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# Cash flow and cash position measures in the prediction of business failure: An empirical study

Bukovinsky, David Martin, Ph.D.

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U·M·I
300 N. Zeeb Rd.
Ann Arbor, MI 48106

DISSERTATION

David M. Bukovinsky

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DISSERTATION

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at The University of Kentucky

By

David M. Bukovinsky

Lexington, Kentucky

Director: Dr. Michael G. Tearney, Professor of Accounting

Co-Director: Dr. Myrtle W. Clark,

Associate Professor of Accounting

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David M. Bukovinsky

Michael G. Tearney
(Director of Dissertation)

Myrtle W. Clark
(Co-Director of Dissertation)

W. W. Easton
(Director of Graduate Studies)

4/20/93
(Date)

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## ABSTRACT OF DISSERTATION


### CASH FLOW AND CASH POSITION MEASURES IN THE PREDICTION OF BUSINESS FAILURE: AN EMPIRICAL STUDY

The use of financial ratios in the prediction of business failure has been explored in numerous studies since the 1960s. Most of these studies have relied upon accrual accounting measures, proxies of cash flow information, or measures of cash flow from operations. Several of these models have achieved impressive classification accuracies. No studies have examined the effectiveness of ratios derived from information contained in the statement of cash flows. This study explored the usefulness of such ratios for the prediction of bankruptcy. The continuing effectiveness of previous accrual-based studies was also examined, as was the effectiveness of combining cash-based ratios with existing accrual-based models.

The research methodology for the test of the first hypothesis involved calculating various cash-based ratios for failed and nonfailed publicly-traded companies and developing

a prediction model based on these ratios. The effectiveness of the model was compared to a naive model which classifies all firms as failed. The second hypothesis was evaluated by comparing the accuracy of the cash-based model to that of models composed of variables used in previous studies. The third hypothesis was tested by modifying models developed by other researchers to determine whether the inclusion of cash-based ratios could improve the accuracies of the models.

The cash-based prediction model proved to be no better than the naive model for classifying firms. The model also proved to be no better or worse than models comprised of accrual-based ratios used in other bankruptcy prediction studies. Finally, the addition or substitution of cash-based ratios into accrual-based models did not result in any significant improvement in the accuracies of those models. The foremost conclusion to be drawn from this study is that ratios based on cash flow and cash position measures do not appear to be useful predictors of business failure. In addition, the poor accuracies achieved by the accrual-based models may indicate that these models do not generalize well to other time periods.

David M. Buchowsky
(Author's Name)

April 20, 1993
(Date)

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# CHAPTER 1

# INTRODUCTION

The Financial Accounting Standards Board (FASB) identifies several objectives of financial reporting in Statement of Financial Accounting Concepts No. 1, Objectives of Financial Reporting by Business Enterprises (FASB, 1978). The primary thrust is that published financial statements should provide information which is useful in making investment and credit decisions. To facilitate the decision-making process, financial information should enable the user to assess the amount and timing of enterprise cash flows and thereby evaluate the future prospects and hence the present value of the firm. Such analyses involve assessments of probabilities associated with prospective cash flows. The end result is a determination and evaluation of risk.

At present, published financial information needed to facilitate the decision-making process is in the form of four general purpose financial statements: the income statement; balance sheet; statement of retained earnings; and statement of cash flows. The obviously quantitative nature of these statements is, by itself, not sufficient for achieving the objectives of financial reporting. The information must possess certain qualitative characteristics as well. In Statement of Financial Accounting Concepts No. 2, Qualitative Characteristics of Accounting Information, the FASB identifies relevance as one of the primary determinants of the usefulness of accounting information. The Board states that to be relevant, "accounting information must be capable of making a difference in a decision by helping users to form predictions about the outcomes of past, present and future events, or to confirm or correct expectations" (FASB, 1980, para. 47). The Board also states that timeliness is an important determinant of relevancy. Information lacks relevance and is of little or no use if it "is not available when it is needed or becomes available only so long after the reported events that it has no value for future action" (FASB, 1980, para. 56).

Financial reporting requirements are the result of an evolutionary process. The requirements change as the perceived relevance of particular items changes. This evolutionary process is apparent in the 1987 decision of the Financial Accounting Standards Board to replace the statement of changes in financial position with the cash flow statement.

Presumably, the FASB perceives the cash flow statement to be more useful than the former "funds"-based statement of changes in financial position. One use that is frequently made of financial statements, as acknowledged by the FASB in its objectives of financial reporting, is to predict future cash flows which, in turn, allows the user to assess the probability of bankruptcy. The purpose of this study is to determine whether the statement of cash flows provides information which is more useful than the accrual-based information provided by the other general purpose financial statements for predicting bankruptcy. This study develops a cash flow-based bankruptcy prediction model, compares the effectiveness of the resulting model to existing accrual-based bankruptcy models, combines cash- and accrual-based models into more elaborate models for the prediction of bankruptcy, and determines the effectiveness of the latter models.

## RELEVANCE OF CASH FLOW INFORMATION

The FASB's decision to replace the statement of changes in financial position with a statement of cash flows is supported by two arguments. First, the reporting requirements for the statement of changes in financial position allowed a good deal of latitude in the definition and presentation of "funds". Second, the decision seems to indicate an increasing recognition of cash-based information as a useful supplement to the accrual-based information provided by the income statement, balance sheet and statement of retained earnings (FASB, 1987).

The reporting requirements for the statement of changes in financial position were marred by too much latitude in the definition and presentation of "funds". According to APB Opinion No. 19, Reporting Changes in Financial Position, funds could have been defined in terms "of cash, of cash and temporary investments combined, of all quick assets, or of working capital" (AICPA, 1971, p. 375). Consequently, the "funds" reported by one entity may have been an entirely different measure than the "funds" reported by other entities. As a result, the inter-firm comparability of this information was weakened, thus reducing the relevance of the information. In addition, no particular format was required for the statement. Individual reporting entities were allowed to determine what constituted appropriate presentation (Meigs, et al., 1978). This latitude in presentation hindered comparability across firms and within firms across years. These problems were largely corrected by the issuance of Statement of Financial Accounting Standards No. 95, Statement of Cash Flows which specifically requires the reporting of changes in cash and cash equivalents and provides a more standardized format that allows less leeway in presentation (FASB, 1987). Greater standardization allows for the systematic financial analysis of firms' funds (cash) flows which was not easily accomplished with the less-standardized statement of changes in financial position (Grossman and Pearl, 1988).

Cash flows are also recognized as providing information which is not provided by the accrual-based measures common to financial accounting. Supplemental cash flow information has been found to be useful for a number of different purposes. In a capital market study, Bowen, et al. (1987) compared the ability of cash and accrual flows to explain changes in security prices, finding that cash flow data "has incremental explanatory power beyond that contained in accrual flows" (Bowen, et al., 1987, p. 746). Rock (1989) emphasized the usefulness of cash flow from operations as a guide for selecting investments, claiming that cash flow, unlike earnings, is not influenced by the imagination of the company's accountants and may be a good indicator of possible takeover targets.

Cash flow reporting is most useful in the area of evaluating liquidity and long-term solvency. Other measures of liquidity, such as quick assets or working capital, may be inflated by large amounts of receivables, inventories and other current assets that obscure the entity's true debt-paying ability. Other measures of "funds" flows have come under similar criticism. Traditional accrual accounting measures may obscure debt-paying ability and hide financial difficulties (Kochanek and Norgaard, 1987). While accrual accounting measures are useful in and of themselves, such measures may, in some instances, fail to provide information which may be particularly useful to financial statement users. Shuffrey (1987) claims that, unlike other measures of funds flow, cash flow reporting makes possible the determination of whether a company will have sufficient cash flows from operations to make the repayments to which it is committed. Kenneth Hackel, quoted by Rock (1989), summarizes the importance of cash flow reporting by stating "companies that consistently generate high cash flow are very profitable when the economy booms and also have the financial flexibility to survive lean times" (Rock, 1989, p. 162).

The final argument for reporting cash flows is that other measures of funds flow have been shown to be inadequate proxies for cash flow. Prior to the introduction of the cash flow statement, cash flow from operations was usually approximated by net income plus depreciation. This proxy for cash flow was used in the bankruptcy studies of Beaver (1966, 1968), Altman (1968), Deakin (1972), Blum (1974) and others, and was imprecisely labelled as "cash flow".

Several studies conducted during the 1970s and 1980s have shown net income-based measures to be very different from cash flows. Net income may be far removed from cash flow from operations. The primary differences between the two are: (1) depreciation and other noncash charges; (2) accruals; and (3) equity earnings (Cassino, 1987). Working capital from operations, often used as a proxy for cash flow, is calculated as income from operations plus depreciation and other long-term accruals and deferrals. Studies by Kochanek and Norgaard (1987) and Frantz and Thies (1988) indicated that significant differences exist between net income, working capital from operations and cash flow from operations. These differences are becoming greater with the passage of time as new pronouncements on the recognition of revenue and expenses reduce the correlation between income and cash flow. Kochanek and Norgaard concluded "results of analysis may be misleading if the user tries to substitute working capital from operations for cash from operations" (Kochanek and Norgaard, 1987, p. 30).

Factor analytic studies by Gombola and Ketz (1983a) and Casey and Bartczak (1985) further substantiated the differences between the information content of cash flow from operations and other measures of funds flow. These studies, discussed in greater detail in Chapter 2, indicate that cash flow measures load on a separate factor from net income or working capital from operations. The identification of a separate factor indicates that the attributes measured by cash flow are different from those measured by other funds flow measures.

The FASB saw the inclusion of the cash flow statement as one of the basic financial statements as a way to correct the problems with the statement of changes in financial position and to provide relevant information not contained in the other financial statements. The provision of this information is beneficial to the users of financial statements as it is useful in determining the liquidity of firms, as well as the sources and uses of cash by the firms. As Richardson states, "The financial statement user is being far better served by FASB Statement No. 95 than users of financial statements have ever been before" (Richardson, 1991, p.54).

The information contained in the cash flow statement is presumed to be useful for investment and credit decisions, particularly in the evaluation of liquidity and debt-paying ability. If so, it may prove useful in the prediction of business failure. This study investigates the information content of the cash flow statement within the context of bankruptcy prediction. This study develops a business failure prediction model based solely on measures of cash position and cash flow, and ratios derived from those measures, compares the resulting model to earlier models based primarily on accrual accounting measures, and evaluates the contribution, if any, of the addition or substitution of cash-based variables in the earlier, accrual-based models.

