The coefficient parameters for the above model were estimated by ordinary least squares (OLS) techniques. The data used in the OLS regression consisted of the monthly returns over a 48-month estimation period preceding the 16-quarter event window for each firm in the sample (both failed and nonfailed). The coefficient parameter estimates from the regression model then were used to calculate the abnormal returns for the sample firms (failed and nonfailed) during the event window period. All return data were collected from the Compustat PDE file of monthly stock information. Sufficient market data were available on 20 of the 32 bankrupt firms and 22 of the 32 nonbankrupt firms in the model-development sample for inclusion in this part of the study (See Table 3-2). The remaining 22 firms had to be dropped from the sample because of insufficient data. As in the first part of the study, the sampling procedure may introduce a survivorship bias. All the firms observed in this part of the study have been in existence for at least eight years. If the age of a firm influences how capital market agents in the aggregate react to information about a firm, then it may not be reasonable to make inferences from the results of this part of the study to firms that have not been existence long enough to meet the requirements of the sampling procedure.

The quarterly changes in bankruptcy prediction model probabilities are compared with the abnormal securities returns to determine if the market is using the information in the model. An underlying assumption of this study is that the market is efficient, at least in the semi-strong form. Accordingly, if the bankruptcy prediction model possesses information content, the model bankruptcy probabilities are expected to be negatively correlated with market behavior.

Market Perception Time and Strength of Model Signals

The third part of the study is a test for an association between market behavior and model probabilities and between market behavior and information from sources other than the quarterly financial statements. Ramaswami (1987) found that the interval between stock market perception time ("switching point" in the mean and/or variance of stock returns) and the date of bankruptcy differed cross-sectionally, and hypothesized that this market lead time interval was affected by the strength of the bankruptcy signal. However, he was unable to test this hypothesis directly because he did not have an exogenously determinable measure of the strength of the bankruptcy signal. This study focuses on the relationship between the strength of the bankruptcy signal and the switching point in the mean and/or variance of stock returns. The magnitude of the quarter-to-quarter changes in the model bankruptcy probability assessments is used as a surrogate for the strength of the bankruptcy signal. Ramaswami noted that under the semi-strong form of the efficient market hypothesis (EMH), stock return parameters, μ and σ^2, impound all the publicly-available information pertinent to a firm available at a given time. These parameters change only when new information becomes available. Thus, if the logit bankruptcy models are a valid surrogate for the decision processes of capital market agents in the aggregate, structural changes in the stock return parameters, μ and σ^2, should be expected to correspond with the greatest changes in the quarterly model probability assessments. In their alternative form, the hypotheses to be tested are:

H_{2A}: The switching point in the mean of the stock return for a company occurs at the point in time at which the greatest increase or decrease in probability of failure occurs for each of the failed and nonfailed firms in the sample.

H_{3A}: The switching point in the variance of the stock return for a company occurs at the point in time at which the greatest increase or decrease in probability of failure occurs for each of the failed and nonfailed firms in the sample.

As noted previously, earlier studies have been unable to find conclusive evidence of an association between stock price behavior and model bankruptcy predictions. Zavgren et al. (1988) suggested that the lack of association may be attributable to information from sources other than financial statements. If information other than that found in the financial statements has a strong impact on stock prices, then it would be expected that the switching point of a company's stock price (in terms of mean and/or variance) would be related to the release of unfavorable news about the company in the financial press (e.g., The

Wall Street Journal). This suggests the following hypotheses (in their alternative form):

H_{4A}: The switching point in the mean of the stock return for a company occurs at the point in time at which negative information about the company is released in The Wall Street Journal.

H_{5A}: The switching point in the variance of the stock return for a company occurs at the point in time at which negative information about the company is released in The Wall Street Journal.

In order to determine the switching point, Ramaswami used a method developed by Hillmer and Yu (1979) " . . . to measure the time it takes security market attributes to reflect new information" (Ramaswami 1987, 268). The Hillmer-Yu technique is used in the current study.

The Hillmer-Yu technique is concerned with determining the time at which the switching point for μ and σ^2 occurs. Assuming that stock price changes are lognormally distributed (as Ramaswami did), changes in stock prices in period t may be stated as follows:

$$\log(S_t/S_{t-1}) = X_t = \mu + \mathcal{E}_t$$

where:

S_t = stock price at time t;

μ = mean of log return; and

$_t = N(0,\sigma^2)$.

If $(X_t|\ t = 0,1,2, \ldots ,t_2)$ is a stochastic process of returns with t_0 some start date, t_1 the time at which a structural shift in the mean occurs, and t_2 the bankruptcy date, then:

$$X_t = \mu + \varepsilon_t \qquad \text{if } t = 0,1,2, \ldots, t_{1-1}$$

and

$$X_t = \mu_c + \varepsilon_t \qquad \text{if } t = t_1, t_{1+1}, \ldots, t_2.$$

where:

t_1 = time at which the market perceives the future state of bankruptcy (indicated by a change from μ to μ_c); and

t_2 = date of bankruptcy.

Similarly, for the variance of returns, the problem is to determine t_{1v}, the time at which the variance of the return changes in response to market perception of future bankruptcy:

$$X_t = \mu + \varepsilon_t, \qquad t = 0,1,2, \ldots, t_{1v-1}$$
$$= \mu + \varepsilon_{tv}, \qquad t = t_{1v}, t_{1v+1}, \ldots, t_2$$

where:

$$\varepsilon_t = N(0,\sigma^2); \quad tv = N(0,\sigma_c^2).$$

Stock market perception time, t_1, is computed as follows:

$$t_1 = T - \delta_t \,/\, (\theta_c - \theta)$$

where:

T = time when a statistically significant change in the parameter is signalled;

δ_t = critical value estimated for a given level of confidence;

θ = parameter (mean or variance of return) before change; and

θ_c = parameter after change.

Hillmer and Yu (1979) calculated t_1 using time intervals of one hour or smaller to determine if abnormal returns can be earned during the period surrounding the announcement of new information. Monthly returns are used to calculate the switching point (t_1 or t_{1v}) in this study. Ramaswami (1987, 270) notes that " . . . the longer term nature of bankruptcy is likely to be discerned by monthly returns rather than by the more volatile daily returns, which are subject to the impact of day-to-day events."

The steps involved in applying the Hillmer-Yu technique to calculate t_1 may be described as follows:

Step 1: Visually inspect the graph of the total monthly stock returns of the firm to determine a preliminary estimate of the switching point (t_1), the preadjustment period, and the adjustment period. (In this study, the adjustment period normally began 12 months before the preliminary estimate of t_1. The preadjustment period consisted of the thirty months ending two months before the adjustment period.)

Step 2: Obtain the mean ($\bar{x}$) and standard deviation (s) of the monthly stock returns for the preadjustment period.

Step 3: Calculate the cumulative deviations of observations during the adjustment period from the preadjustment period mean (accumulated $x - \bar{x}$).

Step 4: Calculate the critical values, β_k, to determine when a significant change in stock price behavior has occurred (period $k = T$) (thus, β_T is the critical value in the period in which a significant change is determined to have occurred). The critical value, β_k, is calculated as follows:

$$\beta_k = -\sqrt{k} * s * z_{(\alpha / 2)},$$

where: k = time periods during the adjustment period,

s = standard deviation of stock returns during the preadjustment period.

z = critical value for a two-tailed test of a normal distribution ($z = 1.96$ at $\alpha = .05$).

Step 5: Calculate the switching point, t_1 (shown below). The final t_1 is determined iteratively. Step 5 is repeated until t_1's for two successive iterations are not significantly different. The switching point, t_1, is calculated as follows:

$$t_1 = T - (\beta_T / (\bar{X}_c - \bar{X}))$$

where: T = the period, k, in which a significant change in the stock return parameter is determined to have occurred,

β_T = the critical value in period T,

$\bar{X}_c$ = mean of stock returns during the adjustment period, and

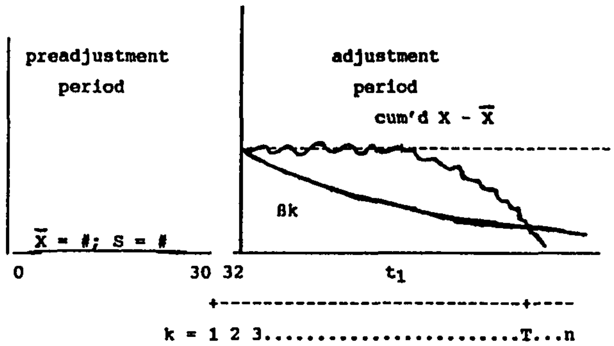
$\bar{X}$ = mean of stock returns during the preadjustment period.

The above steps are illustrated graphically in Figure 3-1. These procedures are followed for the calculation of the switching point for the mean (t_1) of stock returns.

Similar procedures are followed to calculate the switching point for the variance (t_{1V}) of stock returns.

The sample includes 17 of the 20 bankrupt firms that were used in the correlation study (see Table 3-3). The remaining three bankrupt firms included in the correlation study sample were dropped from this portion of the study because of lack of return data. Thus, the sample includes all bankrupt firms for which quarterly bankruptcy models were constructed and for which the monthly stock return information necessary to estimate the switching point(s) is available.

Figure 3-1
Graphical Illustration
of Hillmer-Yu Technique



where:

$\bar{x}$ = mean of monthly stock returns for the preadjustment period.

s = standard deviation of monthly stock returns for the preadjustment period.

k = time periods (months) during the adjustment period.

β_k = Critical value in period k.

T = time period in which a significant change in the stock return parameter is determined to have occurred.

t_1 = switching point

Table 3-1
Sample Firms for
Bankruptcy Prediction Models

Bankrupt Companies Ind. Code	CUSIP Number	Company Name	Pair-Matched Nonbankrupt Companies Ind. Code	CUSIP Number	Company Name
3911	765516	Richton Int'l.	3911	481088	Jostens Inc.
5311	382073	Good (L. S.)	5311	228093	Crowley Milner & Co.
2300	366064	Garland Corp.	2300	624590	Movie Star Inc.
2510	112061	B. Brody Seating Co.	2520	786449	Safeguard Scientifics
3689	038213	Applied Magnetics	3651	157186	Cetec Corp.
2010	888837	Tobin Pkg.	2016	127703	Cagle's Inc.
3590	967442	Wickes Cos., Inc.	3590	896678	Trinova Corp.
5331	404269	HRT Inds.	5311	014752	Alexander's Inc.
3555	001723	A.M. International	3550	413345	Harnischfeger Inds.
5945	536257	Lionel Corp.	5945	875386	Tandycrafts Inc.
3350	761406	Revere Copper & Brass	3350	410306	Handy & Harman
3910	521078	Lazare-Kaplan	3911	250568	Designcraft Inds.
5093	858263	Steelmet Inc.	5094	477205	Jewelcor Inc. (477205)
3652	482724	K-Tel	3684	924240	Vermont Research Inc.
2400	886498	Tidwell Inds.	2430	872534	Trus Joist Corp.
5040	001348	AIC Int'l.	5040	948662	Weiman Co. Inc.
3663	883084	Texscan Corp.	3663	591503	Metex Corp.
5900	338517	Flanigan's Enterprises	5900	462614	IPCO Corp.
2834	770706	Robins (A. H.)	2834	071707	Bausch & Lomb
3312	502210	LTV Corp.	3312	042170	ARMCO Inc.
3533	832110	Smith International	3533	133429	Cameron Iron Works
3520	858359	Steiger Tractor Co.	3541	609150	Monarch Machine Tool Co.
5051	903035	U.N.A. Corp.	5064	389190	Gray Communication
7830	456632	Inflight Services	7814	518686	Laurel Entertainment Inc.
1311	292701	Energy Management Corp.	1311	427879	Hershey Oil Corp.
5331	422686	Heck's Inc.	5331	470736	Jamesway Corp.
3499	483098	Kaiser Steel	3460	983085	Wyman-Gordon Co.
1382	816068	Seiscom Engineering	1389	675232	Oceaneering Int'l.
3564	019645	Allis Chalmers	3560	458702	Interlake Corp.
3634	017372	Allegheny Int'l.	3630	963320	Whirlpool Corp.
2750	070121	Basix Corp.	2750	103043	Bowne & Co., Inc.
1389	958043	Western Co. (N. Amer.)	1381	423452	Helmerich & Payne