**BUSINESS FAILURES AND THE GOING CONCERN ASSUMPTION**

One of the assumptions commonly followed in the preparation of financial accounting information is that the business enterprise will continue to operate into the foreseeable future, barring evidence to the contrary. This "going concern" assumption allows for the allocation of costs and revenues to future periods, the recording of assets and liabilities, and other practices common to accrual accounting. In most instances, the assumption that an enterprise will continue as a going concern is unquestionably correct. However, when significant questions arise about the enterprise's ability to continue operating, the going concern assumption may have to be abandoned and the financial statements adjusted to reflect the questionable future of the enterprise.

The inability to continue as a going concern, as evidenced by business closings, is by no means an uncommon event. The <u>Dun and Bradstreet Record of Business Closings</u> (1988-1990) indicates the average annual number of business closings exceeded 57,000 during the period 1986-1989, with average annual liabilities exceeding $37 billion. The rate of business closings during the 1986-1989 period exhibited a steady downward trend with the number of business closings declining by an average approximately 7% per year, but with the dollar value of related liabilities remaining almost constant from year to year. This downward trend in business closings reversed during 1990 and 1991. Business failures for the first nine months of 1990 were up 11.7% over the same period in 1989 (Wall Street Journal, 4 Sept., 1990, p. B2). The bad news continued in 1991 with a new record of 87,266 businesses failing during the year, up 44% from the previous year. The liabilities associated with these failures, $108.8 billion, nearly doubled the $55 billion figure for 1990 (Wall Street Journal, 21 Feb., 1992, p. A3). Figures for the first half of 1992 indicate 50,282 failures during the first six months, up 16.8% over the same period in 1991 (Wall Street Journal, 6 August, 1992, p. A2).

The effects of these failures extend beyond the failed firm itself. Liquidity problems and ultimate failure may affect the financial condition of employees, customers, suppliers, creditors, stockholders and others with an economic interest in the failed firm. While some businesses will fail even during the best of times, the incidence of failure becomes even more pronounced during periods of economic weakness. When failure occurs during a period of general economic weakness the effects on the related parties may be particularly burdensome and may result in economic hardships for those parties. Two groups, creditors and investors, are particularly at risk.

## IMPORTANCE OF THE STUDY

The magnitude of the business failure problem makes the need for studies of business failure prediction particularly important at this time. Additionally, the recent availability of cash flow information provides a new and potentially useful angle from which to approach the bankruptcy prediction problem.

The failure of a business enterprise has far-reaching effects. Many groups - including investors and creditors - are affected by failure of the enterprise. This section describes the importance of the study to investors and creditors, as well as the effects of failures on those parties. The role of the auditor in determining the validity of the going concern assumption and the importance of the study to the auditor is also discussed.

### IMPORTANCE TO INVESTORS AND CREDITORS

Investors and creditors are among the primary users of financial statements. Decisions regarding prospective or continued financial dealings with a given entity are often made on the basis of information provided by the financial statements. Consequently, the statements should provide information which is useful for assessing the potential risks and rewards of entering into a financial agreement with a particular entity. An analytic tool which can predict failure or nonfailure within a given time period with some degree of certainty would be of obvious use to current and prospective investors and creditors. Previous models of failure prediction have been quite useful for this purpose. Nevertheless, present day use of existing models may prove less effective than in the past. The financial accounting measures on which these models are based have progressively gotten further and further away from cash flows - the very thing they are designed to predict. This study develops a model of failure prediction based solely on measures of cash position and cash flow, and ratios derived from those measures, and investigates whether the classification accuracy of earlier, accrual-based models may be improved by the addition or substitution of cash-based variables.

Investors and creditors face enormous potential risks from the failure of business entities. The increased amount of investments in equity and debt securities during the economically prosperous 1980s has heightened the exposure to risk of loss from business failures. The risk of loss is not faced solely by those institutions and individuals directly invested in such securities. The growth of pension and mutual funds and increased holdings by insurance companies has extended the exposure to loss from business failure to those individuals who are indirect investors through such funds. By early 1990, mutual fund assets were at an all-time high, with over $1 trillion of investors' money (Wall Street Journal, 16 Jan., 1990, p. B3 and 9 May, 1990, p. C1). During the first six months of 1991 bond funds alone pulled in $25.3 billion of new investments (Wall Street Journal, 31 July, 1991, p. C1).

Creditors, as evidenced by the banking and savings and loan crises, are not immune to the effects of business failures either. A major cause of the problems in the banking and savings and loan industry was the granting of loans to companies which ultimately could not make the required repayments. Effective failure prediction models, focusing on cash flow, may be able to improve the credit-granting decision process.

Economic downturns have the potential to cause many companies to fail if financial commitments cannot be met because cash flow from operations decreases and external sources of new borrowings or investment cannot be found. Such failures could in turn cause significant losses to investors and creditors. The user of financial statements would benefit from tools which could improve the user's ability to distinguish those firms headed toward bankruptcy from those which are not in danger of failing.

Failing to identify a firm headed toward bankruptcy carries the obvious risk that the investor or creditor will lose the amount invested or loaned. However, another type of risk can also occur - the risk that a nonfailing firm will be incorrectly predicted to fail. When this occurs, the loss to the investor or creditor will not be as great because they stand to lose, at most, the income which could have been earned on the investment or loan. In most cases however, little or no loss would occur as the investor or creditor would simply invest in, or loan to, another company. A greater cost is likely to be incurred by the firm that was denied the capital infusion. Incorrectly evaluating a nonfailing firm could result in a self-fulfilling prophecy if the firm ultimately fails due to a lack of capital. This situation would entail costs to the firm's investors, creditors, employees and others with a financial interest in the firm. The probability of making this type of error could also be reduced by an effective model of failure prediction.

**THE ROLE OF THE AUDITOR**

The role of the independent auditor in the financial reporting process is well-documented. The auditor's responsibility has traditionally been one of certifying the fairness and appropriateness of the presentation of the financial information presented to external parties. This responsibility requires the auditor to make a determination regarding the appropriateness of the going concern assumption in the presentation of the financial statements.

In response to growing public concern over the number of business failures which occurred with little or no apparent forewarning, the AICPA issued SAS No. 59, The Auditor's Consideration of an Entity's Ability to Continue as a Going Concern. SAS No. 59 places more responsibility on the auditor for the identification of entities whose continued existence is in question. The auditor is required to take a more proactive role in evaluating "whether there is substantial doubt about the entity's ability to continue as a going concern for a reasonable period of time, not to exceed one year beyond the date of the financial statements being audited" (AICPA, 1988, sec. 341.02). Among the audit procedures suggested for use in identifying going concern problems are analytical procedures and consideration of negative trends such as liquidity problems, negative cash flows and adverse financial ratios.

The auditor is not expected to predict the future. Rather, the auditor is expected to use his skills to analyze the economic conditions facing the entity and to use his professional judgement to determine whether those conditions warrant disclosure of doubts about the entity's ability to continue as a going concern. The auditor's judgement is particularly important as the disclosure of going concern doubts, whether justified or not, could result in a self-fulfilling prophecy if concerned parties elect to terminate their economic dealings with the entity. A possible benefit of this study is the development or refinement of analytic tools which may aid the auditor, among others, in assessing the entity's ability to continue as a going concern for a reasonable length of time.

## ISSUES ADDRESSED

Investors, creditors, auditors and others make decisions regarding the ability of an entity to continue as a going concern. These decisions would be aided by the development of analytic tools which can distinguish between those firms headed toward failure and those which are not headed in that direction.

This study addresses three questions. First, can measures of cash position and cash flows, and ratios derived primarily from those measures, be used to construct an effective model for the prediction of business failure? In answering these questions, this study determines whether the cash flow statement provides information which is useful, within the context of the model developed, for predicting bankruptcy. Thus, this research documents evidence regarding the contribution of the cash flow statement toward the achievement of the objectives of financial reporting set forth in SFAC No. 1 relative to the prediction of prospective cash flows and, ultimately, bankruptcy or nonbankruptcy.

Second, are cash-based prediction models more or less effective than previous models of failure prediction which are primarily based on accrual accounting information? The answer to this question indicates whether cash-based variables alone provide information which is more effective at assessing the likelihood of business failure than the primarily accrual-based variables used in previous studies.

Third, do the measures and ratios derived from the cash flow statement provide information which can be a useful addition to, or substitute for, the primarily accrual-based information used in previous studies? The answer to this question indicates whether existing models of failure prediction can be improved through the inclusion or substitution of cash-based information.

This study differs from previous bankruptcy studies (reviewed in Chapter 2) in three respects. First, total cash flows are decomposed into finer components than in previous studies. Second, previous studies have largely ignored the use of cash-based ratios, particularly in the areas of investing and financing activities. This study investigates the usefulness of such ratios in bankruptcy studies. Finally, previous studies have not combined cash- and accrual-based variables, nor have they assessed the effect of such combinations on classification accuracy to the extent that this study does.

## STATEMENT OF HYPOTHESES

Three hypotheses, each stated in null form, can be derived from the above questions.

$H_1$: Models based on cash flow data have no ability to distinguish firms proceeding toward bankruptcy from firms which are not proceeding toward bankruptcy.

This hypothesis is tested to evaluate whether cash-based information by itself is useful for differentiating entities with going concern problems from those without such problems.

$H_2$: There is no difference between cash flow-based models and other models used for assessing the likelihood of bankruptcy.

This hypothesis is tested to determine whether a cash-based model is as effective at assessing the likelihood of bankruptcy as are other models using a wider variety of financial information.

$H_3$: The inclusion or substitution of cash-based information into an existing model has no effect on the ability of the model to distinguish firms proceeding toward bankruptcy from those which are not proceeding toward bankruptcy.

This hypothesis is tested to evaluate whether existing bankruptcy prediction models can be improved by the inclusion or substitution of cash-based variables.

## OVERVIEW OF METHODOLOGY

The hypotheses listed above are investigated through the use of an empirical study. Information is collected from the financial reports of a sample of publicly held companies which have filed for bankruptcy protection under Chapter 11 of the bankruptcy code. Similar information is collected for matched samples of companies which have not filed for protection.

The variable set to test $H_1$ is comprised of measures of cash position and performance and related ratios. Cash-based information is collected from the cash flow statement and balance sheet. Ratios are developed by relating the cash-based measures to each other and to other measures of financial position and performance from the income statement and balance sheet. This variable set measures aspects of the cash position and cash flows from operating, investing and financing activities which are intuitively presumed to represent differences between failing and nonfailing firms.

The original variables are factor-analyzed to arrive at a parsimonious variable set which contains most of the information available in the entire set, but which avoids the problem of multicollinearity among the variables. A model derived from the final set of cash-based variables is developed and statistically evaluated through the use of discriminant analysis and logit to test the first hypothesis. The second hypothesis is tested by using the same sample of companies to replicate five previous bankruptcy studies. Nonparametric tests are used to compare the predictive accuracies of the cash-based model to the existing accrual-based models. For the third hypothesis, cash-based variables are introduced into existing accrual-based models as either additions to the models or substitutions for variables already in the existing models. Factor analysis of the cash-and accrual-based variables is used to determine which variables may be added or substituted into the models without creating multicollinearity problems. Nonparametric tests are used to compare the predictive accuracies of the combined models to the original, existing accrual-based models.

## LIMITATIONS OF THE STUDY

Certain limitations relating to this study are acknowledged. First, the sample is chosen from larger, publicly-traded companies. Consequently, questions arise about the generalizability of the results to smaller or privately-held corporations, partnerships or proprietorships. The sample is also chosen from a cross-section of industries. Therefore the resulting models may be different than if they had been developed from industry-specific data. The stability of the models across time is also a possible limitation.

Another limitation is that the information contained in the variables examined may not be stable. While cash flow is less likely to be affected by new accounting pronouncements than is accrual-based income, the ratios which include accrual-based items may be subject to such effects across time, thereby weakening the generalizability of the results to other time periods.

A final limitation is the assumption of equal costs for Type I and Type II errors. Clearly the costs are not equal, nor are the costs the same for all users. The assumption of equal costs is made to determine the classification accuracies in an unbiased manner. Users of the models would have to determine their own subjective error costs and make the appropriate adjustments to the models.

## GENERAL FORMAT OF THE DISSERTATION

The dissertation consists of five chapters. The first chapter introduces the subject and discusses the need for the study. The second chapter provides a review of significant studies in the area of bankruptcy prediction and information content of cash flows. The methodology to be followed in the dissertation is discussed in detail in the third chapter. Analysis of the data is discussed in chapter four. Chapter five provides conclusions, limitations and recommendations for future research.

# CHAPTER 2

# LITERATURE REVIEW

Several studies have been conducted on the use of accounting measures as predictors of bankruptcy. This chapter reviews the significant studies in the area. Studies of the classification of financial ratios used as predictors are also reviewed. This chapter is divided into five sections: (1) the evolution of bankruptcy prediction; (2) univariate bankruptcy studies; (3) multivariate bankruptcy studies; (4) factor-analytic studies of financial ratios; and (5) cash-based bankruptcy studies.

## EVOLUTION OF BANKRUPTCY PREDICTION

The use of financial ratios as measures of credit-worthiness can be traced back to the early 1900s and the development of the current ratio (Beaver, 1966, p. 71). Formal studies, conducted as early as the 1930s, provided evidence that firms approaching bankruptcy exhibit significantly different financial ratio values than those which are not headed toward failure (Altman, 1968, p. 590). The results of these early studies provided evidence that fundamental differences in firm performance and financial position, manifested as financial ratio values, exist between failing and nonfailing firms, and that such measures may be useful in evaluating the likelihood of failure. The first empirical studies to assess the usefulness of selected financial ratios as a means of distinguishing between those firms heading toward failure and those not heading in that direction were conducted in the mid-1960s.

## UNIVARIATE BANKRUPTCY STUDIES

The first empirical studies into the usefulness of financial ratios as predictors of bankruptcy focused on identifying a single ratio with the best predictive ability. This section reviews the 1966 and 1968 univariate studies of William H. Beaver.

### WILLIAM H. BEAVER (1966)

In his 1966 study, Beaver posited that "the usefulness of ratios can only be tested with regard to some particular purpose" (p. 71). Beaver chose to test the usefulness of ratios for the purpose of predicting business failure. Prior to Beaver's research, ratios had been widely used as informal predictors of business failure, but their effectiveness had not been empirically tested.

Moody's Industrial Manual and a list of bankrupt companies provided by Dun and Bradstreet were used to identify a sample of 79 companies which failed during the period 1954-1964. "Failure" was defined as "bankruptcy, bond default, an overdrawn bank account, or nonpayment of a preferred stock dividend" (p. 71). A matched sample of 79 nonfailed firms, selected on the basis of SIC code and asset size, was chosen. Financial information was gathered on these pairs of failed and nonfailed firms for up to five years prior to failure.

Thirty financial ratios were selected based on three criteria: (1) popularity in the literature; (2) performance in previous studies; and (3) the ratio was defined in terms of a "cash flow" (proxied by net income plus depreciation) concept. Each ratio was classified into one of six categories: (1) cash flow; (2) net income; (3) debt to total assets; (4) liquid assets to total assets; (5) liquid assets to current debt; and (6) turnover.

A dichotomous classification test was performed for each of the thirty ratios. The sample was split and the ratio values from each subsample were arranged in order of magnitude. A cutoff value which minimized classification error was visually selected. These cutoff values were then used to classify the firms of the other subsample. The ratio in each category which exhibited the lowest classification error rate over the five year period was selected for further analysis through the calculation of likelihood ratios.

The best performing ratio in Beaver's study was "cash flow"/total debt. This ratio achieved an overall classification error rate of 13% one year prior to failure. The Type I error rate (misclassifying a failed firm) was 21.5% and the Type II error rate (misclassifying a nonfailed firm) was 5%. The error rates deteriorated as the number of years prior to failure increased, peaking at an overall error rate of 24% four years prior to failure. The next best performing ratio was net income/total assets. The superiority of these "flow" ratios over "position" ratios, such as total debt/total assets, seems to imply that flows of liquid assets are better predictors of failure than are stocks of such assets.

**WILLIAM H. BEAVER (1968)**

In a 1968 follow-up study, Beaver examined the predictive ability of 14 ratios, primarily based on liquid assets. The sample and methodology of this study were identical to his previous study. As in the previous study, "cash flow"/total debt and net income/total assets proved to be superior to ratios based on measures of liquid assets. Beaver reasoned that this is due to the ability to "window dress" current assets to mask liquidity problems, whereas "cash flow," net income and debt position represent more permanent aspects of the firm and cannot be easily manipulated.

The true contribution of this study comes from Beaver's analysis of the components of the ratios. Beaver decomposed the ratios into their component parts and calculated the mean values of the components for the failed and nonfailed groups. Analysis of the mean values of the components revealed significant differences between failed and nonfailed firms on many items. This analysis resulted in two important findings. First, combining data in ratio form may obscure information contained in the individual components. For example, failed firms exhibited significantly lower values for current assets and sales than did nonfailed firms, but the current assets/sales ratios were almost identical for the two groups.

Second, cash position, while being a much less popular measure of liquidity than either current or quick assets, performed better than those more popular measures. Ratios based on cash position exhibited greater predictive ability than similar ratios based on current or quick assets. Beaver suggested two reasons for this occurrence. First, while failed firms tended to have less cash than nonfailed firms, they also had greater amounts of receivables. Use of current or quick assets as a measure of liquidity obscures this information. Second, Beaver suggested that failing firms may intentionally window dress the financial ratios which are most likely to be used to assess liquidity. This may involve intentionally offsetting low cash balances with other, less liquid current assets to bolster the quick and current asset positions.

A significant weakness of Beaver's studies, as he himself recognized, is that the studies focused on the predictive ability of one ratio at a time. These studies failed to address the question of whether models composed of two or more ratios would be better able to discriminate between failing and nonfailing firms. Other researchers began to investigate the usefulness of multivariate models shortly after Beaver's studies were conducted.

## MULTIVARIATE ACCRUAL-BASED STUDIES

Several failure prediction models utilizing multivariate analysis were developed between 1968 and 1985. This section summarizes those studies that significantly extended knowledge of the failure prediction area. Studies conducted by Altman (1968), Edmister (1972), Deakin (1972), Blum (1974), Ohlson (1980), Rose and Giroux (1984), and Zavgren (1985) are reviewed.

**EDWARD I. ALTMAN (1968)**

The first multivariate study of the relationship between financial ratios and the likelihood of failure was conducted by Altman in 1968. Altman reasoned that use of only one ratio as an indicator of business failure is susceptible to faulty interpretation if the ratio in question is window-dressed or offset by other ratios which indicate a much different likelihood of failure. For example, focusing on a healthy current ratio while ignoring poor debt/asset or cash flow ratios may lead to incorrect predictions about the firm's future. Incorrect decisions are less likely to be made if they are based on analysis of several ratios measuring different aspects of a firm's financial health.

Altman selected a sample of thirty-three firms which failed between 1946 and 1965. A matched sample of thirty-three nonfailed firms from the same time period, matched on industry and asset size, was also selected. Twenty-two ratios were calculated for the firms. Selection of the ratios was based upon popularity in the literature and relevance to the study. In addition, Altman devised a few "new" ratios from available financial information.

Multiple discriminant analysis (MDA) was selected as the method of statistical analysis. The MDA technique analyzes a profile of characteristics of an observation (firm) and then classifies the observation into one of several a priori categories based upon the observation's individual characteristics and the interactions between the characteristics. MDA attempts to derive a linear combination of these characteristics which will best discriminate between the categories. The primary advantage of using MDA over univariate analysis is that MDA analyzes the entire profile of characteristics simultaneously rather than individually.

The twenty-two ratios used in the study were reduced to five which proved to be the best combination for discriminating between failed and nonfailed firms. The screening process involved four steps: (1) observation of the statistical significance of various combinations of ratios, including the relative statistical contributions of individual ratios; (2) analysis of intercorrelations between the ratios; (3) analysis of the predictive accuracy of various combinations of ratios; and (4) analyst's judgement. This process resulted in the following discriminant function:

$$Z = .012X_1 + .014X_2 + .033X_3 + .006X_4 + .999X_5$$

where $X_1$ = Working capital/Total assets
$X_2$ = Retained earnings/Total assets
$X_3$ = Earnings before interest and taxes/Total assets
$X_4$ = Market value of equity/Book value of total debt
$X_5$ = Sales/Total assets
$Z$ = Overall index

When applied to the original sample, the above model achieved an overall classification error rate of 5% (Type I = 6%, Type II = 3%) one year prior to failure. The overall classification error rate rose to 17% (Type I = 28%, Type II = 6%) two years prior to failure. The overall error rates rose dramatically to 52%, 71% and 64% for the third, fourth and fifth years prior to failure. Validation of the model was attempted by using a split-half procedure applied to the original sample and by using secondary samples. Five replications using half of the original firms to develop the model and the other half to test it resulted in classification error rates ranging from 3% to 9% one year prior to failure. A secondary sample of twenty-five bankrupt firms was classified with an error rate of 4% one year prior to bankruptcy. Another secondary sample of sixty-six financially weak but nonfailed firms was classified with an error rate of 21% over the five year period.