Table 3-2
Sample Firms for
Spearman's Rho Correlation Analysis

Ind. Code	CUSIP Number	Company Name	Bankrupt (BR)/ Nonbankrupt (N)
3911	765516	Richton Int'l	BR
3911	481088	Jostens Inc.	N
2300	624590	Movie Star Inc.	N
3689	038213	Applied Magnetics	BR
3590	967442	Wickes Cos., Inc	BR
3590	896678	Trinova Corp.	N
5311	014752	Alexander's Inc.	N
3555	001723	A.M. International	BR
3550	413345	Harnischfeger Inds.	N
5945	536257	Lionel Corp.	BR
3350	410306	Handy & Harman	N
3910	521078	Lazare-Kaplan	BR
3911	250568	Designcraft Inds.	N
5094	437205	Jewelcor Inc.	N
3652	482724	K-Tel	BR
2400	886498	Tidwell Inds.	BR
5040	948662	Weiman Co. Inc.	N
3663	883084	Texscan Corp.	BR
3663	591503	Metex Corp.	N
5900	338517	Flanigan's Enterprises	BR
5900	462614	IPCO Corp.	N
2834	770706	Robins (A. H.)	BR
2834	071707	Bausch & Lomb	N
3312	502210	LTV Corp.	BR
3312	042170	ARMCO Inc.	N
3533	832110	Smith International	BR
3533	133429	Cameron Iron Works	N
3541	609150	Monarch Machine Tool Co.	N
5051	903035	U.N.A. Corp.	BR
7830	456632	Inflight Services	BR
5331	422686	Heck's Inc.	BR
5331	470736	Jamesway Corp.	N
3460	983085	Wyman-Gordon Co.	N
1389	675232	Oceaneering Int'l.	N
3564	019645	Allis Chalmers	BR
3560	458702	Interlake Corp.	N
3634	017372	Allegheny Int'l.	BR
3630	963320	Whirlpool Corp.	N
2750	070121	Basix Corp.	BR
2750	103043	Bowne & Co., Inc.	N
1389	958043	Western Co. (N. Amer.)	BR
1381	423452	Helmerich	N

Table 3-3
Sample Firms for
Hillmer-Yu Analysis

Richton International
Applied Magnetics
Wickes Cos., Inc.
A.M. International
Lionel Corp.
Lazare-Kaplan
K-Tel
Tidwell Inds.
Texscan Corp.
Flanigan's Enterprises
Robins (A. H.)
LTV Corp.
Smith International
U.N.A. Corp.
Inflight Services
Heck's Inc.
Allis Chalmers

CHAPTER IV

RESULTS AND ANALYSIS

In this chapter, the results of the hypothesis tests described in Chapter 3 are presented and discussed. First, the bankruptcy prediction models are discussed, relative to their overall significance and the significance of specific predictor variables. Second, model classification accuracy is addressed. Comparisons of model classification accuracy among periods as well as comparisons with the classification accuracy of earlier models are presented. Third, the results of the correlation analysis between changes in bankruptcy model probability assessments and abnormal stock returns are presented and discussed. Fourth, the results of the tests for association between information from sources other than the financial statements and the switching point of the mean and variance of stock returns are reported and analyzed.

Bankruptcy Models

Overall Model Significance

Table 4-1 presents the estimation results for the logit models for quarters one to sixteen prior to bankruptcy. Table 4-2 contains comparable information for the annual models (years one to five prior to bankruptcy). Zavgren

(1985) notes that the likelihood ratio test provides a strong test of the logit model's ability to distinguish between healthy and bankrupt firms. The p-values for the quarterly models, based on the likelihood ratio test statistic asymptotically distributed as a Chi-square with seven degrees of freedom, are presented in Table 4-1. For quarters one through thirteen, the p-values all are less than .005, which indicates that these models are significant at the 0.995 confidence level. The models for quarters fourteen through sixteen indicate p-values of less than .03, and thus are significant at the .970 confidence level. Table 4-2 gives the estimation results for the annual models. The p-values for the annual models are all less than .025, which translates to overall model significance at the .975 confidence level.

Significance of Individual Predictors

Return on assets (ROA) (net income/total assets) was expected to be inversely related to the response variable, bankruptcy. However, both Zavgren (1985) and Ohlson (1980) found little or no significant relationship between ROA and bankruptcy. Both authors attributed this finding to the possibility that reported earnings are subject to choice of accounting methods and thus are "managed" figures. This study's results are similar to those of the two studies noted above. In the current study, ROA is a significant predictor in quarters 2, 3, and 14 prior to bankruptcy at the 95% confidence level. In the annual models, ROA is significant only in year one prior to bankruptcy at the 95% confidence level. These results support the previous findings. In both the quarterly and annual models, ROA tends to be more significant in periods immediately prior to bankruptcy. This result may indicate that during the more remote periods prior to bankruptcy, management increases or decreases discretionary accruals as required to be able to report relatively smooth income figures. As bankruptcy approaches, and the discretionary component of accruals is exhausted, ROA becomes a less "managed" figure and a more significant predictor of bankruptcy.

An alternative explanation may be that the relationship between ROA and bankruptcy in the models is confounded by collinearity. Consistently throughout the five years and the sixteen quarters, ROA is strongly inversely correlated with Leverage (debt/total assets). The relationship between these two variables is summarized for all 21 annual and quarterly models in Table 4-3. Pairwise correlations for all the predictor variables are presented in the Appendix. Tables A-1 through A-5 in the Appendix report the correlations between pairs of predictor variables for the annual models. Tables A-6 through A-21 in the Appendix report the same information for the quarterly models.

Capital Turnover (sales/net plant) was expected to be negatively associated with bankruptcy. High (low) capital turnover indicates a high (low) level of plant utilization. Generally, this variable was found to be insignificant in predicting bankruptcy. This result is consistent with the findings of Zavgren (1985), who concluded that short-term changes in asset turnover are difficult to distinguish. Capital turnover was found to be significant in quarters 2 (p-value = .0001) and 3 (p-value = .0568) prior to bankruptcy. These findings may indicate that potentially bankrupt firms experience a sharp drop in sales shortly prior to bankruptcy as their customers begin to sense problems and turn to other suppliers. Capital turnover does not appear to suffer from pairwise collinearity with other predictor variables.

Given the manner in which they were calculated, both inventory turnover (inventory/sales) and receivable turnover (accounts receivable/sales) were expected to be positively related to bankruptcy. These ratios, along with capital turnover, are measures of management efficiency. Inventory turnover was significant only in quarter 3 prior to bankruptcy (p-value = .0443) and in year 1 (p-value = .0883) prior to bankruptcy. These results appear to be consistent with the asset turnover findings. Sales drop in the periods leading up to bankruptcy, resulting in an increase in inventory. Inventory turnover is not significant in the last quarter prior to bankruptcy, perhaps because by then, firms on the verge of bankruptcy have written down inventories to their market values. Receivable turnover was not significant in any of the quarterly or annual models. This finding is consistent with the Zavgren model results. Perhaps, as sales decline in the periods immediately preceding bankruptcy, firms make greater effort to collect their outstanding accounts, while new receivables are not being generated by sales. Thus, both receivables and sales may be falling, with little change in the ratio. Neither inventory turnover nor receivable turnover appears to suffer from consistent problems of pairwise collinearity with other predictor variables.

Leverage (total debt/total assets) was expected to be positively related to bankruptcy. Leverage is significant at the 95% confidence level in 13 of the 16 quarterly models, and at the 90% confidence level in one quarterly model. Leverage is the most significant predictor variable in each of the two remaining quarters (quarters 11 and 13). In quarter 11, leverage is significant at the 86% confidence level. In quarter 13, leverage is significant at the 88% confidence level. In the annual models, leverage is significant at the 95% confidence level for the first three years prior to bankruptcy. In year four, leverage is the most significant predictor variable in the model (confidence level = 88%). In year five before bankruptcy, leverage is not significant. In all quarterly and annual models, the leverage coefficient is positive, as expected. These results clearly indicate that potentially bankrupt firms are more highly financially leveraged than healthy firms. As noted earlier, Table 4-3 reports a high degree of inverse correlation between leverage and ROA. This result suggests that potentially bankrupt firms often overinvest in plant assets with borrowed funds. Their return on these assets is lower, and their interest obligation is higher, relative to healthy firms. Eventually, their high debt obligation appears to be their undoing.

Both the quick ratio and the cash position ratio (cash/total assets) are measures of short-term liquidity and were expected to be inversely related to bankruptcy. Because they are short-term measures, they were expected to gain in significance as the date of bankruptcy drew closer. A study of the pairwise correlation tables (Tables A-1 through A-21) reveals that these two variables are highly collinear. In addition, the quick ratio suffers from some collinearity problems with the leverage ratio. This result may explain why the quick ratio coefficient is consistently positive and insignificant. The cash position coefficient is consistently negative as expected and tends to become more significant as the bankruptcy date approaches, both as expected. Cash position is significant at the 90% confidence level in the second, third, and fourth quarters before bankruptcy. The only other quarter in which cash position is significant is quarter 13. In the annual models, cash position is significant at the 90% confidence level in years 1 and 3, and is significant at the 85% confidence level in year 2. In years 4 and 5 before bankruptcy, cash position is not significant.

In summary, leverage and liquidity appear to be the most useful predictors of bankruptcy. Leverage is significant generally throughout the sixteen quarter period before bankruptcy. Cash position becomes more significant as the bankruptcy event comes closer. Perhaps, this result is obtained because firms that have been highly leveraged for several years and that continue to borrow in order to pay short-term liabilities exhaust their sources of new debt or reach the limits allowed by their existing debt covenants. Once they can no longer borrow additional funds, their cash position deteriorates quickly. The efficiency ratios (capital turnover, inventory turnover, and receivables turnover) are not significant predictors of bankruptcy. This finding is consistent with the Zavgren (1985) model results and may indicate that bankruptcy most often results from structural factors (i.e., high leverage).

Model Classification Accuracy

Table 4-4 contains a summary of the classification accuracy of the sixteen quarterly models when applied to sample firms. As expected, the models developed for the quarters closest to the event date generally have higher classification accuracy than the models developed for the more remote time periods. The correct classification rate for the first three quarters before bankruptcy ranges from 89% to 94%, and declines to between 68% and 72% for quarters 14 to 16 before bankruptcy. Because previous models have not been constructed using quarterly data, direct comparison with the previous models is not possible. However, an "eyeball" analysis indicates that the quarterly model results generally are consistent with the annual model results, and the classification accuracy of the annual models can be compared with the accuracy of previous annual models (see Table 4-5).

It was not expected that the current models would classify firms as accurately as previous models, because the conditions that are required to exist to enter into bankruptcy were relaxed by the Bankruptcy Code of 1978. The previous models were constructed using firms that entered into bankruptcy prior to the new Code; the current study used data for firms that filed for bankruptcy subsequent to the passage of the new Code. Despite this difference, the annual models are comparable to previous models in terms of classification accuracy. This finding is consistent with the findings of Zavgren (1988) that, on average, despite a few highly publicized examples, firms that file for bankruptcy under the new code are not profitable firms using the provisions of the new Code to invalidate obligations. The model for year 1 before bankruptcy achieved an overall correct classification rate of 94%, which was higher than the accuracy of the earlier models reported in Table 4-5. The correct classification rate declines to 75% in year 2, which is slightly lower than the other models. In years 3 through 5, classification accuracy fluctuates between 72% and 75%. This result is somewhat lower than the accuracy obtained in the Altman et al. (1977) "Zeta" model, but generally consistent with the classification accuracy of the Zavgren (1985) and Blum (1974) models. The classification rates indicate that while factors other than the selected financial ratios may relate to the incidence of bankruptcy, the ratios contain useful information in explaining and/or predicting bankruptcy.