Analysis of the original sample indicated that firms with a Z-score above 2.99 clearly fall into the nonfailed category as no failed firm exhibited a Z-score of that magnitude. Conversely, a Z-score below 1.81 clearly indicated failure, with no nonfailed firm having a Z-score below that figure. Altman termed the range between 1.81 and 2.99 the "zone of ignorance." Both failed and nonfailed firms achieved Z-scores within that range. By examining the firms which fell into the zone of ignorance, Altman determined that using a Z-score of 2.675 resulted in the lowest number of classification errors. Altman contended that these Z-scores could have practical applications for business loan evaluations by indicating which firms warrant little evaluation because they are almost certain to fail (or not fail) and which firms warrant additional evaluation because of their position within the zone of ignorance.

**ROBERT O. EDMISTER (1972)**

Edmister applied MDA to the prediction of small business failure. Edmister's review of previous failure prediction studies indicated that certain individual ratios, or small groups of ratios, were effective in predicting bankruptcy. However, Edmister noted that the previous studies could not agree on a common set of ratios. This indicated that discriminant functions could only be reliably applied to situations similar to those from which the function was developed. Consequently, the results of previous studies could not be generalized to small business failure prediction.

Two samples were used in the study. Financial statement data for the three years prior to failure was collected for a sample of twenty-one recipients of Small Business Administration (SBA) loans which eventually failed. Similar data was collected for twenty-one nonfailed SBA loan recipients. One year of data was collected for 562 SBA borrowers, half of which failed. No matching procedure was used. The nonfailed firms were selected randomly from SBA files.

Edmister focused on ratios which were advocated by theorists or found to be significant in other studies. In addition to the ratio value as a possible predictor, Edmister also considered the ratio value relative to the industry average, the three-year trend of the ratio, the three-year average of the ratio, and the interaction of industry-relative trend by industry-relative value of the ratio. The ratios were converted to dichotomous variables by comparing the individual ratio value to the industry quartiles. If the individual ratio value is less than the lower quartile for the industry, it was assigned a value of "1", otherwise, it was assigned a value of "0".

MDA was used to derive the discriminant function which would attempt to classify the firms as failed or nonfailed. Stepwise selection was used to limit multicollinearity. This procedure excluded any variable from the model if its correlation coefficient with a variable already in the model exceeded .31.

Results of the study were mixed. An accurate discriminant function based on data one year prior to failure could not be found. Attempted validation of the functions with a holdout sample resulted in poor predictive ability. Significantly better results were achieved with data for the three years prior to failure. The following seven-variable discriminant function was developed:

$$Z = .951 - .423X_1 - .293X_2 - .482X_3 + .277X_4 - .452X_5 - .352X_6 - .924X_7$$

where $X_1$ = Annual funds flow/Current liabilities
$X_2$ = Equity/Sales
$X_3$ = (Net working capital/Sales)/Industry average
$X_4$ = (Current liabilities/Equity)/Industry average
$X_5$ = (Inventory/Sales)/Industry average (*)
$X_6$ = Quick ratio/Industry average (**)
$X_7$ = Quick ratio/Industry average

* - Interaction variable. Ratio must be less than industry lower quartile and exhibit an upward three-year trend.

** - Interaction variable. Ratio must by less than industry lower quartile and exhibit a downward three-year trend.

Z-scores below .47 were obtained only by failed firms and only nonfailed firms obtained Z-scores above .53. A "gray zone" similar to Altman's zone of ignorance existed between .47 and .53. Both failed and nonfailed firms exhibited scores within this area. Analysis of the gray zone indicated a cutoff point of .52 provided the best overall classification accuracy. The model was validated through a reassignment procedure using the original sample. Overall classification accuracy of this sample was 93%.

Edmister's study reaffirmed Altman's findings that a small group of ratios has better predictive accuracy than any single ratio. Edmister also found that standardizing the ratios by dividing them by industry averages and conversion of continuous variables to dichotomous variables added to the significance of the model. Failure to find a significant discriminant function based only on data one year prior to failure was an unexpected result in light of the success previous studies achieved with similar data.

**EDWARD B. DEAKIN (1972)**

Edward Deakin combined the research of Beaver and Altman into a single study in 1972. In his study, Deakin noted that Beaver's univariate model obtained better predictive results than did Altman's multivariate model, but that "the method used by Altman has more intuitive appeal" (p. 167). Deakin replicated Beaver's 1968 study, then used Altman's MDA methodology to search for the combination of Beaver's fourteen ratios which would best indicate the potential for failure.

Deakin studied thirty-two firms which experienced bankruptcy, insolvency or liquidation for the benefit of creditors during the period 1964-1970. A control sample of thirty-two nonfailed firms was selected based on industry classification and asset size. Replication of Beaver's dichotomous classification test produced results which "would tend to confirm Beaver's observations" (p. 169). Application of the Spearman rank-order correlation coefficient test indicated a high degree of correlation between the relative predictive ability of the ratios used in Beaver's study and in Deakin's replication in all but the third year prior to failure. Analysis of the data underlying the components of the ratios indicated the failed firms in Deakin's replication tended to expand rapidly in the third and fourth years prior to failure, and that this expansion was financed through increased debt and preferred stock. Deakin believed the discrepancy in the relative predictive power of the ratios in the third year before failure was due to this phenomenon which did not occur in Beaver's data.

Application of MDA to the fourteen ratios used in Beaver's study produced two interesting findings based on the scaled vector which indicates the relative contribution of each variable to the discriminant function. First, Deakin found that decreasing the number of variables by eliminating those which provide a relatively small contribution to the function resulted in a substantial increase in the number of misclassification errors. Deakin argues that this "would tend to support the use of many of the variables considered important in the literature for the prediction of business failure" (p. 173). In addition, Deakin found that the relative contributions of the ratios changed over time, with some providing a more significant contribution close to the point of failure while others made more significant contributions when failure was not so imminent. This finding may indicate that a single model may be sufficient to predict failure if failure is likely to occur, but insufficient to predict how far into the future it is likely to occur.

Tests of significance on the discriminant functions for each of the five years prior to failure indicated the functions were significant at less than .001 for each of the first three years prior to failure, at .011 for the fourth year prior, and at .05 five years prior to failure. Unlike previous researchers, Deakin did not establish a "critical value" to use as a cutoff point between firms predicted to fail and those predicted to not fail. Instead, the multivariate extension of the univariate Z test was used to determine the probability of a given firm belonging to either the failed or nonfailed group. Using this method, the misclassification error rates for the original sample were 3%, 4.5%, 4.5%, 17%, and 21% respectively for each of the five years prior to failure. When applied to a cross-validation sample of eleven failed and twenty-three nonfailed firms, the error rates increased to 22%, 6%, 12%, 23% and 15% respectively. Deakin was unable to explain the severe deterioration in the first year prior to failure. Furthermore, Deakin warned that "from an ex ante viewpoint, it is only possible to apply these functions to obtain probability statements that the firm will fail in year t+1, t+2, . . . into the future" (p. 177).

**MARC BLUM (1974)**

In 1974, Marc Blum developed the "Failing Company Model". This study continued the evolution of multivariate bankruptcy studies by including variables to measure the change in ratios over time and the variability of accounting data. Blum's study also analyzed the predictive ability of raw accounting data and investigated the effect of incorporating in the model data from a range of years as opposed to data from just a single year.

Blum studied a sample of 115 failed and 115 nonfailed firms from the period 1954-1968. The paired samples were matched on industry, sales in the fourth year prior to failure, number of employees and fiscal year. This sample was divided in half, with one half being used to develop the models and the other half used to validate the model in a split-half procedure.

Twelve ratios were selected to measure liquidity flow and position, profitability, and variability of short-term liquidity and profitability measures. Of particular interest are the variability measures being introduced into failure prediction models for the first time. For net income and net quick assets to inventory over a given time period, Blum included measures of the standard deviation, trend breaks (defined as performance by a variable which is less favorable in one year than in the preceding year), and slope of the values.

Data was collected for eight years prior to failure. Twenty-one models were developed. Each model contained from three to eight years of data, the most recent of which occurred from one to six years prior to failure. For example, one model was based on five years of data up to and including the third year before failure while another model was based on the three years immediately prior to the year of failure. Blum contended that this procedure was an improvement over previous methods to predict failure more than one year prior to its occurrence. Blum criticized previous studies for using data one year prior to failure to develop the model, then, assuming the coefficients to be invariant over time, data was input from previous years to predict failure two or more years into the future. Blum contended that a "proper" model to predict failure X years prior to its occurrence would be developed from data X years prior to failure. The ability of the Failing Company Models to distinguish between failed and nonfailed firms was tested by using discriminant analysis.

The results of the study confirmed the findings of previous studies - classification accuracy is best one year prior to failure and declines as the number of years prior to failure increases. In addition, the "cash flow"/total debt ratio (where "cash flow" is again defined as net income plus depreciation) appears to be the most significant variable for distinguishing between failed and nonfailed firms. Overall classification accuracy one year prior to failure ranged from 64% to 95% depending on the number of years of data used in to develop the model. The highest accuracy rates occurred when four, five or six years of data were used. Inclusion of data from the seventh and eighth years prior to failure seemed to confound the models and accuracy dropped dramatically. The models developed to predict failure two to six years prior to actual failure achieved classification accuracies of between 57% and 80%. Again, the best results occurred when four to six years of data was incorporated into the models.

The standardized discriminant coefficient of the ratio "cash flow"/total debt was consistently ranked among the most significant variables in all twenty-one models. This result is consistent with Beaver's study (Beaver, 1966). Net quick assets/inventory exhibited the second highest significance when predicting one or two years prior to failure. Blum conceded that multicollinearity was a problem in his study. Consequently, the discriminant function coefficients were unstable, making an accurate assessment of the relative significance of variables impossible.

Blum also developed discriminant functions using only raw accounting data. The results indicated that models based on raw data had greater predictive accuracy two years prior to failure than did the models based on ratios. Blum offered no explanation for this result, suggesting that it be the focus of future research. Blum also suggested that future research should include an investigation into the predictive ability of ratios other than those used in traditional financial statement analysis. This echoes the view of Beaver, who expressed concern over the possible "window-dressing" of the more popular ratios (Beaver, 1968).

**JAMES A. OHLSON (1980)**

A significant change in the statistical methods of evaluating bankruptcy prediction models was presented by James A. Ohlson in a 1980 study in which logit was used in place of the traditional MDA methodology. Two methods were cited for the use of nonparametric probability procedures such as logit. First, as a nonparametric method, logit places no restrictions on the distributions of the predictor variables.

Consequently, logit is more appropriate than MDA, which requires the predictor variables to be normally distributed and the groups to have equal variance-covariance matrices. Along the same lines, logit does not require an estimate of the prior probability that an observation will fall within some given group, as does MDA. Ohlson cited the violation of these requirements as reason to question the validity of MDA-based studies. Second, an MDA score has little interpretative value as it is simply an order-ranking device. Conversely, logit scores represent the probability that an observation will fall within a given group, as in the probability that a particular firm will experience failure within a given time period.

Firm size and measures of financial structure, performance, and current liquidity were advanced by Ohlson as the major determinants of success or failure. Based on this theory, Ohlson constructed a failure prediction model using nine predictor variables including firm size and commonly cited ratios and measures of position, performance and changes in position and performance. Data for the model consisted of three years of data for 105 publicly traded industrial firms which filed Chapter 10 or 11 bankruptcy during the period 1970-1976. The control group consisted of one year of data for every nonfailed industrial firm on the Compustat tapes, for a total of 2,058 observations of nonfailed firms. All observations were used to develop the model. No holdout sample was used for validation purposes.

Little correlation was found between the position and performance variables, and both types provided significant contributions to the model. Firm size was also found to be a significant predictor of failure. Ohlson's model correctly classified 96.12% of the sample firms one year prior to failure. However, given that the sample was highly skewed in favor of nonfailed firms, Ohlson noted that a naive decision rule to classify all firms as nonfailed would have achieved a correct classification rate of 91.15%. Classification results two years prior to failure were only slightly worse at 95.55%. Examination of the logit scores for the individual firms (probabilities of failure) indicated that the combined Type I and Type II error rates are minimized at a cutoff point of .038. At this point 17.4% of the nonfailed firms and 12.4% of the failed firms are misclassified. If applied to an infinite population composed of half failed and half nonfailed firms, Ohlson's model would have an expected overall error rate of 14.9%.

Ohlson acknowledged that the results of his study appear to be somewhat worse than those of previous studies and suggested four possible explanations. First, the lead times from the last fiscal year-end to the filing of bankruptcy is significantly longer in his study than in previous studies. Consequently, previous studies may have used data that was already adjusted for impending bankruptcy. Second, Ohlson used data from the 1970s, whereas previous studies used data from earlier periods. Third, the choice of predictor variables varied across studies. Finally, the results may have been influenced by the choice of statistical methodology.

**ROSE AND GIROUX (1984)**

Rose and Giroux moved away from the traditional use of commonly cited ratios as predictors of bankruptcy. In this study, 130 "new" ratios were developed and tested for their ability to discriminate between failed and nonfailed firms. T-tests on a sample of forty-six failed and forty-six nonfailed firms indicated that thirty-four of the 130 ratios exhibited significant differences between the two groups.

The thirty-four "new" ratios were combined with twenty-seven other ratios which had been found to be significant in previous bankruptcy studies. MDA with a stepwise screening procedure resulted in an eighteen-variable model which exhibited significant predictive ability for up to seven years prior to bankruptcy. Of particular interest is the fact that thirteen of the eighteen ratios were "new" ratios, indicating that creativity in the choice of predictors may lead to advances in the study of bankruptcy prediction. Linear and quadratic discriminant functions were developed and validated using the Lachenbruch holdout method. Classification accuracy over the seven-year period ranged from 97.4% to 88.0% for the linear function and from 86.7% to 74.5% for the quadratic function. Rose and Giroux favored the quadratic function despite its lower overall accuracy because it exhibited less erratic predictive ability over the seven years and also had a consistently lower misclassification rate for failed firms. In addition, an F-test indicated different variance-covariance matrices for the two groups, suggesting the quadratic function to be the preferred approach.

**CHRISTINE V. ZAVGREN (1985)**

The issue of the lack of a theory guiding the selection of predictor variables was addressed by Zavgren. Zavgren used the results of a factor analytic study by Pinches, et al. (1973) to reduce the number of variables under consideration to a manageable number, reduce the likelihood of multicollinearity, and still measure all facets of the financial position and performance of the firm. The final model was composed of seven ratios which load highly on the seven factors of financial position and performance identified by the 1973 Pinches, et al. study (described in detail in the following section). The ratios and their related factors were:

| Factor | Ratio |
|---|---|
| Return on investment | Total income/Total capital |
| Capital turnover | Sales/Net plant |
| Inventory turnover | Inventory/Sales |
| Financial leverage | Debt/Total capital |
| Receivable turnover | Receivables/Inventory |
| Short-term liquidity | Quick assets/Current liabilities |
| Cash position | Cash/Total assets |

A sample of forty-five failed and forty-five nonfailed manufacturing firms from the period 1972-1978 was selected for analysis. Zavgren selected logit as the preferred estimation method, realizing that the probability of failure is more important than a simple fail/no fail classification as it allows the user to assess and adjust for potential risks. Analysis indicated that the probabilities of failure are markedly different between the two groups of firms for each of the five years prior to failure and that different ratios were significant in different years. In the years closest to failure, the cash/total assets and quick assets/current liabilities ratios were significant. The debt/total capital ratio was significant in all five years, and the inventory and capital turnover ratios were more significant as the number of years prior to bankruptcy increased. The return on investment measure was marginally significant in only the fourth year prior to failure, indicating "accounting measured profits do not distinguish failing from healthy firms" (p. 41). Zavgren stated that this finding may be due to "managed" profits, use of alternative accounting measures, or that profitability actually does not differ between failed and nonfailed firms.

As with most previous studies, Zavgren assumed the costs of Type I and Type II errors to be equal. Consequently, the cutoff probability of failure (logit score) was determined by locating the cutoff score which resulted in the lowest total error rate. Classification error rates determined in this manner for the original sample were 18%, 17%, 28%, 27% and 20% for the first through fifth years prior to failure. A holdout sample of firms from 1979-1980 was classified with error rates of 31% for each of the first through fifth years prior to failure.

**SUMMARY OF MULTIVARIATE STUDIES**

Methodologies used in bankruptcy prediction studies have increased in complexity since Beaver's pioneering work in the mid-1960s. Univariate studies have given way to studies based on multiple measures of financial position and performance. Short-term classification accuracy of original samples has been quite good. The 87% classification accuracy of Beaver's univariate model has been surpassed by Edmister's 93%, Altman's and Blum's 95%, Ohlson's 96% and Deakin's 97%. Those studies validated against holdout samples have also achieved an impressive level of short-term classification accuracy. Rose and Giroux achieved a classification accuracy of 92% using the Lachenbruch holdout validation method. Zavgren, using a true holdout sample, was able to achieve a classification accuracy of only 69%.

**"CASH FLOW" IN EARLY BANKRUPTCY STUDIES**

A primary criticism of the bankruptcy studies conducted prior to the mid-1980s is that the studies relied on accrual-based proxies as measures of cash flow. Proxies such as net income plus depreciation or net income plus depreciation and nonrecurring income and expense items were utilized in models by Beaver (1966), Edmister (1972), Deakin (1972), Blum (1974) and Ohlson (1980).

The use of proxies may be partially justified by the lack of available cash flow information at the time these studies were undertaken. Reporting of cash flows did not become mandatory until the issuance of Statement of Financial Accounting Standards No. 95, Statement of Cash Flows in 1987 (FASB, 1987).

Even if the use of proxies is justified, three points need to be made. First, labelling the proxies as "cash flow" may be misleading to users of the models. Second, a proxy of cash flow may not contain the same information as an actual measure of cash flow. In fact, studies to be discussed in a later section of this chapter provide evidence that the information contained in the common cash flow proxies is not equivalent to the information contained in actual measures of cash flow from operations. Finally, the proxies acted as surrogates for measures of cash flow from operations. Other sources and uses of cash were not considered in these early bankruptcy studies. Consequently, the early bankruptcy studies may have overlooked potentially useful sources of information such as cash flows from specific components of operating, investing and financing activities and ratios based on the various cash flow measures. This study investigates the usefulness of such information in the prediction of bankruptcy.

## SAMPLE SELECTION PROBLEMS IN EARLY BANKRUPTCY STUDIES

Some of the early bankruptcy studies were criticized for their lack of a theory to guide the selection of predictor variables. Several studies, including Altman (1968), Edmister (1972), Deakin (1972) and Ohlson (1980), used ratios based upon popular use in the literature. Beaver (1966, 1968) and Blum (1974) selected ratios based on Helfert's theory of the firm as a pool of liquid resources whose size was dependent on the inflows and outflows of the liquid resources. Rose and Giroux (1984) developed several new ratios, seemingly without any guiding theory.

Haphazard selection of predictors may leave out important information about the financial condition of the firm. The resulting misspecified model may not have the explanatory or predictive ability of a model which incorporates information on all facets of the firm's condition. This is somewhat less of a problem if the purpose of the study is to assess the explanatory or predictive ability of a particular type of information, as in this study. In this situation, inclusion of too much information may only confound the model's interpretation.

A larger problem created by the haphazard selection of variables is the potential for multicollinearity within the model. Multivariate studies of financial ratios are likely candidates for multicollinearity problems given that commonly cited financial ratios are merely different combinations of the same finite set of accounting measures. Multicollinearity can result in inaccurate, unstable estimates of model coefficients and their variability (Kleinbaum, Kupper and Muller, 1988). In addition, the relative value of the variables cannot be determined because several variables may be measuring the same attribute (Blum, 1974).

Johnson criticized the common use of collinear variables in MDA studies, stating:

> The assumption of mutually independent ratios necessary for multivariate discriminant analysis does not hold. The use of highly correlated multiple ratios is redundant and introduces instability into the function's coefficients for different samples as well as generating large standard errors for these coefficients. (Johnson, 1970, p. 1168).

Horrigan (1965) contends that collinearity presents opportunities as well as problems for the researcher. Collinearity between financial ratios allows most of the information contained in ratios to be captured by a relatively small number of ratios. However, he cautions that the ratios must be carefully selected to avoid multicollinearity problems.

Some attempts were made in early bankruptcy studies to limit multicollinearity and still capture as much information as possible from financial ratios. Altman (1968) analyzed intercorrelations between the independent variables under consideration before selecting the final variables for his model. This method is questionable as it only analyzes correlations between two variables at a time. Analysis of bivariate intercorrelations does not adequately address multiple correlations. Edmister (1972) and Rose and Giroux (1984) used the stepwise selection technique to determine which variables entered the model, based on the relative contribution of the entering variable and its correlation with variables already in the model. The stepwise technique helps to limit multicollinearity, but is somewhat arbitrary, as the researcher must decide what level of correlation is acceptable (Edmister, 1972).