Association Between Changes in the Bankruptcy Model Probability Assessments and Abnormal Stock Returns

Because the multivariate bankruptcy prediction models discussed in Part A exhibit the ability to discriminate reasonably well between bankrupt and pair-matched nonbankrupt firms, then financial ratios as filtered through the models seem to indicate the relative financial health of the companies involved. Accordingly, it was expected that, assuming capital market efficiency, changes in bankruptcy model predicted probabilities of failure would be inversely related to abnormal stock returns (Hypothesis 1A). Thus, assuming market efficiency, this part of the study tests for information content of the bankruptcy prediction models.

Monthly abnormal returns, calculated as discussed in chapter 3, were accumulated for each quarter in the study window to determine quarterly abnormal returns. A correlation analysis then was conducted to compare the quarterly abnormal returns to the changes in bankruptcy model predicted probabilities of failure. Since there were sixteen quarterly models, there were fifteen "model change" periods. The relationship between market behavior and bankruptcy model signals has been examined by previous researchers (e.g., Katz et al. 1985; Zavgren et al. 1988; Burgstahler et al. 1989). Their results have been somewhat inconclusive.

Hypothesis 1A was tested using the Spearman's Rho nonparametric correlational statistic because of non-normality and outliers in the sample of abnormal returns. The results of the current study are consistent with those obtained in earlier studies. The abnormal returns and bankruptcy model changes are significantly correlated for only two of the 42 sample firms, and their correlation is not in the expected direction (see Table 4-6). Because quarterly information generally is released at least one month after quarter-end, a second correlation analysis was undertaken using quarterly returns based on the three-month period ending one month after the quarter for which financial information is prepared. This lagged correlation analysis produced results similar to those of the previous analysis. The abnormal returns and bankruptcy model changes are significantly correlated for four of the 42 sample firms, with three not in the expected direction.

A possible explanation for the lack of significant results is that the bankruptcy model probability assessments are not stable. Instability of the probability assessments may be attributable to at least one of two factors. First, in some cases, the underlying ratios themselves are not stable. The most extreme example of a shift in probability assessments resulting from the ratios is A. H. Robins. From quarter 4 before bankruptcy to quarter 3 before bankruptcy, the bankruptcy model probability assessment of A. H. Robins changed from .02 to 1.0. This result is obtained because in quarter 3 before bankruptcy, A. H. Robins recognized a contingency loss of $613 million related to a class-action suit brought by former users of the Dalcon Shield interuterine device. The recognition of the contingency loss caused the leverage ratio (total debt/total assets) to increase from .325 to 1.2. Because leverage was consistently the most significant predictor variable in the model, such a change had a dramatic impact on the bankruptcy model probability assessments. Instability resulting from changes in the underlying ratios is not a problem, but rather an indication that the models are responsive to changes in financial position.

A second reason for the instability of probability assessments is related to sample size. As noted in Chapter

3, the sample used to construct the bankruptcy prediction models (32 pair-matched bankrupt and nonbankrupt firms) is small for the number of variables (seven predictor variables) contained in the models. As a result, the models may be overfitted, resulting in correlated parameter estimates. Unstable model coefficients and large shifts in quarterly probability assessments provide strong evidence that the parameters estimates are correlated. A study of Table 4-1 reveals that the coefficients are unstable. For example, during the eight quarters immediately prior to bankruptcy, the coefficient associated with ROA fluctuates between -1.561 and -59.94. The coefficient associated with leverage (total debt/total assets) fluctuates between 45.97 and 100.50. Coefficients for the other predictor variables exhibit similar behaviors. Thus, it would appear that the models suffer from correlation between and among the parameter estimates, and that at least some of the instability in bankruptcy model probability predictions may be a direct result. Such instability may obscure whatever relationship actually exists between abnormal stock returns and changes in the information set contained in the seven predictor variables. Unfortunately, techniques designed to ameliorate the problem of correlation between and among the predictor variables in logit models are not well developed.

Further discussion of the insignificant results obtained from the correlation analysis is subdivided into two categories: (1) market-based explanations and (2) model-based explanations.

Market-Based Explanations

If capital market efficiency is assumed, as it is here, then the correlation study tests for information content of the bankruptcy prediction models. The fact that the models exhibit high classification accuracy indicates that model predictions of likelihood of failure are representative of a firm's financial health. Given the low correlation between abnormal returns and changes in bankruptcy model probability scores, it appears that capital market agents in the aggregate use a broader information set than that contained in the bankruptcy models. For example, information releases in the financial press (e.g., The Wall Street Journal) or information contained in the Management Discussion and Analysis section of the annual reports may have a significant impact on the aggregate investment decisions of market agents.

An alternative explanation is that capital market agents in the aggregate rely on accounting information as published in financial statements in making investment decisions, but the relationship between accounting information signals and stock price behavior is not monotonic, and thus is undetected by the Spearman's Rho statistic. For example, the bankruptcy model predicted probabilities of failure do not include the effect of market expectations (i.e., information indicating "bad" performance may be better than anticipated, thus resulting in a positive stock price adjustment after the release of such information, or vice versa). Alternatively, performance in a given quarter (relative to a previous quarter) may not be viewed as an indication of a firm's future earnings or performance potential. In other words, it may take several quarters of poor (or good) performance for investors in the aggregate to adjust their assessment of the present value of the firm's future cash flows.

A third explanation may be related to the fact that entering Chapter 11 bankruptcy does not necessarily signal the end of a firm's existence. Altman (1983) notes that as many as 30% of publicly-traded bankrupt firms successfully reorganize. Casey et al. (1986) found that firms that eventually emerged from Chapter 11 bankruptcy systematically differed from those that eventually liquidated with respect to proportion of free assets (uncollateralized assets) and extent of profitability in the periods immediately preceding filing for bankruptcy. This result suggests that investors can make distinctions among firms that have filed for bankruptcy. In other words, filing for bankruptcy does not represent the same degree of deterioration with respect to financial health for all firms that file for bankruptcy. That investors can make distinctions as to the survivability of firms that have filed for bankruptcy may weaken the relationship between abnormal stock returns and bankruptcy model probability assessments.

The variable identified by the bankruptcy prediction models as the one most significantly related to bankruptcy is the leverage ratio. Thus, it may be argued that the test for association between changes in bankruptcy model probability assessments and abnormal stock returns was indirectly a test for association between changes in the leverage ratio and abnormal stock returns. The lack of association observed in this study is consistent with the results of Eckbo (1986), who found no significant association between debt offerings (i.e., increase in leverage ratio) and stock price.

Model-Based Explanations

Any study of this type may be considered a test of joint hypotheses. The information content of the bankruptcy prediction models is being tested jointly with the validity of the market model. Therefore, the lack of an association between changes in the bankruptcy model probability assessments and abnormal stock returns may be, in part, the result of a misspecified model of stock returns (Brenner 1977).

As stated in Chapter 3, the one-factor market model is employed to determine abnormal stock returns. The decision to use this model was made for two reasons. First, the one-factor market model has wide acceptance in the accounting literature. Second, in a simulation study that compared the performances of several methods of computing abnormal returns, including mean adjusted returns, market adjusted returns, and market model residuals, Brown and Warner (1980) concluded that the one-factor performed as well as or better than other methods in minimizing both Type I errors (rejecting the null hypothesis of no abnormal returns when it is true) and Type II errors (failing to reject the null hypothesis of no abnormal returns when it is false).

In this study, the market model beta coefficients were estimated using ordinary least squares regression data from the forty-eight month period immediately preceding the original 20-quarter study period (because of insufficient data, a 16-quarter study period was finally used). An underlying assumption of this approach is that the beta coefficient is stationary. Although the procedures employed in this study represent the most common approach to measuring abnormal stock returns, some evidence exists that beta is non-stationary (e.g., Blume 1975; Brenner and Smidt 1977; Gonedes 1973; Meyers 1973). However, as Brenner and Smidt (1977) note, no specific useable alternative to the assumption of stability has received general acceptance. To the extent that the assumption of stationary beta coefficients is unrealistic, the reliability of the results presented above may be questioned.

If beta is non-stationary, then individual firms' abnormal returns computed using the single-factor market model, which assumes stationarity of beta, may be noisy. In order to mitigate the potential impact of noise at the individual firm level, the Spearman's Rho nonparametric correlational statistic was computed at the portfolio level using portfolio-wide averages for changes in bankruptcy model probability assessments and abnormal securities returns. This test yielded insignificant results, which are consistent with the results of the correlation tests conducted at the individual firm level.

Market Perception Time and Financial Information

One of the explanations given above for the low observed correlation between changes in bankruptcy model probability assessments and abnormal stock returns was that although a relationship between the two variables may exist, the relationship may not be monotonic and thus may go undetected by Spearman's Rho statistic. Hypotheses 2A and 3A, which suggest an association between the changes in the bankruptcy model probability assessments and switching point in a firm's stock returns in terms of mean (H2A) and variance (H3A), were tested as an alternative to the monotonic relationship suggested by hypothesis 1A. An association was deemed to exist if the switching point occurred within the three-month window beginning with the month of quarter-end and ending in the second month after quarter-end for the quarter in which the greatest decrease in bankruptcy probability assessment was observed. Thus, if a quarter ends in December, the window of interest includes December, January and February. This decision rule was adopted because such a window should be wide enough to include the effects of the early release of some information, such as quarterly earnings projections, as well as the actual publication of the quarterly financial statements. Table 4-7 presents a summary of the findings.

The results of these tests by firm are presented in the Appendix in Tables A-22 through A-36.

It should be noted that of the seventeen firms for which data were available to apply the Hillmer-Yu technique, no switching point for either mean or variance of stock returns was detected for two firms; a switching point for the mean of stock returns, but not the variance, was detected for six firms; a switching point for the variance, but not the mean, was detected for one firm; and switching points for both the mean and variance of stock returns were detected for the remaining eight firms (see Table 4-8).

An inspection of Tables A-22 through A-36 in Appendix (summarized in Table 4-7) indicates some association between the switching point and the magnitude of the increase in bankruptcy model probability assessments. The switching point for the mean of stock returns for only one of the firms occurred during the one-quarter event window. However, the switching point for the mean of stock returns of six of the firms occurred within one quarter (either before or after) of the event window. The switching point for the mean of stock returns for one of the sample firms occurred in the quarter of the second largest increase in bankruptcy model probability assessments. In this case, the second largest increase in model probability assessments occurred three quarters before the largest increase. This result suggests that stock market agents adjusted their valuation of this firm's stock prior to the quarter in which greatest single period deterioration in the firm's financial statements occurred, thereby eliminating the need for a dramatic readjustment in a later period. The switching point for the variance of stock returns for one firm occurred during the quarter of the greatest increase in bankruptcy model probability assessments. For four other firms, the switching point for the variance of stock returns occurred in the quarter following the quarter of the greatest increase in bankruptcy model probability assessments. In all, the switching points for the mean and/or variance of stock returns of ten firms occurred within one quarter of the event window. This result provides some evidence that information contained in the financial statements is being used by capital market agents. However, that five of the fifteen firms' switching points occurred at times seemingly unrelated to the quarter of the greatest increase in bankruptcy model probability assessments indicates that information other than that contained in the financial statements also is being used by the market in assessing the value of a firm's stock, as suggested in hypotheses 4A and 5A.