**FACTOR-ANALYTIC STUDIES**

Analysis of intercorrelations and use of stepwise procedures may help to limit multicollinearity in studies using financial ratios, but more statistically-sound methods are available. Factor analysis is the general term applied to a variety of such methods. The common objective of factor-analytic techniques is to reduce a set of variables to a smaller number of hypothetical "factors" based on the interrelations of the original variables. The result is a minimum number of factors which account for most or all of the observed covariation of the original variables (Kim and Mueller, 1978b). Factor analysis allows the financial researcher to distill the original variable set down to a few factors which contain approximately the same amount of information. These factors may then be used as independent variables for the model. Alternately, the original variable which is most closely related to each of the factors may be used in the model. In either case, the result is a set of independent variables which capture the information contained in the original variable set but which are not intercorrelated.

Factor analysis has been used in a variety of accounting studies. The work of Pinches, Mingo and Caruthers (1973), Pinches, et al. (1975), and Chen and Shimerda (1981) is relevant to the study of business failure. The work of Gombola and Ketz (1983a), Casey and Bartczak (1985), and Gombola et al. (1987) is relevant to the study of cash position and flows in business failure prediction.

**PINCHES, MINGO AND CARUTHERS (1973)**

In a study of forty-eight financial ratios, Pinches, Mingo and Caruthers used factor analysis to identify seven factors of financial position and performance. The seven factors identified were: (1) return on investment; (2) capital intensiveness; (3) inventory intensiveness; (4) financial leverage; (5) receivables intensiveness; (6) short-term liquidity; and (7) cash position. The study was replicated using data from 1951, 1957, 1963 and 1969, with the same seven factors appearing in each year. The seven factors accounted for 87% to 92% of the information contained in the original forty-eight variables. The composition of the factors remained stable across time periods, but the importance of the individual ratios within each factor, as measured by their factor loadings, varied. This shift in importance of individual ratios within the factors may be explained by the changing financial patterns of industrial firms during the time periods examined.

Two findings of this study are significant for bankruptcy research in general and for research into the usefulness of cash-based data in particular. First, cash position is a separate factor, distinct from short-term liquidity. Second, "cash flow" variables loaded most heavily on the return on investment factor, as did income-based variables. This may be due to the fact that "cash flow" was defined as net income plus depreciation and nonrecurring income and expense items. A true cash flow measure may behave differently. Even so, an association between cash flow and return on investment may indicate long-run ability to sustain company operations. As such, cash flow measures may prove to be good predictors of solvency.

**PINCHES, EUBANK, MINGO AND CARUTHERS (1975)**

In a follow-up study, Pinches, Eubank, Mingo and Caruthers analyzed the same forty-eight ratios to determine the short-term stability of factors over the period 1966-1969. The same seven factors as in the previous study were identified in each of the four years. Higher-order factor analysis was performed on the seven factors. The seven first-order factors were further distilled into three second-order factors: (1) return on invested capital; (2) overall liquidity, composed of the capital turnover, short-term liquidity and cash position factors; and (3) short-term capital turnover, composed of the inventory and receivable turnover factors.

Eight of the original forty-eight ratios did not load heavily onto any of the seven factors. Among the ratios not loading heavily were working capital to total assets and

Beaver's "best" predictor - cash flow to total debt. Both of these ratios were found to be significant in studies of business failure (see Beaver, 1966, Altman, 1968, and Deakin, 1972). The authors suggested that either the activities measured by these ratios are adequately measured by other ratios, or that they measure unique activities and are therefore not associated with other ratios. This finding seems to suggest that ratios found to be useful in previous studies should not be disregarded simply because they do not load heavily on a particular factor. Such ratios may contain unique information.

**CHEN AND SHIMERDA (1981)**

Chen and Shimerda conducted a study of more than one hundred financial items used in twenty-six previous studies. Forty-one of the ratios considered significant or useful in prior studies were reconciled to the seven-factor model identified by Pinches, Mingo and Caruthers (1973). In addition, thirty-four ratios found to be significant in various failure prediction studies were also analyzed. All but ten of these ratios loaded heavily on one of the seven factors. As in Pinches et al. (1975), "cash flow"/total debt did not load heavily on any factor, nor did "cash flow"/current liabilities. Each of the remaining ten ratios was found to be highly correlated with some other ratio which was included in one of the factors. Chen and Shimerda concluded that "the financial ratios used in previous predictive studies of bankruptcy can be classified by a substantially reduced number of factors" (p. 59).

Chen and Shimerda cautioned that their work does not resolve the question of which ratio best represents a given factor. Each ratio contains some information common to other ratios as well as information unique to the particular ratio. Consequently, ratios selected for inclusion in a model should be chosen so that they "capture most of the common information contained in their factors and, as a group, contain more unique information than any other set of ratios" (p. 59). In practice, the ratio which loads most heavily on a given factor is usually chosen to represent the factor. This procedure was used by Zavgren (1985) to select the seven ratios used in her bankruptcy prediction model.

**GOMBOLA AND KETZ (1983a)**

Gombola and Ketz applied factor analysis to forty-one ratios over the period 1962-1980. The study included ratios using the traditional cash flow surrogate of net income plus depreciation (NIPD) and similar sets of ratios using working capital from operations (WCFO) and cash flow from operations (CFFO). CFFO was calculated as net income adjusted for all noncash items and changes in noncash working capital accounts other than short-term indebtedness. This calculation conformed to that outlined by the FASB in <u>Reporting Income, Cash Flows and Financial Positions of Business Enterprises: Exposure Draft</u> (FASB, 1981).

Results of the study indicated that ratios based on NIPD and WCFO were highly intercorrelated. Ratios based on CFFO were moderately correlated with those based on either NIPD or WCFO. This result was corroborated through the use of factor analysis on all forty-one ratios. Gombola and Ketz arrived at the same seven factors as had Pinches, et al. (1973, 1975). However, Gombola and Ketz also identified an eighth factor for cash flows from operations. Ratios based on NIPD and WCFO loaded primarily on the return on investment factor. Identical ratios based on CFFO all loaded on a separate factor. This result indicates that surrogates for CFFO do not contain the same information as does CFFO and their use may lead to spurious results or misspecification of the model. Previous research aimed at measuring cash flows may have actually measured a different dimension of firm performance, i.e., return on investment.

**GOMBOLA AND KETZ (1983b)**

In a second study, Gombola and Ketz calculated seven measures of asset flows: (1) net income (NI); (2) operating net income (OPNI); (3) net income plus depreciation (NIPD); (4) operating net income plus depreciation (OPNIPD); (5) working capital from operations (WCFO); (6) quick flow from operations (QFFO); and (7) cash flow from operations (CFFO). Analysis of these measures for 597 companies over the period 1960-1977 indicated that NI and OPNI had similar mean values. NIPD, OPNIPD, WCFO and QFFO also exhibited similar means, significantly larger than those of NI and OPNI. CFFO exhibited a mean value falling between those of the other two groups of asset flow measures. Gombola and Ketz contend that these results "provide preliminary indications that cash flow may differ from both net income plus depreciation and working capital from operations" (p. 68). If these findings are valid "it would be most improper to refer to net income plus depreciation as if it were cash flow . . . [or] to contend that funds flow statements based on working capital contain the same information as cash flow statements" (p. 68). Further support for this argument was obtained by calculating a correlation matrix for the seven measures. NI, OPNI, NIPD, OPNIPD and WCFO were all highly correlated, above .85. QFFO and CFFO showed much lower correlations with the other five flow measures but were correlated with each other at .86. The authors suggest that "net income plus depreciation and working capital from operations may not provide the analyst with much more information than net income" (p. 69). In addition, the high correlations with net income suggest that NIPD and WCFO, the most commonly used surrogates for cash flow, would be better classified as profitability measures, not liquidity measures.

**CASEY AND BARTCZAK (1985)**

Gombola and Ketz's results were somewhat substantiated by Casey and Bartczak. In this study, six accrual-based ratios and three ratios based on CFFO were subjected to a factor-analytic technique. The results indicated that the "accrual-based ratios could explain no more than 30% of the variance in the set of operating cash flow ratios" (p. 391 fn.). Casey and Bartczak interpreted this result as justification for further investigation into the value of ratios based on cash flow from operations.

**GOMBOLA, HASKINS, KETZ AND WILLIAMS (1987)**

Gombola, et al. expanded on the 1983 studies of Gombola and Ketz by examining the behavior of CFFO-based ratios across time. Twenty-four ratios were calculated based on accounting data from 1967-1981. Included in the variables set were similar sets of ratios based on NIPD, WCFO and CFFO. Separate factor analyses were performed for different time periods - one for 1967-1972, and one for 1973-1981.

The results of the factor analyses indicated that the factors were not stable over time. During the earlier period, a separate factor for cash flow did not materialize. The CFFO ratios loaded on the return on assets and return on sales factors, as did the NIPD and WCFO ratios. A separate factor for CFFO did emerge in the later period. The cash flow factor identified in the later period contained only CFFO-based ratios, and these ratios did not load on any other factor. This finding indicated that, in the later years, ratios based on CFFO contained unique information not captured by NIPD or WCFO. The authors attributed this phenomenon to the accelerated issuance of new accounting standards during the

1970s. Citing several examples of items affecting net income but not cash flow, the authors state that the effect of the new standards is to "decrease the correlation between earnings and cash flow" (p. 55).

Gombola, et al. criticized early bankruptcy studies for the use of surrogates, stating "those studies that reportedly examined the usefulness of CFFO but instead utilized income plus depreciation are suspect" (p. 58). However, if net income and CFFO were highly correlated in earlier years, bankruptcy studies based on data from those years may have been valid at the time, but the results may not be generalizable across time. As the authors suggest, "if CFFO is a significant predictor it will be so from the mid-1970s and on, and probably not before" (p. 58).

**SUMMARY OF FACTOR-ANALYTIC STUDIES**

Early bankruptcy prediction studies often included "cash flow" variables. However, the "cash flow" variables used were only surrogates for cash flow, normally net income plus depreciation or working capital from operations (Gombola, et al., 1987). The factor-analytic studies of Pinches, et al. (1973, 1975) indicated that the cash flow surrogates do not contain the same information as actual cash flows and, consequently, may fail to properly depict the financial profile of an entity. The commonly used proxies for cash flow were shown to be more closely associated with measures of return on sales or return on investment than with actual cash flow. In addition, cash position was shown to be a separate factor, distinct from the short-term liquidity measures (Pinches, Mingo and Caruthers, 1973).

Actual cash flows from operations could be calculated by either of two methods, both of which are acceptable under the guidelines of SFAS No. 95. The direct method calculates cash collections from, and payments for, operating activities. Alternately, cash flows from operations could be indirectly calculated by beginning with net income before extraordinary items and "(1) removing the effects of accruals, deferrals and allocations which produced revenues or expenses but did not provide or use cash; and (2) adjusting for operating sources and uses of cash which did not produce revenues or expenses" (Drtina and Largay, 1985, p. 315). Measures of actual cash flow from operations based on these calculations, along with measures of other sources and uses of cash, were used in several bankruptcy studies conducted in the 1980s.