Hypotheses 4A and 5A call for a test of an association between the switching point and the release of unfavorable news in the financial press (e.g., The Wall Street Journal). These hypotheses were tested informally, as were the previous two hypotheses. Table 4-9 presents a summary of the findings, including a description of the items that were deemed to constitute unfavorable news. In eleven of the fifteen cases, the switching point for either the mean or variance of stock returns occurred after several months of persistent unfavorable news releases (including unfavorable earnings announcements). In only one case did the switching point occur subsequent to unfavorable news releases that were not part of a general pattern. Specifically, the switching point in the mean of stock returns of Tidwell occurred in the month subsequent to the announcement of positive net income for the previous year. However, the fourth quarter component of those annual earnings was a loss. Apparently, the fourth-quarter loss was interpreted as a signal of a deterioration in future performance, or possibly unfavorable news was reported in local or regional publications, but not in the The Wall Street Journal. The switching points for the mean of stock returns of three firms occur independently of unfavorable news releases. However, the switching points of two of them, Richton and

Texscan, appear to be related to changes in bankruptcy model probability assessments. As reported in Table 4-7, the switching point for the mean of Richton's stock returns occurs during the quarter with the second largest increase in bankruptcy model probability assessments; the switching point for the mean of Texcan's stock returns occurs within one quarter of the greatest increase in bankruptcy model probability assessments. Only K-Tel's switching point occurs with no apparent relationship with either financial statement information as reflected in changes in bankruptcy model probability assessments or unfavorable news releases in the national press.

In summary, the switching point of the mean and variance of stock returns appears to be related both to financial statement information as measured by changes in bankruptcy model probability assessments and the release of unfavorable news in the The Wall Street Journal. With regard to the latter, the evidence suggests that it is usually the cumulative effect of a series of unfavorable news releases, rather than the effect of a single devastating news story, that motivates capital market agents in the aggregate to adjust downwardly their valuations of a firm's stock.

Summary of Results

With respect to both the quarterly and annual bankruptcy prediction models, leverage is the most consistent predictor throughout the observation period. This result confirms the earlier findings of Zavgren (1985). In the periods immediately prior to bankruptcy, cash position becomes a significant predictor. This finding suggests that companies that file for bankruptcy generally are more highly leveraged than their healthier counterparts. Eventually, their high debt and the cost of servicing such debt result in short-term liquidity problems, and subsequently they are forced to take drastic action (e.g., file for bankruptcy).

No significant linear relationship between changes in bankruptcy model probability assessments and abnormal stock returns was found. This result does not imply, however, that financial statement information is not used by capital market agents in assessing the value of a firm's securities. As the switching point analysis indicated, financial information seems to be used, but its relationship with abnormal stock returns probably is not linear. The switching point analysis also indicated that firm-specific information released in the national press (The Wall Street Journal) is used by the market in setting stock prices.

This may have helped obscure whatever linear relationship exists between financial statement information (as measured by changes in bankruptcy model probability assessments) and abnormal stock returns.

Table 4-1

Logit Estimation Results--Quarters 1-16

Qtrs. Prior to Failure	Variable Name	Intercept	Return on Assets	Sales/ PPE	Inv./ Sales	Debt/ T.A.	Rec./ Sales	Quick Ratio	Cash/ T.A.	Overall Model
1	Coefficient	-61.106	-10.276	6.243	15.304	72.514	-4.561	7.315	-67.171	
	Std. Error	108.100	6.999	4.231	10.210	26.960	12.520	14.050	65.380	
	P-value	0.5718	0.1430	0.1401	0.1340	0.0072	0.7157	0.6026	0.3042	0.0000
	Chi-Squared									58.8010
2	Coefficient	145.370	-59.940	0.687	9.573	100.500	19.681	4.055	-234.190	
	Std. Error	129.638	1.988	1.951	9.396	43.786	20.061	24.233	127.120	
	P-value	0.2621	0.0001	0.7249	0.3083	0.0217	0.3266	0.8671	0.0654	0.0001
	Chi-Squared									24.4000
3	Coefficient	124.812	-40.048	3.102	22.463	96.043	-7.129	21.988	-224.569	
	Std. Error	147.900	21.030	2.377	11.170	40.820	12.570	16.330	128.000	
	P-value	0.3986	0.0568	0.1920	0.0443	0.0187	0.5707	0.1780	0.0792	0.0000
	Chi-Squared									59.7260
4	Coefficient	36.235	-2.755	2.963	2.863	52.674	-2.850	9.819	-92.767	
	Std. Error	83.84	2.957	2.413	4.426	19.15	4.985	6.809	51.45	
	P-value	0.6656	0.3515	0.2194	0.5178	0.0059	0.5675	0.1493	0.0714	0.0000
	Chi-Squared									38.5530
5	Coefficient	-69.749	-1.561	3.651	7.028	62.281	-3.618	6.339	-38.265	
	Std. Error	88.770	5.293	2.210	5.700	24.380	5.931	7.294	43.430	
	P-value	0.4320	0.7680	0.0985	0.2176	0.0106	0.5419	0.3848	0.3783	0.0000
	Chi-Squared									36.8930
6	Coefficient	-18.944	-4.725	2.261	5.852	50.550	2.544	6.591	-61.111	
	Std. Error	73.980	12.580	2.048	4.583	20.590	5.404	6.293	42.470	
	P-value	0.7979	0.7073	0.2697	0.2017	0.0141	0.6378	0.2949	0.1501	0.0000
	Chi-Squared									34.2040

Table 4-1 (Cont'd)

Qtrs. Prior to Failure	Variable Name	Intercept	Return on Assets	Sales/ PPE	Inv./ Sales	Debt/ T.A.	Rec./ Sales	Quick Ratio	Cash/ T.A.	Overall Model
7	Coefficient	-50.967	-9.893	1.968	3.426	45.976	2.667	5.196	-31.982	
	Std. Error	58.860	16.740	1.682	4.256	19.980	5.303	5.479	29.790	
	P-value	0.3865	0.5546	0.2418	0.4209	0.0214	0.6151	0.3430	0.2830	0.0002
	Chi-Squared									28.6350
8	Coefficient	-29.589	8.712	1.595	0.265	53.293	1.489	5.893	-48.533	
	Std. Error	48.970	5.760	1.177	2.429	17.890	6.341	5.121	30.040	
	P-value	0.5457	0.1304	0.1755	0.9132	0.0029	0.8144	0.2499	0.1062	0.0002
	Chi-Squared									28.6560
9	Coefficient	-59.573	-5.316	1.468	0.818	56.192	2.432	5.667	-34.319	
	Std. Error	51.010	15.380	1.142	3.346	18.300	6.320	4.763	29.010	
	P-value	0.2428	0.7295	0.1984	0.8076	0.0021	0.7003	0.2341	0.2367	0.0001
	Chi-Squared									29.5640
10	Coefficient	-65.581	-16.756	1.822	2.538	60.936	1.038	9.142	-40.242	
	Std. Error	47.890	14.030	1.468	4.645	20.690	6.312	6.116	26.470	
	P-value	0.1709	0.2324	0.2147	0.5848	0.0032	0.8694	0.1350	0.1285	0.0000
	Chi-Squared									32.0120
11	Coefficient	10.273	-14.338	1.617	1.156	25.713	3.682	2.635	-43.440	
	Std. Error	46.940	15.100	1.358	3.556	17.220	7.074	7.068	29.470	
	P-value	0.8268	0.3423	0.2339	0.7450	0.1353	0.6027	0.7093	0.1405	0.0024
	Chi-Squared									22.1660
12	Coefficient	2.047	10.099	1.398	3.956	37.879	-0.753	6.037	-53.122	
	Std. Error	50.080	11.620	1.144	4.299	17.240	4.043	5.875	28.730	
	P-value	0.9674	0.3848	0.2220	0.3574	0.0280	0.8523	0.3041	0.0645	0.0039
	Chi-Squared									20.8910

Table 4-1 (Cont'd)

Qtrs. Prior to Failure	Variable Name	Intercept	Return on Assets	Sales/ PPE	Inv./ Sales	Debt/ T.A.	Rec./ Sales	Quick Ratio	Cash/ T.A.	Overall Model
13	Coefficient	1.691	-14.524	0.992	2.470	23.038	-0.335	-0.430	-28.309	
	Std. Error	47.260	12.620	0.962	4.715	14.820	5.054	6.038	31.200	
	P-value	0.9715	0.2497	0.3024	0.6004	0.1200	0.9471	0.9432	0.3642	0.0049
	Chi-Squared									20.3170
14	Coefficient	-33.718	-46.303	0.580	1.805	26.616	-4.314	3.207	-8.693	
	Std. Error	40.850	22.620	1.088	3.809	15.570	3.838	5.189	22.340	
	P-value	0.4091	0.0407	0.5937	0.6357	0.0874	0.2610	0.5366	0.6972	0.0105
	Chi-Squared									18.3560
15	Coefficient	-16.801	-17.891	1.431	-0.667	29.818	-1.061	3.445	-24.678	
	Std. Error	41.000	15.540	0.925	4.114	12.740	2.319	4.123	22.700	
	P-value	0.6820	0.2496	0.1221	0.8713	0.0193	0.6473	0.4033	0.2770	0.0209
	Chi-Squared									16.5080
16	Coefficient	-0.422	9.783	1.708	1.174	31.372	1.911	2.729	-41.269	
	Std. Error	46.230	8.444	1.074	3.676	13.660	3.267	4.784	26.580	
	P-value	0.9927	0.2466	0.1116	0.7498	0.0217	0.5585	0.5683	0.1205	0.0264
	Chi-Squared									15.8600

Table 4-2
Logit Estimation Results--Years 1 - 5

Yrs. Prior to Failure	Variable Name	Intercept	Return on Assets	Sales/ PPE	Inv./ Sales	Debt/ T.A.	Rec./ Sales	Quick Ratio	Cash/ T.A.	Overall Model
1	Coefficient	45.434	-11.339	1.627	57.365	75.997	-55.935	18.286	-133.704	
	Std. Error	126.300	5.729	1.857	33.660	26.630	43.600	9.467	79.950	
	P-value	0.7190	0.0478	0.3812	0.0883	0.0043	0.1995	0.0534	0.0945	0.0000
	Chi-Squared									60.0960
2	Coefficient	-14.336	0.252	0.908	-4.077	42.006	7.761	3.579	-44.748	
	Std. Error	64.370	4.301	0.707	11.500	18.310	25.270	6.259	30.360	
	P-value	0.8238	0.9533	0.1988	0.7229	0.0218	0.7587	0.5674	0.1405	0.0001
	Chi-Squared									29.4910
3	Coefficient	-7.977	-1.891	0.796	12.088	43.249	-18.217	6.844	-43.379	
	Std. Error	61.0000	4.8030	0.6729	17.7600	18.2100	18.9500	5.7830	24.8700	
	P-value	0.8960	0.6937	0.2371	0.4961	0.0176	0.3365	0.2366	0.0811	0.0007
	Chi-Squared									25.0990
4	Coefficient	-60.982	-7.816	0.680	8.903	22.627	3.036	1.825	-1.323	
	Std. Error	67.080	5.427	0.651	16.970	14.290	14.970	4.942	27.940	
	P-value	0.3633	0.1498	0.2955	0.5998	0.1132	0.8392	0.7119	0.9623	0.0215
	Chi-Squared									16.4310
5	Coefficient	-50.931	-7.650	1.304	-11.116	14.660	33.142	-5.073	-2.401	
	Std. Error	65.940	4.753	0.759	17.950	13.440	26.220	6.478	23.850	
	P-value	0.4399	0.1075	0.0856	0.5357	0.2754	0.2062	0.4336	0.9198	0.0102
	Chi-Squared									18.4230