## CASH-BASED BANKRUPTCY STUDIES

Cash-based bankruptcy studies were conducted in the 1980s as a result of the mounting evidence on the differences between actual cash flows and the commonly-used surrogates. The cash-based studies were conducted using similar statistical methodologies as the previous accrual-based studies. Bankruptcy studies based on cash flow variables are included here as a separate section to emphasize their importance to the present study. The more significant of the cash-based studies include those by Largay and Stickney (1980), Casey and Bartczak (1984), Casey and Bartczak (1985), Gombola, et al. (1987), Gentry, Newbold and Whitford (1985a, 1985b), Gahlon and Vigeland (1988), Dambolena and Shulman (1988), and Aziz and Lawson (1989).

**LARGAY AND STICKNEY (1980)**

Largay and Stickney recognized the value of cash flow information in assessing the likelihood of corporate failure in their analysis of the failure of the W.T. Grant Company. In this one-company study of corporate failure, the authors found that operating cash flows provided a more accurate and timely indicator of impending bankruptcy than did traditional accrual-based position and performance measures or changes in stock prices. Downward changes in the level and trends of CFFO occurred earlier and were more pronounced than similar moves in other indicators. While generalizations made from a one-company study would be tenuous at best, the results of this study may lend credence to the belief that accrual-based figures are more open to manipulation and window-dressing than are cash flow measures.

**CASEY AND BARTCZAK (1984)**

A more comprehensive study of the use of CFFO in bankruptcy prediction was performed by Casey and Bartczak in 1984. Recognizing the growing support among the financial analysts' community for operating cash flow data as well as its superiority over accrual measures in the W.T. Grant case, Casey and Bartczak contended that supporters of CFFO "would be hard pressed to produce objective evidence of its superiority" (p. 62). The authors calculated CFFO, CFFO/current liabilities, and CFFO/total debt for sixty failed and 230 nonfailed companies during the period 1971-1982. Initial analysis of the mean values of these measures for each group indicated significantly lower values for the failed firms for each of the five years prior to failure. Despite the differences between the groups, graphic analysis indicated considerable overlap of the two groups. Many nonfailed firms exhibited CFFO measures similar to those of the failed firms, while a much smaller number of nonfailed firms exhibited significantly greater measures of CFFO. These nonfailed firms lying in the tail of the distribution caused the difference in the group means between the nonfailed group and the failed group. The reason given for the overlap was that many nonfailed firms produce relatively little CFFO because cash is tied up in the form of expanding inventory and receivable balances.

Casey and Bartczak performed a univariate analysis of the classification ability of each of the three CFFO measures. Overall classification ability on the original sample was only slightly better than chance. CFFO/current liabilities proved to have the best classification ability, correctly classifying 75% of the sample one year before failure and decreasing to 62% five years prior to failure. CFFO was the worst indicator, correctly classifying only 60% of the sample one year prior to failure and less than 50% three or more years before failure. The classification accuracy of the bankrupt firms was better than for the nonbankrupt firms. The large Type II error rate could be attributed to the large number of nonfailed firms which exhibited CFFO measures similar to those of the failed firms.

None of the CFFO measures could classify the firms as well as a six-variable MDA model using traditional accrual-based measures. The six-variable model achieved overall classification accuracy of from 86% to 61% from one to five years prior to failure. The greater ability of this model was attributed to its increased ability to correctly classify nonfailed firms. Finally, each of the CFFO variables was added to the accrual-based model. This expanded model was not significantly better than the accrual-based model, indicating that the CFFO measures provided no marginal classification ability.

The results of this study seem to cast doubt on the usefulness of CFFO in classifying failed firms. However, the authors suggest that other measures "such as a company's debt level, its access to the debt and equity markets, the salability of its capital assets and its reservoir of liquid assets, may be better indicators of its survival prospects" (p. 65). This explanation hints at the possible usefulness of cash flows from financing and investing activities, and cash position measures as opposed to simply cash flow from operations.

**CASEY AND BARTCZAK (1985)**

In a 1985 follow-up study on the same sample, Casey and Bartczak investigated the marginal predictive ability of CFFO. MDA was applied to a nine-variable model consisting of six accrual-based ratios identified by Chen and Shimerda (1981) and three CFFO measures: CFFO; CFFO/current liabilities; and CFFO/total liabilities. The CFFO measures proved to be statistically significant components of the models. CFFO/current liabilities was significant in each of the first three years prior to failure. CFFO/total liabilities was significant for the first two years, and CFFO for years one, four and five. However, when validated with a holdout sample, the nine-variable model's classification accuracy was not significantly better than a model based on only the six accrual-based ratios.

Stepwise logistic regressions were run for each of the five years prior to failure. First order interactions between the accrual and CFFO ratios were allowed to enter the models in addition to the nine variables used in the MDA analysis. The stepwise selection of variables resulted in the inclusion of at least one CFFO variable into the model in all but the third year prior to failure. These results indicated that CFFO variables do exhibit explanatory power. The logistic models achieved results similar to those of the MDA models when applied to a holdout sample. The logistic models which included CFFO variables did not result in greater classification accuracy than did logistic models which excluded CFFO measures. These results confirm the findings of Casey and Bartczak's 1984 study that CFFO measures do not provide incremental predictive ability over accrual-based ratios. The authors suggest that other cash flow measures, such as total cash flows, may lead to improved accuracy as may cash flow data used in combination with other financial or nonfinancial data.

**GOMBOLA, HASKINS, KETZ AND WILLIAMS (1987)**

Gombola, et al. provide additional evidence against the usefulness of CFFO in the prediction of business failure. In this study, CFFO-based ratios were found to load on a different factor than did ratios based on income plus depreciation or working capital from operations (see previous section on factor-analytic studies for a more complete discussion of the factor-analytic portion of this study). Additionally, CFFO-based ratios exhibited significantly different means for failed companies as compared to nonfailed ones. However, results for MDA models constructed for each of the four years prior to failure indicated that the inclusion of the CFFO ratio with the highest factor loading on the cash flow factor, CFFO/total assets, could not improve the classification accuracies of the models.

In the MDA study, models were constructed for each of the four years prior to failure. The base model was composed of six accrual-based ratios found to load heavily on the six factors identified in the factor analytic study. Three additional models were constructed for each year prior to failure by adding CFFO/total assets, NIPD/total assets and WCFO/total assets to the base model. These models were then used to analyze data from 1967-1972 (early period), 1973-1981 (late period), and the entire 1967-1981 period. The CFFO/total assets variable was significant (at .10) in the third and fourth years prior to failure for the early period and in the first year prior to failure for the late period. Over the entire period, CFFO/total assets was significant (at .05) only in the third year prior to failure. Not only was this variable inconsistent in its significance to the models, in no case did its inclusion improve the classification accuracy of the models. Conversely, the addition of NIPD/total assets was consistently significant at .05 and also improved the classification accuracy with relative consistency. Consistent with the studies of Casey and Bartczak (1984, 1985), Gombola et al. conclude that "it therefore appears that CFFO is not an important predictor of corporate failure" (p. 64).

**GENTRY, NEWBOLD AND WHITFORD (1985a)**

Gentry, Newbold and Whitford expanded on previous research in the use of cash flow information by constructing a model of the firm based on all cash flows as opposed to only CFFO. A redesign of the model of the firm proposed by Helfert (1982) resulted in a seven-variable model of total cash flows. The seven variables (of which the first three combine to form cash flow from operations) were: (1) net funds flows from operations (NOFF); (2) working capital (NWCFF); (3) fixed coverage expenses (FCE); (4) financing (NFFF); (5) capital expenditures (NIFF); (6) dividends (DIV); and (7) other asset and liability flows (NOA&LF). Analysis of the mean values for these items for thirty-three failed and thirty-three nonfailed firms revealed significant differences between the two groups. In addition, the failed group exhibited much larger standard deviations than did the nonfailed group.

A logit model composed of the seven variables correctly classified 83% of the sample firms one year prior to failure when using data from one year prior to failure, and 77% when using the means of the data from the three-year period preceding failure. A secondary sample of "weak" and "nonweak" firms obtained classification accuracies of 72% (one year of data) and 74% (mean of three years' data). Only the DIV variable proved to be significant at the .05 level when using either one year's or mean of three years' data. NOA&LF was significant at .10 when using the mean of three years' data. The variables comprising cash flows from operations; NOFF, NWCFF and FCE, were not significant. This finding is consistent with that of Casey and Bartczak (1984, 1985).

**GENTRY, NEWBOLD AND WHITFORD (1985b)**

Gentry, Newbold and Whitford fine-tuned their previous model by replacing the NWCFF variable with five components comprising working capital funds flow: (1) receivables; (2)

inventory; (3) other current assets; (4) payables; and (5) other current liabilities. The means of these items were found to be significantly different between the failed and nonfailed groups. Receivables, inventory and other current assets were often found to be inflows to failed firms but outflows to nonfailed firms. This observation suggests that failing companies tend to liquidate current assets to generate cash while nonfailing companies tend to invest in such assets.

A probit analysis of the revised model correctly classified 83% of the firms one year prior to bankruptcy when using one year's data and 79% when using the mean of the data for the three-year period preceding failure. Variables representing the cash flows for capital expenditures (NIFF), dividends (DIV) and receivables were all found to be significant at .05 when using one year's data. DIV and total net flow/total assets were significant at .05 when using the mean of three years' of data. These results seem to indicate the usefulness of disaggregating cash flows, especially operating cash flows, into their component parts.

A test was performed to determine the comparative advantage, if any, of using cash flows as opposed to accrual-based ratios. Seven accrual-based ratios found to be useful in other bankruptcy studies were added to the cash flow model. In the expanded model, DIV was significant at .05, NIFF and receivables were significant at .10, and none of the accrual-based ratios proved to be significant. While none of the additional variables proved to be individually significant, the increase in the explanatory power of the model, as measured by the likelihood ratio test, was significant at the .05 level. Based on these results, the authors conclude that the addition of cash flow variables to accrual-based prediction models "results in significantly improved predictive performance" (p. 54). However, this conclusion is based only on the overall statistical significance of the models. The ultimate test of the incremental predictive ability of the models would involve the use of the models to classify a sample of firms and to compare the classification accuracies of the models. No such test of the comparative classification accuracies of the models was performed.