Table 4-3
Pairwise Correlation Between
ROA & Leverage

Annual Models:

Years Before Bankruptcy	Correlation
1	-0.6680
2	-0.6770
3	-0.6780
4	-0.5971
5	-0.3708

Quarterly Models:

Quarters Before Bankruptcy	Correlation
1	-0.3186
2	-0.2205
3	-0.4519
4	-0.1969
5	-0.3091
6	-0.2002
7	-0.6011
8	-0.6301
9	-0.4617
10	-0.3673
11	-0.4601
12	-0.3078
13	-0.4099
14	-0.2548
15	-0.2161
16	-0.3310

Table 4-4
Quarterly Model Classification Accuracy

All Firms		Bankrupt Firms		Nonbank- rupt firms	
Quarter	Overall Model	Correct	Type I Error	Correct	Type II Error
1	89.1%	87.5%	12.5%	90.6%	9.4%
2	93.8%	93.8%	6.2%	93.8%	6.2%
3	92.2%	93.8%	6.2%	90.6%	9.4%
4	82.8%	84.4%	15.6%	81.3%	18.7%
5	81.3%	87.5%	12.5%	75.0%	25.0%
6	78.1%	84.4%	15.6%	71.9%	28.1%
7	75.0%	78.1%	21.9%	71.9%	28.1%
8	78.1%	84.4%	15.6%	71.9%	28.1%
9	79.7%	87.5%	12.5%	71.9%	28.1%
10	75.0%	78.1%	21.9%	71.9%	28.1%
11	78.1%	87.5%	12.5%	68.8%	31.2%
12	78.1%	81.3%	18.7%	75.0%	25.0%
13	75.0%	84.4%	15.6%	65.6%	34.4%
14	71.9%	71.9%	28.1%	71.9%	28.1%
15	68.8%	75.0%	25.0%	62.5%	37.5%
16	71.0%	74.2%	25.8%	67.7%	32.3%

Table 4-5
Comparison with Previous Models

Overall Classification Accuracy						
Quarterly Models		Annual Models				
Quarter	Model	Year	Current Study	Zavgren (1985)	AHN[1] (1977)	Blum (1974)
1	89.1%					
2	93.8%					
3	92.2%					
4	82.8%	1	94%	82%	93%	93%
5	81.3%					
6	78.1%					
7	75.0%					
8	78.1%	2	75%	83%	89%	80%
9	79.7%					
10	75.0%					
11	78.1%					
12	78.1%	3	73%	72%	85%	70%
13	75.0%					
14	71.9%					
15	68.8%					
16	71.0%	4	72%	73%	80%	70%
		5	75%	80%	77%	70%

[1] Altman, Haldeman, and Narayanan (Zeta Model [1977])

Table 4-6
Spearman's Rho Correlations Between Abnormal Stock Returns
and Changes in Bankruptcy Probability Assessments -
Results by Firm

Industry Code	CUSIP Number	Company Name	Bankrupt (BR)/ Nonbankrupt (N)	Spearman's Rho	P-value
3911	765516	Richton Int'l	BR	-0.250	0.3688
3911	481088	Jostens	N	0.593	0.0198
2300	624590	Movie Star	N	-0.204	0.4668
3689	038213	Applied Magnetics	BR	0.154	0.5848
3590	967442	Wickes	BR	0.246	0.3760
3590	896678	Trinova	N	-0.272	0.3273
5311	014752	Alexander's	N	0.275	0.3212
3555	001723	A.M. International	BR	0.043	0.8795
3550	413345	Harnischfeger	N	-0.039	0.8894
5945	536257	Lionel	BR	0.136	0.6296
3350	410306	Handy	N	0.268	0.3344
3910	521078	Lazare-Kaplan	BR	0.279	0.3147
3911	250568	Designcraft	N	-0.271	0.3278
5094	437205	Jewelcor	N	0.014	0.9597
3652	482724	K-Tel	BR	-0.243	0.3831
2400	886498	Tidwell	BR	0.032	0.9095
5040	948662	Weiman	N	-0.104	0.7134
3663	883084	Texscan	BR	0.011	0.9698
3663	591503	Metex	N	0.225	0.4201
5900	338517	Flanigan's	BR	0.046	0.8695
5900	462614	IPCO	N	-0.375	0.1684
2834	770706	Robins (A. H.)	BR	-0.121	0.6664
2834	071707	Bausch & Lomb	N	0.143	0.6115
3312	502210	LTV	BR	0.454	0.0895
3312	042170	ARMCO	N	0.382	0.1598
3533	832110	Smith International	BR	-0.254	0.3618
3533	133429	Cameron Iron Works	N	-0.286	0.3019
3541	609150	Monarch Machine Tool Co	N	-0.150	0.6097
5051	903035	U.N.A.	BR	0.132	0.6387
7830	456632	Inflight Services	BR	-0.107	0.7040
5331	422686	Heck's	BR	-0.171	0.5413
5331	470736	Jamesway	N	0.325	0.2372
3460	983085	Wyman-Gordon	N	-0.304	0.2714
1389	675232	Oceaneering	N	0.257	0.3549
3564	019645	Allis Chalmers	BR	0.014	0.9600
3560	458702	Interlake Corp.	N	-0.175	0.5327
3634	017372	Allegheny Int'l	BR	0.200	0.4748
3630	963320	Whirlpool	N	0.122	0.6661

Table 4-6 (continued)

Industry Code	CUSIP Number	Company Name	Bankrupt (BR)/ Nonbankrupt (N)	Spearman's Rho	P-value
2750	070121	Basix	BR	-0.186	0.5075
2750	103043	Bowne	N	0.068	0.8101
1389	958043	Western	BR	0.091	0.7458
1381	423452	Helmerich	N	-0.082	0.7710

TABLE 4-7
Hillmer-Yu Analysis--Bankruptcy Model Probability Assessments

Company Name	Mean	Variance
	(Numbers refer to notes below.)	
A.M. International	1	1
Heck's	3	3
Inflight Services	1	1
K-Tel	3	4
Lazare-Kaplan	1	4
Lionel	3	3
LTV	1	3
Richton	2	3
A.H. Robins	1	1
Smith International	3	1
Texscan	1	4
Tidwell	1	4
UNA	3	4
Wickes	3	4
Allis Chalmers	4	1

Notes:

1. Switching point occurred during the quarter of or within one quarter of the quarter with the greatest increase in bankruptcy model probability assessments.

2. Switching point occurred during the quarter with the second largest increase in bankruptcy model probability assessments.

3. No association was observed between switching point and increase in bankruptcy model probability assessments.

4. No switching point was detected during the 48 months prior to bankruptcy.

Table 4-8
Hillmer-Yu Analysis--Detection of Switching Point

Company Name	Mean	Variance
	(Numbers refer to notes below.)	
A.M. International	1	1
Heck's	1	1
Inflight Services	1	1
K-Tel	1	3
Lazare-Kaplan	1	2
Lionel	1	1
LTV	1	1
Richton	1	1
A. H. Robins	1	1
Smith International	1	1
Texscan	1	3
Tidwell	1	3
UNA	1	4
Wickes	1	4
Applied Magnetics	2	2
Flanigan's	2	2
Allis Chalmers	2	1

Notes:

1. A switching point was detected during the 48 months prior to bankruptcy.

2. No switching point was detected during the 48 months prior to bankruptcy.

3. Switching point was detected after bankruptcy filing.

4. Switching point was detected during month of bankruptcy filing.

Table 4-9
Hillmer-Yu Analysis--Association Between Switching Point and The Wall Street Journal News Releases

Company Name	Mean	Variance
	(Numbers refer to notes below.)	
A.M. International	1, 2	1, 2
Heck's	1, 2	1, 2
Inflight Services	2, 3	2
K-Tel	4	8
Lazare-Kaplan	2	8
Lionel	5	1, 2
LTV	1, 2	1, 2
Richton	4	4
A. H. Robins	6	1
Smith International	1, 2	1, 2
Texscan	4	8
Tidwell	7	8
UNA	2	8
Wickes	1, 2	8
Allis Chalmers	8	1, 2

Notes:

1. Series of unfavorable news releases for several months prior to switching point.

2. Series of unfavorable earnings announcements prior to switching point.

3. Company president resigns in month of switching point.

4. No observed association between switching point and news releases.

5. Public offering of substantial number of new shares; announcement of 6-month (YTD) loss after earlier release of favorable earnings projections.

6. Several unfavorable news releases during month of switching point.

7. Negative quarterly earnings announcement at the end of the month prior to switching point; first in a series of negative earnings announcements.

8. No switching point was detected during the 48 months prior to bankruptcy.

CHAPTER V

CONCLUSION

Contributions

In light of the increased incidence of bankruptcy, this research has potential value for several reasons. First, the quarterly prediction models were constructed on firms that have declared bankruptcy since the implementation of the 1978 Bankruptcy Code. Prior to the 1978 Bankruptcy Code, firms had to demonstrate insolvency to be declared bankrupt. Under the new code, this requirement no longer exists. Thus, it was not clear that variables used in earlier models would have explanatory/predictive ability under the new code. This study found that although the conditions necessary to file for bankruptcy have been relaxed, ratios calculated entirely from financial statement information have virtually the same classification accuracy as before the implementation of the Bankruptcy Code of 1978.

This study also provided insight into the use of financial information by the market. Although the evidence does not support the existence of a monotonic relationship between changes in bankruptcy model probability assessments and abnormal stock returns, the switching point analysis provides evidence that a combination of financial statement information and news releases in the financial press is used by the market in assessing the value of a firm's securities. This result confirms the conclusion of Zavgren et al. (1988) that information other than that contained in the financial statements impacts stock market behavior.

A third contribution is that the study provides further evidence about factors associated with the incidence of bankruptcy. The results of this study are consistent with those of Zavgren (1985), who found leverage to be the most important independent variable in predicting bankruptcy up to four years before filing for bankruptcy; and of Ohlson (1980), who found leverage to the most important predictor variable in his three-year bankruptcy prediction study.

Limitations

An alleged limitation of research of this type is that it lacks a coherent theoretical basis. Jones (1987, 135) notes that without a theory of bankruptcy, it is " . . . difficult to ascertain whether a model developed from data from one set of companies is appropriate for predicting the bankruptcy of a company operating in a different economic or temporal setting." However, despite the lack of a theory of bankruptcy, the findings of bankruptcy studies can provide economic interpretations, and thus, lead to a better understanding of the phenomenon of bankruptcy (Jones 1987, 136). As stated above, the findings of this study confirm the results of earlier studies (Zavgren 1985; Ohlson 1980) regarding the relationship between leverage and bankruptcy.

Another limitation of research of this nature is the reliance on certain assumptions that cannot be empirically verified. For example, the validity of the market model used in calculating abnormal stock returns is questionable. In addition, the calculation of the switching point of the mean and/or variance of a firm's stock returns using the Hillmer-Yu technique (Hillmer and Yu 1979) is sensitive to the choice of preadjustment period. The original preadjustment and adjustment periods are established by a visual inspection of the graph of a firm's monthly stock returns. The term "preadjustment period" implies that little or no changes in stock prices occur during the period. If sizeable stock price changes do indeed occur during the preadjustment period, then its usefulness in establishing a baseline against which to measure changes in stock prices during the adjustment period is limited for two reasons. First, the mean and variance of the stock returns during the preadjustment period can be affected by choice of the window of observation. Second, the existence of sizeable stock price changes during the preadjustment period suggests that information is being received by capital market agents in the aggregate that induces them to realign their investment portfolios. If such information is related to the bankruptcy event, then the interval during which such information was released should not be included in preadjustment period.

As stated in Chapter 3, the sampling process used in this study may introduce a potential survivorship bias that could limit making inferences to firms that file for bankruptcy before they have been in existence for at least five years. In addition, the small sample size may result in bankruptcy prediction models that are overfitted to sample data, and thus, the ability to extrapolate the findings of this research to non-sample firms may be limited.

Suggestions for Future Research

This study is concerned with the ability of accounting numbers to explain/predict bankruptcy, and with the use of these numbers by the market in assessing the value of firms' securities. Thus, its purpose was not strictly to construct the "best" prediction model. A logical extension would be to develop a more accurate prediction model by incorporating sources of information other than financial ratios. For example, Rose et al. (1982) and Foster (1986) found that macroeconomic variables may be helpful indicators of firm vulnerability to failure. Several researchers (Edmister 1972; Altman et al. 1977; Dambolena and Khoury 1980) have found ratio stability measures to be useful in predicting failure. If the purpose is merely to predict bankruptcy, it may be useful to include capital market information as predictor variables in a bankruptcy prediction model (Foster 1986).

As with previous studies, the results of this study do not provide evidence of a strong association between changes in bankruptcy prediction model scores, based on accounting information, and abnormal stock returns. This finding was explained, at least partially, by the results of the third part of the study in which it was indicated that non-financial statement information has an impact on stock returns. Given this result, it may be useful to include in future bankruptcy prediction models indicator variables to serve as a proxy for the existence of favorable or unfavorable (or neither) non-financial statement information released in the financial press during the period of interest. While such an approach would entail a degree of subjectivity, the inclusion of the favorable and unfavorable non-financial statement information may result in a more accurate bankruptcy prediction model, as well as capture more fully the decision processes of capital market agents in the aggregate.

APPENDIX

Table A-1
Pairwise Correlations--Predictor Variables
One Year Before Bankruptcy

Variable	Return on Assets (ROA)	Sales/ PPE (CAPTUR)	Inv./ Sales (INVTUR)	Debt/ T.A. (LEV)	Rec./ Sales (RECTUR)	Quick Ratio (QUICK)	Cash/ T.A. (CASH)
ROA	1.0000						
CAPTUR	-0.0426	1.0000					
INVTUR	0.2469	0.2131	1.0000				
LEV	-0.6680	-0.0257	-0.2734	1.0000			
RECTUR	-0.2857	-0.2107	0.2228	0.1755	1.0000		
QUICK	0.3652	-0.1928	0.0159	-0.5300	0.2510	1.0000	
CASH	0.3081	-0.1700	-0.0356	-0.2540	0.1380	0.7167	1.0000

Table A-2
Pairwise Correlations--Predictor Variables
Two Years Before Bankruptcy

Variable	Return on Assets (ROA)	Sales/ PPE (CAPTUR)	Inv./ Sales (INVTUR)	Debt/ T.A. (LEV)	Rec./ Sales (RECTUR)	Quick Ratio (QUICK)	Cash/ T.A. (CASH)
ROA	1.0000						
CAPTUR	0.2056	1.0000					
INVTUR	-0.1273	0.1329	1.0000				
LEV	-0.6770	-0.0392	0.0142	1.0000			
RECTUR	-0.2906	-0.1674	0.1155	0.1024	1.0000		
QUICK	0.3690	-0.1139	-0.1626	-0.5977	0.2698	1.0000	
CASH	0.2950	0.2483	-0.0268	-0.4129	-0.0280	0.6740	1.0000

Table A-3
Pairwise Correlations--Predictor Variables
Three Years Before Bankruptcy

Variable	Return on Assets (ROA)	Sales/ PPE (CAPTUR)	Inv./ Sales (INVTUR)	Debt/ T.A. (LEV)	Rec./ Sales (RECTUR)	Quick Ratio (QUICK)	Cash/ T.A. (CASH)
ROA	1.0000						
CAPTUR	0.1751	1.0000					
INVTUR	-0.0093	0.3128	1.0000				
LEV	-0.6780	0.0047	-0.1188	1.0000			
RECTUR	-0.3002	-0.2149	0.0320	0.1143	1.0000		
QUICK	0.2750	-0.2101	-0.1882	-0.6832	0.2372	1.0000	
CASH	0.0909	0.0655	-0.0777	-0.3578	0.2645	0.5897	1.0000

Table A-4
Pairwise Correlations--Predictor Variables
Four Years Before Bankruptcy

Variable	Return on Assets (ROA)	Sales/ PPE (CAPTUR)	Inv./ Sales (INVTUR)	Debt/ T.A. (LEV)	Rec./ Sales (RECTUR)	Quick Ratio (QUICK)	Cash/ T.A. (CASH)
ROA	1.0000						
CAPTUR	0.1304	1.0000					
INVTUR	0.1192	0.3202	1.0000				
LEV	-0.5971	0.0001	-0.1016	1.0000			
RECTUR	-0.0407	-0.2161	-0.1452	0.0873	1.0000		
QUICK	0.2574	-0.1812	-0.2594	-0.6210	0.3668	1.0000	
CASH	0.1541	0.1086	-0.2066	-0.3361	0.1742	0.6133	1.0000

Table A-5
Pairwise Correlations--Predictor Variables
Five Years Before Bankruptcy

Variable	Return on Assets (ROA)	Sales/ PPE (CAPTUR)	Inv./ Sales (INVTUR)	Debt/ T.A. (LEV)	Rec./ Sales (RECTUR)	Quick Ratio (QUICK)	Cash/ T.A. (CASH)
ROA	1.0000						
CAPTUR	0.0777	1.0000					
INVTUR	-0.1665	-0.1776	1.0000				
LEV	-0.3708	-0.1341	0.1803	1.0000			
RECTUR	0.1310	-0.1965	-0.1675	0.0640	1.0000		
QUICK	0.2513	-0.0018	-0.2097	-0.6086	0.3215	1.0000	
CASH	0.1865	0.1054	0.1547	-0.0995	-0.0901	0.3988	1.0000

Table A-6
Pairwise Correlations--Predictor Variables
One Quarter Before Bankruptcy

Variable	Return on Assets (ROA)	Sales/ PPE (CAPTUR)	Inv./ Sales (INVTUR)	Debt/ T.A. (LEV)	Rec./ Sales (RECTUR)	Quick Ratio (QUICK)	Cash/ T.A. (CASH)
ROA	1.0000						
CAPTUR	0.0327	1.0000					
INVTUR	0.1881	0.1595	1.0000				
LEV	-0.3186	-0.0985	-0.1970	1.0000			
RECTUR	-0.2681	-0.0998	0.1355	0.2850	1.0000		
QUICK	0.2699	-0.0838	-0.0269	-0.5711	0.1544	1.0000	
CASH	0.2689	-0.1726	0.0089	-0.2993	0.0355	0.7371	1.0000

Table A-7
Pairwise Correlations--Predictor Variables
Two Quarters Before Bankruptcy

Variable	Return on Assets (ROA)	Sales/ PPE (CAPTUR)	Inv./ Sales (INVTUR)	Debt/ T.A. (LEV)	Rec./ Sales (RECTUR)	Quick Ratio (QUICK)	Cash/ T.A. (CASH)
ROA	1.0000						
CAPTUR	-0.0377	1.0000					
INVTUR	-0.1667	0.1306	1.0000				
LEV	-0.2205	-0.0092	-0.1760	1.0000			
RECTUR	-0.1940	-0.1208	0.0698	0.3065	1.0000		
QUICK	0.1754	-0.1275	-0.1219	-0.5829	0.0635	1.0000	
CASH	0.1315	-0.0083	-0.0748	-0.3194	-0.0033	0.7361	1.0000

Table A-8
Pairwise Correlations--Predictor Variables
Three Quarters Before Bankruptcy

Variable	Return on Assets (ROA)	Sales/ PPE (CAPTUR)	Inv./ Sales (INVTUR)	Debt/ T.A. (LEV)	Rec./ Sales (RECTUR)	Quick Ratio (QUICK)	Cash/ T.A. (CASH)
ROA	1.0000						
CAPTUR	0.0572	1.0000					
INVTUR	-0.1127	-0.0171	1.0000				
LEV	-0.4519	-0.0243	-0.0100	1.0000			
RECTUR	-0.2104	-0.1617	0.8236	0.1644	1.0000		
QUICK	0.1776	-0.1390	-0.1223	-0.6052	0.0354	1.0000	
CASH	0.1519	0.1039	-0.0699	-0.3987	-0.0682	0.6641	1.0000

Table A-9
Pairwise Correlations--Predictor Variables
Four Quarters Before Bankruptcy

Variable	Return on Assets (ROA)	Sales/ PPE (CAPTUR)	Inv./ Sales (INVTUR)	Debt/ T.A. (LEV)	Rec./ Sales (RECTUR)	Quick Ratio (QUICK)	Cash/ T.A. (CASH)
ROA	1.0000						
CAPTUR	-0.1030	1.0000					
INVTUR	-0.0471	-0.0661	1.0000				
LEV	-0.1969	0.0188	0.0286	1.0000			
RECTUR	-0.0068	-0.1365	0.9415	0.0996	1.0000		
QUICK	0.2797	-0.1606	-0.1073	-0.6130	-0.0039	1.0000	
CASH	0.2252	-0.0216	0.2052	-0.4061	0.2777	0.6991	1.0000

Table A-10
Pairwise Correlations--Predictor Variables
Five Quarters Before Bankruptcy

Variable	Return on Assets (ROA)	Sales/ PPE (CAPTUR)	Inv./ Sales (INVTUR)	Debt/ T.A. (LEV)	Rec./ Sales (RECTUR)	Quick Ratio (QUICK)	Cash/ T.A. (CASH)
ROA	1.0000						
CAPTUR	0.0590	1.0000					
INVTUR	-0.1604	0.1295	1.0000				
LEV	-0.3091	0.0081	-0.0848	1.0000			
RECTUR	-0.2872	-0.1798	0.3210	0.2464	1.0000		
QUICK	0.0681	-0.1717	-0.0058	-0.6088	0.1555	1.0000	
CASH	0.0968	0.0123	-0.0211	-0.4657	0.0833	0.7454	1.0000

Table A-11
Pairwise Correlations--Predictor Variables
Six Quarters Before Bankruptcy

Variable	Return on Assets (ROA)	Sales/ PPE (CAPTUR)	Inv./ Sales (INVTUR)	Debt/ T.A. (LEV)	Rec./ Sales (RECTUR)	Quick Ratio (QUICK)	Cash/ T.A. (CASH)
ROA	1.0000						
CAPTUR	0.0465	1.0000					
INVTUR	0.1148	0.0840	1.0000				
LEV	-0.2002	0.0378	-0.0587	1.0000			
RECTUR	-0.0096	-0.1647	0.2797	0.2096	1.0000		
QUICK	0.1359	-0.1671	-0.0951	-0.6225	0.1600	1.0000	
CASH	-0.1045	0.0569	-0.2113	-0.4287	0.0262	0.7207	1.0000

Table A-12
Pairwise Correlations--Predictor Variables
Seven Quarters Before Bankruptcy

Variable	Return on Assets (ROA)	Sales/ PPE (CAPTUR)	Inv./ Sales (INVTUR)	Debt/ T.A. (LEV)	Rec./ Sales (RECTUR)	Quick Ratio (QUICK)	Cash/ T.A. (CASH)
ROA	1.0000						
CAPTUR	0.0999	1.0000					
INVTUR	-0.0461	0.2326	1.0000				
LEV	-0.6011	0.0019	-0.0664	1.0000			
RECTUR	-0.2427	-0.1312	-0.1173	0.2092	1.0000		
QUICK	0.2689	-0.1608	-0.1690	-0.6064	0.2032	1.0000	
CASH	0.3357	0.0723	-0.1306	-0.5192	0.0400	0.7285	1.0000

Table A-13
Pairwise Correlations--Predictor Variables
Eight Quarters Before Bankruptcy

Variable	Return on Assets (ROA)	Sales/ PPE (CAPTUR)	Inv./ Sales (INVTUR)	Debt/ T.A. (LEV)	Rec./ Sales (RECTUR)	Quick Ratio (QUICK)	Cash/ T.A. (CASH)
ROA	1.0000						
CAPTUR	0.0230	1.0000					
INVTUR	-0.0110	0.1203	1.0000				
LEV	-0.6301	-0.0334	0.0993	1.0000			
RECTUR	-0.1510	-0.0927	0.0074	0.1870	1.0000		
QUICK	0.2048	-0.0702	-0.2464	-0.6774	0.2371	1.0000	
CASH	0.1010	0.2757	-0.0465	-0.4619	0.0395	0.6746	1.0000

Table A-14
Pairwise Correlations--Predictor Variables
Nine Quarters Before Bankruptcy

Variable	Return on Assets (ROA)	Sales/ PPE (CAPTUR)	Inv./ Sales (INVTUR)	Debt/ T.A. (LEV)	Rec./ Sales (RECTUR)	Quick Ratio (QUICK)	Cash/ T.A. (CASH)
ROA	1.0000						
CAPTUR	0.1471	1.0000					
INVTUR	-0.1921	0.1984	1.0000				
LEV	-0.4617	-0.0263	0.0346	1.0000			
RECTUR	-0.2092	-0.0208	0.0828	0.0053	1.0000		
QUICK	0.2648	-0.0809	-0.1510	-0.7442	0.2743	1.0000	
CASH	0.2599	0.1777	-0.0796	-0.5644	0.0339	0.7282	1.0000

Table A-15
Pairwise Correlations--Predictor Variables
Ten Quarters Before Bankruptcy

Variable	Return on Assets (ROA)	Sales/ PPE (CAPTUR)	Inv./ Sales (INVTUR)	Debt/ T.A. (LEV)	Rec./ Sales (RECTUR)	Quick Ratio (QUICK)	Cash/ T.A. (CASH)
ROA	1.0000						
CAPTUR	0.1249	1.0000					
INVTUR	-0.3253	0.1248	1.0000				
LEV	-0.3673	-0.0104	0.1149	1.0000			
RECTUR	-0.1788	-0.1698	0.4299	0.2326	1.0000		
QUICK	0.2768	-0.1463	-0.1738	-0.7744	0.0759	1.0000	
CASH	0.1325	0.1949	-0.1123	-0.4874	-0.0360	0.6850	1.0000

Table A-16
Pairwise Correlations--Predictor Variables
Eleven Quarters Before Bankruptcy

Variable	Return on Assets (ROA)	Sales/ PPE (CAPTUR)	Inv./ Sales (INVTUR)	Debt/ T.A. (LEV)	Rec./ Sales (RECTUR)	Quick Ratio (QUICK)	Cash/ T.A. (CASH)
ROA	1.0000						
CAPTUR	0.4711	1.0000					
INVTUR	-0.0912	0.1299	1.0000				
LEV	-0.4601	-0.0788	-0.0109	1.0000			
RECTUR	-0.3237	-0.1267	-0.0284	0.1525	1.0000		
QUICK	0.3369	-0.0892	-0.2791	-0.7508	0.1506	1.0000	
CASH	0.2135	-0.0506	0.0638	-0.5329	0.0736	0.7310	1.0000

Table A-17
Pairwise Correlations--Predictor Variables
Twelve Quarters Before Bankruptcy

Variable	Return on Assets (ROA)	Sales/ PPE (CAPTUR)	Inv./ Sales (INVTUR)	Debt/ T.A. (LEV)	Rec./ Sales (RECTUR)	Quick Ratio (QUICK)	Cash/ T.A. (CASH)
ROA	1.0000						
CAPTUR	0.3075	1.0000					
INVTUR	-0.1159	0.1152	1.0000				
LEV	-0.3078	0.0389	-0.0474	1.0000			
RECTUR	-0.3862	-0.1886	0.1644	0.1490	1.0000		
QUICK	0.1588	-0.1665	-0.2769	-0.7278	0.1575	1.0000	
CASH	0.1117	0.1458	0.0458	-0.4267	0.3582	0.5950	1.0000

Table A-18
Pairwise Correlations--Predictor Variables
Thirteen Quarters Before Bankruptcy

Variable	Return on Assets (ROA)	Sales/ PPE (CAPTUR)	Inv./ Sales (INVTUR)	Debt/ T.A. (LEV)	Rec./ Sales (RECTUR)	Quick Ratio (QUICK)	Cash/ T.A. (CASH)
ROA	1.0000						
CAPTUR	0.1807	1.0000					
INVTUR	-0.0201	0.2091	1.0000				
LEV	-0.4099	0.0269	-0.0865	1.0000			
RECTUR	-0.2996	-0.1417	-0.0225	0.2159	1.0000		
QUICK	0.0370	-0.1166	-0.2065	-0.6300	0.2819	1.0000	
CASH	-0.1998	0.0714	0.0017	-0.3777	0.0986	0.7375	1.0000

Table A-19
Pairwise Correlations--Predictor Variables
Fourteen Quarters Before Bankruptcy

Variable	Return on Assets (ROA)	Sales/ PPE (CAPTUR)	Inv./ S (INVTUR)	Debt/ (LEV)	Rec./ (RECTUR)	Quick (QUICK)	Cash/ on Assets (CASH)	PPE	Sales	T.A.	Sale
ROA	1.0000										
CAPTUR	0.1513	1.0000									
INVTUR	-0.4872	-0.0524	1.0000								
LEV	-0.2548	0.0879	-0.1491	1.0000							
RECTUR	-0.5696	-0.1644	0.8950	-0.0791	1.0000						
QUICK	0.1494	-0.1602	0.0447	-0.7072	0.2067	1.0000					
CASH	0.0902	0.1839	0.2742	-0.4388	0.3119	0.6469	1.0000				

Table A-20
Pairwise Correlations--Predictor Variables
Fifteen Quarters Before Bankruptcy

Variable	Return on Assets (ROA)	Sales/ PPE (CAPTUR)	Inv./ Sales (INVTUR)	Debt/ T.A. (LEV)	Rec./ Sales (RECTUR)	Quick Ratio (QUICK)	Cash/ T.A. (CASH)
ROA	1.0000						
CAPTUR	0.2115	1.0000					
INVTUR	-0.0481	0.1496	1.0000				
LEV	-0.2161	-0.0021	0.0058	1.0000			
RECTUR	-0.3940	-0.1630	-0.1175	-0.0459	1.0000		
QUICK	0.2227	-0.1001	-0.2102	-0.7268	0.2535	1.0000	
CASH	0.1669	0.1415	-0.0935	-0.3932	0.3383	0.6452	1.0000

Table A-21
Pairwise Correlations--Predictor Variables
Sixteen Quarters Before Bankruptcy

Variable	Return on Assets (ROA)	Sales/ PPE (CAPTUR)	Inv./ Sales (INVTUR)	Debt/ T.A. (LEV)	Rec./ Sales (RECTUR)	Quick Ratio (QUICK)	Cash/ T.A. (CASH)
ROA	1.0000						
CAPTUR	0.1568	1.0000					
INVTUR	-0.0407	0.1196	1.0000				
LEV	-0.3310	-0.0898	0.1050	1.0000			
RECTUR	-0.1459	-0.1555	-0.1069	0.0110	1.0000		
QUICK	0.4048	0.0736	-0.2451	-0.7026	0.2802	1.0000	
CASH	0.4226	0.1817	-0.0798	-0.3736	0.3407	0.6532	1.0000

Table A-22
Switching Point Analysis
Inflight Services

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
1				
2				
3				
4				
5	1	0.9252		
6				X
7				V
8	2	1.0000	0.0534	
9				
10				
11	3	0.9466	0.1642	
12				
13				
14	4	0.7824	0.1076	
15				
16				
17	5	0.6748	0.0334	
18				
19				
20	6	0.6414		
21				
22				
23	7	0.7983		
24				
25				
26	8	0.8683	0.0028	
27				
28				
29	9	0.8655		
30				
31				
32	10	0.8677	0.0872	
33				
34				
35	11	0.7805		
36				

Table A-22 (continued)

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
37				
38	12	0.8380	0.0496	
39				
40				
41	13	0.7884	0.1115	
42				
43				
44	14	0.6768		
45				
46				
47	15	0.7398		
48				
49				
50	16	0.8208		

Note (1): Represents the last 16 quarters before bankruptcy for which financial statements were available.

Note (2): Only positive changes in bankruptcy probability assessments are shown.

Note (3): X = switching point of mean of stock returns.
V = switching point of variance of stock returns.

Table A-23
Switching Point Analysis
A. M. International

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
1				
2				
3	1	0.9930		
4				
5				
6	2	0.9996		V
7				
8				
9	3	1.0000	0.1305	
10				
11				
12	4	0.8695	0.0521	X
13				
14				
15	5	0.8174		
16				
17				
18	6	0.8242	0.0815	
19				
20				
21	7	0.7426		
22				
23				
24	8	0.7881	0.0760	
25				
26				
27	9	0.7121	0.0655	
28				
29				
30	10	0.6466		
31				
32				
33	11	0.6699	0.0311	
34				
35				
36	12	0.6389	0.0638	

Table A-23 (continued)

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
37				
38				
39	13	0.5751	0.0802	
40				
41				
42	14	0.4950	0.0600	
43				
44				
45	15	0.4350	0.0412	
46				
47				
48	16	0.3938		

Note (1): Represents the last 16 quarters before bankruptcy for which financial statements were available.

Note (2): Only positive changes in bankruptcy probability assessments are shown.

Note (3): X = switching point of mean of stock returns.
V = switching point of variance of stock returns.

Table A-24
Switching Point Analysis
Heck's

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
1				V
2				
3	1	0.5930		
4				
5				X
6	2	0.9208	0.0929	
7				
8				
9	3	0.8279	0.0728	
10				
11				
12	4	0.7551	0.0533	
13				
14				
15	5	0.7018	0.0557	
16				
17				
18	6	0.6461	0.1346	
19				
20				
21	7	0.5115	0.0002	
22				
23				
24	8	0.5113		
25				
26				
27	9	0.6285	0.1101	
28				
29				
30	10	0.5184		
31				
32				
33	11	0.5209		
34				
35				
36	12	0.5631	0.0597	
37				

Table A-24 (continued)

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
38				
39	13	0.5034		
40				
41				
42	14	0.5503	0.1052	
43				
44				
45	15	0.4450		
46				
47				
48	16	0.4782		

Note (1): Represents the last 16 quarters before bankruptcy for which financial statements were available.

Note (2): Only positive changes in bankruptcy probability assessments are shown.

Note (3): X = switching point of mean of stock returns.
V = switching point of variance of stock returns.

Table A-25
Switching Point Analysis
K-Tel

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
1	1	0.9976		
2				
3				X
4	2	1.0000	0.0347	
5				
6				
7	3	0.9653	0.1700	
8				
9				
10	4	0.7953		
11				
12				
13	5	0.8123		
14				
15				
16	6	0.9998	0.3124	
17				
18				
19	7	0.6874		
20				
21				
22	8	0.7296	0.0188	
23				
24				
25	9	0.7108	0.1767	
26				
27				
28	10	0.5341	0.0831	
29				
30				
31	11	0.4510		
32				
33				
34	12	0.4580		
35				

Table A-25 (continued)

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
36				
37	13	0.5953		
38				
39				
40	14	0.6613	0.0884	
41				
42				
43	15	0.5729		
44				
45				
46	16	0.6155		

Note (1): Represents the last 16 quarters before bankruptcy for which financial statements were available.

Note (2): Only positive changes in bankruptcy probability assessments are shown.

Note (3): X = switching point of mean of stock returns.
V = switching point of variance of stock returns.

Table B-5
Switching Point Analysis
Lazare-Kaplan

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
1				
2	1	0.9875		
3				
4				
5	2	1.0000	0.1671	
6				
7				
8	3	0.8330	0.2670	
9				
10				
11	4	0.5659		
12				
13				
14	5	0.7735		
15				
16				
17	6	0.9047		
18				
19				
20	7	0.9084	0.3440	
21				
22				X
23	8	0.5644		
24				
25				
26	9	0.7694		
27				
28				
29	10	0.9694	0.1627	
30				
31				
32	11	0.8067	0.2411	
33				
34				
35	12	0.5656		
36				

Table A-26 (continued)

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
37				
38	13	0.7150	0.0594	
39				
40				
41	14	0.6556	0.0214	
42				
43				
44	15	0.6342	0.1032	
45				
46				
47	16	0.5310		

Note (1): Represents the last 16 quarters before bankruptcy for which financial statements were available.

Note (2): Only positive changes in bankruptcy probability assessments are shown.

Note (3): X = switching point of mean of stock returns.
V = switching point of variance of stock returns.

Table A-27
Switching Point Analysis
Lionel

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
1				V
2	1	0.8818	0.1075	
3				
4				
5	2	0.7742		
6				
7				X
8	3	0.9948	0.1620	
9				
10				
11	4	0.8328	0.0537	
12				
13				
14	5	0.7791		
15				
16				
17	6	0.8653	0.1069	
18				
19				
20	7	0.7584	0.0944	
21				
22				
23	8	0.6639	0.1325	
24				
25				
26	9	0.5315		
27				
28				
29	10	0.8659	0.1924	
30				
31				
32	11	0.6736		
33				
34				
35	12	0.7083	0.3137	
36				

Table A-27 (continued)

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
37				
38	13	0.3947		
39				
40				
41	14	0.8762	0.1439	
42				
43				
44	15	0.7324	0.0505	
45				
46				
47	16	0.6819		

Note (1): Represents the last 16 quarters before bankruptcy for which financial statements were 1 available.

Note (2): Only positive changes in bankruptcy probability assessments are shown.

Note (3): X = switching point of mean of stock returns.
V = switching point of variance of stock returns.

Table A-28
Switching Point Analysis
LTV

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
1	1	0.9698		
2				
3				
4	2	0.9978	0.0223	
5				
6				
7	3	0.9756	0.0782	
8				
9				
10	4	0.8973		
11				
12				V
13	5	0.9184	0.0902	
14				
15				
16	6	0.8283	0.0187	
17				X
18				
19	7	0.8096	0.0032	
20				
21				
22	8	0.8064	0.1957	
23				
24				
25	9	0.6108		
26				
27				
28	10	0.7862	0.0984	
29				
30				
31	11	0.6878		
32				
33				
34	12	0.7401	0.0035	
35				
36				

Table A-28 (continued)

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
37	13	0.7367		
38				
39				
40	14	0.8841	0.1439	
41				
42				
43	15	0.7402	0.1100	
44				
45				
46	16	0.6303		

Note (1): Represents the last 16 quarters before bankruptcy for which financial statements were available.

Note (2): Only positive changes in bankruptcy probability assessments are shown.

Note (3): X = switching point of mean of stock returns.
V = switching point of variance of stock returns.

Table A-29
Switching Point Analysis
Richton Int'l

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
1				
2	1	0.4978		
3				
4				
5	2	0.7159	0.0612	
6				
7				
8	3	0.6547	0.3533	
9				
10				
11	4	0.3015		
12				
13				
14	5	0.7120	0.0699	
15				
16				
17	6	0.6421	0.2538	X
18				
19				
20	7	0.3883	0.0665	
21				
22				
23	8	0.3219		
24				
25				
26	9	0.6080		
27				
28				V
29	10	0.6242	0.0874	
30				
31				
32	11	0.5368		
33				
34				
35	12	0.5474		
36				

Table A-29 (continued)

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
37				
38	13	0.5902		
39				
40				
41	14	0.5942	0.0520	
42				
43				
44	15	0.5422	0.0060	
45				
46				
47	16	0.5362		

Note (1): Represents the last 16 quarters before bankruptcy for which financial statements were available.

Note (2): Only positive changes in bankruptcy probability assessments are shown.

Note (3): X = switching point of mean of stock returns.
V = switching point of variance of stock returns.

Table A-30
Switching Point Analysis
A. H. Robins

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
1				
2	1	0.9846	0.0234	
3				V
4				
5	2	0.9612		X
6				
7				
8	3	1.0000	0.9790	
9				
10				
11	4	0.0210	0.0065	
12				
13				
14	5	0.0145		
15				
16				
17	6	0.0188		
18				
19				
20	7	0.0425		
21				
22				
23	8	0.0642	0.0241	
24				
25				
26	9	0.0401		
27				
28				
29	10	0.0441		
30				
31				
32	11	0.1144		
33				
34				
35	12	0.1607	0.0550	
36				

Table A-30 (continued)

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
37				
38	13	0.1057		
39				
40				
41	14	0.1191		
42				
43				
44	15	0.1405		
45				
46				
47	16	0.1875		

Note (1): Represents the last 16 quarters before bankruptcy for which financial statements were available.

Note (2): Only positive changes in bankruptcy probability assessments are shown.

Note (3): X = switching point of mean of stock returns.
V = switching point of variance of stock returns.

Table A-31
Switching Point Analysis
Smith Int'l

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
1				
2				V
3	1	0.9875	0.4695	
4				
5				
6	2	0.5180		
7				
8				
9	3	0.7170	0.4315	
10				
11				
12	4	0.2854		
13				X
14				
15	5	0.3012		
16				
17				
18	6	0.3558	0.0185	
19				
20				
21	7	0.3372	0.1396	
22				
23				
24	8	0.1976		
25				
26				
27	9	0.2680		
28				
29				
30	10	0.4818	0.0494	
31				
32				
33	11	0.4324	0.0837	
34				
35				
36	12	0.3487		

Table A-31 (continued)

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
37				
38				
39	13	0.4811	0.1646	
40				
41				
42	14	0.3165	0.0547	
43				
44				
45	15	0.2618		
46				
47				
48	16	0.4210		

Note (1): Represents the last 16 quarters before bankruptcy for which financial statements were available.

Note (2): Only positive changes in bankruptcy probability assessments are shown.

Note (3): X = switching point of mean of stock returns.
V = switching point of variance of stock returns.

Table A-32
Switching Point Analysis
Texscan

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
1	1	0.9982		
2				
3				
4	2	1.0000		
5				
6				
7	3	1.0000	0.2146	
8				
9				
10	4	0.7854		
11				
12				
13	5	0.8244		
14				
15				
16	6	0.9029	0.1871	
17				
18				
19	7	0.7159	0.0234	
20				
21				
22	8	0.6925	0.0016	
23				
24				
25	9	0.6909		
26				
27				X
28	10	0.8306	0.6725	
29				
30				
31	11	0.1581	0.0215	
32				
33				
34	12	0.1366	0.0838	
35				
36				
37	13	0.0529		

Table A-32 (continued)

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
38				
39				
40	14	0.1088	0.0146	
41				
42				
43	15	0.0943		
44				
45				
46	16	0.4604		

Note (1): Represents the last 16 quarters before bankruptcy for which financial statements were available.

Note (2): Only positive changes in bankruptcy probability assessments are shown.

Note (3): X = switching point of mean of stock returns.
V = switching point of variance of stock returns.

Table A-33
Switching Point Analysis
Tidwell

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
1				
2	1	0.9231		
3				
4				
5	2	0.9711		
6				
7				
8	3	0.9956	0.0732	
9				
10				
11	4	0.9224	0.1535	
12				
13				
14	5	0.7689	0.2703	
15				
16				X
17	6	0.4986	0.0774	
18				
19				
20	7	0.4211		
21				
22				
23	8	0.6149		
24				
25				
26	9	0.8405		
27				
28				
29	10	0.8607	0.1532	
30				
31				
32	11	0.7075		
33				
34				
35	12	0.7272	0.1086	
36				

Table A-33 (continued)

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
37				
38	13	0.6186		
39				
40				
41	14	0.6574		
42				
43				
44	15	0.7570	0.0555	
45				
46				
47	16	0.7016		

Note (1): Represents the last 16 quarters before bankruptcy for which financial statements were available.

Note (2): Only positive changes in bankruptcy probability assessments are shown.

Note (3): X = switching point of mean of stock returns.
V = switching point of variance of stock returns.

Table A-34
Switching Point Analysis
U.N.A. Corp.

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
1				
2	1	0.9997		
3				
4				
5	2	1.0000		
6				
7				
8	3	1.0000	0.0191	
9				
10				
11	4	0.9808		
12				
13				
14	5	0.9930	0.0103	
15				
16				X
17	6	0.9828	0.0229	
18				
19				
20	7	0.9599	0.0215	
21				
22				
23	8	0.9384	0.0100	
24				
25				
26	9	0.9284	0.0130	
27				
28				
29	10	0.9154	0.1535	
30				
31				
32	11	0.7619		
33				
34				
35	12	0.8705	0.0329	
36				

Table A-34 (continued)

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
37				
38	13	0.8376		
39				
40				
41	14	0.8746	0.0334	
42				
43				
44	15	0.8412	0.0579	
45				
46				
47	16	0.7833		

Note (1): Represents the last 16 quarters before bankruptcy for which financial statements were available.

Note (2): Only positive changes in bankruptcy probability assessments are shown.

Note (3): X = switching point of mean of stock returns.
V = switching point of variance of stock returns.

Table A-35
Switching Point Analysis
Wickes Cos.

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
1				
2				
3	1	0.9940	0.1021	X
4				
5				
6	2	0.8919	0.0905	
7				
8				
9	3	0.8015		
10				
11				
12	4	0.8991		
13				
14				
15	5	0.9248	0.0810	
16				
17				
18	6	0.8438	0.1372	
19				
20				
21	7	0.7066		
22				
23				
24	8	0.7601	0.0262	
25				
26				
27	9	0.7339		
28				
29				
30	10	0.7641	0.0828	
31				
32				
33	11	0.6813		
34				
35				
36	12	0.8121	0.0848	

Table A-35 (continued)

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
37				
38				
39	13	0.7273	0.1174	
40				
41				
42	14	0.6099		
43				
44				
45	15	0.7309		
46				
47				
48	16	0.7580		

Note (1): Represents the last 16 quarters before bankruptcy for which financial statements were available.

Note (2): Only positive changes in bankruptcy probability assessments are shown.

Note (3): X = switching point of mean of stock returns.
V = switching point of variance of stock returns.

Table A-36
Switching Point Analysis
Allis Chalmers

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
1				
2				
3	1	0.9502		
4				
5				
6	2	0.9694	0.0546	
7				
8				
9	3	0.9148		
10				
11				
12	4	0.9277		
13				
14				
15	5	0.9768	0.0355	
16				
17				
18	6	0.9413		
19				
20				
21	7	0.9761	0.0427	
22				
23				
24	8	0.9334		
25				
26				
27	9	0.9546		V
28				
29				
30	10	0.9973	0.4222	
31				
32				
33	11	0.5751		
34				
35				
36	12	0.5851		
37				

Table A-36 (continued)

Months Before Bankruptcy	Quarters Before Bankruptcy Note (1)	Model Probability Assessment	Change in Model Probability Assessment Note (2)	Switching Point Note (3)
38				
39	13	0.7340		
40				
41				
42	14	0.9000	0.2005	
43				
44				
45	15	0.6995	0.2371	
46				
47				
48	16	0.4624		

Note (1): Represents the last 16 quarters before bankruptcy for which financial statements were available.

Note (2): Only positive changes in bankruptcy probability assessments are shown.

Note (3): X = switching point of mean of stock returns.
V = switching point of variance of stock returns.

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