**GAHLON AND VIGELAND (1988)**

Further evidence of the usefulness of decomposing total cash flows into component parts comes from Gahlon and Vigeland. Gahlon and Vigeland examined cash flow data for sixty failed and 204 nonfailed firms. Cash flows were presented in accordance with the Uniform Credit Analysis format which is similar to the direct method of presenting cash flows from operations on the cash flow statement, as preferred by FASB. Cash flow data was standardized by dividing by total assets. Analysis of the median values of the failed and nonfailed groups for each of the five years preceding bankruptcy indicated several cash flow components which differed significantly between the two groups. Almost all of the components which differed were in the investing and financing areas. Cash flows from sales, cost of goods sold, and operating expenses, the primary components of CFFO, did not exhibit significant differences in any of the five years. Total change in cash differed significantly only in the fourth year. Conversely, cash paid for income taxes, mandatory debt retirement, cash flow after debt retirement, cash flow before financing, and total financing activity differed significantly in at least four of the five years. In addition, eight ratios which were not used in previous bankruptcy studies were analyzed. Significant differences between the two groups were found for the cash coverage ratio [CFFO/(total financing cost + mandatory debt retirement)], and the age of accounts payable ratio in each of the five years.

This study did not attempt to derive a classification or prediction model. However, the results of the analysis of the differences in the median values of cash flow components suggests further research is warranted. The authors suggest that several of the components are possible candidates for inclusion into failure prediction models, although significant differences do not necessarily indicate predictive ability. Gahlon and Vigeland also warn that the Uniform Credit Analysis format is a direct format and cash flow statements prepared under an indirect format would not contain the same information.

**DAMBOLENA AND SHULMAN (1988)**

In their 1988 study, Dambolena and Shulman provided evidence of the increased predictive ability which may be gained by adding a cash-based variable to existing bankruptcy prediction models. The additional variable, net liquid balance, is defined as the "difference between all liquid financial assets (cash and marketable securities) and all callable liabilities (essentially short-term notes payable and current maturities of long-term debt)" (p. 74). The marginal contribution of net liquid balance was tested by adding it to two previous models: Aitman's accrual-based model, and Gentry, Newbold and Whitford's cash flow-based model (Altman, 1968; Gentry, Newbold and Whitford, 1985a). Models were developed using the variables from the Altman and Gentry models and 1977-1980 data from twenty-five failed and twenty-five nonfailed firms. These models were then used to classify a holdout sample. The net liquid balance variable was added to each model and the procedure was repeated.

The results supported the addition of the net liquid balance variable. For the Altman model, classification accuracy increased from 85% to 92% one year prior to failure and from 82% to 84% two years prior. The Gentry model's classification accuracy increased from 74% to 89% and from 68% to 76% for one and two years prior to failure, respectively. Net liquid balance was found to be a statistically significant variable in both models. The addition of the net liquid balance variable also increased to Chi-square goodness of fit of both models from .68 and .61 to .94 and .99 for the Altman and Gentry models, respectively. These results seem to indicate that some creativity in the use of cash-based data may result in improvements to failure prediction models which may not be achievable by analyzing only raw cash flow numbers.

**AZIZ AND LAWSON (1989)**

Aziz and Lawson decomposed total cash flows to study the comparative effectiveness of cash flow-based models and accrual-based models. The cash flow identity developed by Lawson (1985) was used to construct a cash flow-based model for comparison to Altman's Z model (Altman, 1968) and the Zeta model (Altman, Haldeman and Narayanan, 1977). A mixed model developed by adding selected ratios to the cash flow model was also used in the comparison. The cash flow identity decomposed total cash flows into operating flows, taxes paid, net capital improvements, lender flows, and shareholder flows. This is essentially the format used for the cash flow statement except that taxes paid are separated from operating activities and financing activities are split between lenders and shareholders. Logit models were constructed to classify a sample of firms and to determine the predictive ability of the models.

The results of the study were mixed. In the cash flow model, taxes paid was found to be significant in all five years prior to failure, while each of the other variables was significant in two of the five years. In the mixed model composed of both cash- and accrual-based variables, taxes paid was only significant in three of the five years, capital expenditures was significant in only one of the five years, and the other cash flow variables were significant in two of the five years. The cash flow and mixed models were found to be no better than the Z or Zeta models at classifying failed and nonfailed firms. The authors concluded "in terms of overall accuracy, i.e., the ability to discriminate between 'bankrupt' and 'not bankrupt' firms, is about the same for all the models tested" (p. 61). For predictive purposes, the cash flow-based model and the mixed model proved superior to the Z and Zeta models at identifying potentially failing or nonfailing firms, particularly in the second through fifth year prior to failure. Finally, the cash flow and mixed models were found to misclassify nonfailed firms more often than failed firms. This difference in misclassification rates is consistent with the findings of Casey and Bartczak (1984) and indicates that these prediction models tend to be overly conservative.

**SUMMARY OF CASH-BASED BANKRUPTCY STUDIES**

Studies into the usefulness of cash-based measures as predictors of business failure have shown that such measures may be useful in differentiating failing and nonfailing firms, but that the measures must be carefully chosen. Researchers tend to agree that failed and nonfailed companies exhibit statistically different values for various cash-based measures. However, not all of these measures proved useful in predicting failure. Studies by Casey and Bartczak (1984,

1985) found that measures based on cash flow from operations did not exhibit much predictive ability by themselves or when added to accrual-based models. Similar results were reported by Gombola, et al. (1987). Gentry, et al. (1985a, 1985b) and Aziz and Lawson (1989) found that components of total cash flow - other than cash flow from operations - did contribute significantly to the prediction of failure.

These mixed results suggest that the analysis of cash flow from operations may be a dead end. However, the analysis of the components of cash flow from operations may lead to improved models of business failure prediction. Analysis of the components of cash flows from investing and financing activities may also yield effective predictors. Finally, previous cash-based studies have largely ignored the possibility of ratios based on cash flow information as potentially effective predictors.

## SUMMARY

This literature review has summarized the evolution of bankruptcy prediction. Selected studies have shown that accounting information is useful in discriminating between failed and nonfailed firms, and in the prediction of business failure.

This area of research has evolved in conjunction with changes in financial reporting practices. Early studies concentrated on the use of accrual-based position and performance measures. The advent of the statement of changes in financial position resulted in increased interest in the use of funds flow measures to discriminate between failed and nonfailed firms. Concern about the decision usefulness of the various concepts of "funds" lead to studies into the information content of the various "funds" measures. These studies, in conjunction with the mandated change to a cash flow statement, focused attention on the usefulness of cash flow information in bankruptcy studies. Ultimately, the results of these cash-based bankruptcy studies indicated that cash-based variables can be effectively used to predict business failure.

The results of both the accrual- and cash-based studies are impressive but mixed. Classification and predictive accuracies have been quite good. However, no consensus has been reached on which predictor variables are the most effective. Each study seems to uncover a new, effective twist to the old problem of model specification. This is particularly evident in the studies based on cash flows. Different cash-based variables have been found to be significant in different studies. More recent studies seem to suggest that additional research into the usefulness of cash-based predictor variables is warranted. Cash flow from operations, as used in previous bankruptcy research, has been shown to be of little value, but the decomposition of all cash flows into component parts may deserve additional attention. In addition, development of cash-based ratios, similar to the traditional accrual-based ratios, may open new opportunities in the area of bankruptcy prediction.

This study investigates the usefulness of cash-based information in greater depth than has been done before. Predictor variables are derived from several sources including components of total cash flow and heretofore unstudied ratios based on cash position and performance. Factor-analytic techniques are used to derive a variable set which captures as much information on cash position and performance as possible, yet avoids problems with multicollinearity. The effectiveness of a model developed with these variables is compared to previous accrual-based bankruptcy models, and the incremental effectiveness of cash-based variables, when added or substituted into accrual-based models, is also examined. The results of this study provide additional insight into the usefulness of cash-based information, particularly cash flow-based ratios, in the prediction of business failure. Chapter three details a methodology for examining these issues.

# CHAPTER 3

# RESEARCH METHODOLOGY

This study explores the usefulness of cash-based accounting data in the prediction of business failure. Three hypotheses are tested to determine whether: (1) models composed of cash-based variables are useful in discriminating between failing firms and those which are not about to fail; (2) models composed of cash-based variables and models composed of accrual-based variables differ in their respective classification accuracies; and (3) the inclusion or substitution of cash-based variables into existing accrual-based models affects the classification accuracy of the existing models. The hypotheses were tested through an empirical study of the financial reports of failed and nonfailed companies.

## SAMPLE SELECTION

This study requires a sample of firms which are known to have failed and matching samples of nonfailed companies. The initial sample of failed companies consists of all firms on the Standard and Poor's COMPUSTAT PC Plus Current and Research files which have filed Chapter 11 bankruptcy proceedings with the Securities and Exchange Commission between October 1, 1988 and January 31, 1991. The names of the firms which have filed Chapter 11 proceedings during this time period were obtained from lists of bankruptcy filings supplied by the SEC and from the Wall Street Journal Index.

The names of bankrupt firms were cross-matched to COMPUSTAT's Company Index to determine data availability. Dates of the filing of the Chapter 11 petitions were gathered from the Wall Street Journal Index, Predicast F & S Index, annual reports or 10-Ks, or correspondence with the companies to insure that the filings occurred after the issuance of the financial statements considered to be the most recent prior to bankruptcy. The beginning date of the SEC fiscal quarter in which the filing occurred was used when the specific month of the filing could not be readily determined. Auditor's reports were examined to determine whether the financial statements were prepared under a "quitting concern" assumption. Data from the prior year, if available, was used in place of data prepared under the "quitting concern" assumption. Otherwise, the company was excluded from the study. Failure to do so would have resulted in the use of financial statement data which has already been adjusted to reflect a departure from the going concern assumption. Few of the failed companies were found to have auditor's reports which were qualified due to a going concern uncertainty, and only one had financial statements which were adjusted for the uncertainty. This appears to substantiate the findings of Levitan and Knoblett (1985) that impending bankruptcy is often not signalled by the auditor's report.

The initial list of bankrupt companies was examined for companies which are unsuitable for the study due to a substantial lack of data. As this study deals with cash flow data, one primary requirement is the availability of the cash flow statement. The data items required for the variables in this study were extracted from the COMPUSTAT files and reviewed for completeness. Other data bases, micro fiche files and other sources of information were searched for data items missing from the COMPUSTAT files. Companies were eliminated from the study if substantial data was missing for the year prior to filing for bankruptcy.

The final sample of bankrupt firms consists of fifty-four companies for which complete data sets could be located. Zmijewski (1984) contends that elimination of firms which do not have complete data sets results in a sample selection bias. Zmijewski's study shows that firms with the greatest probability of failure tend to be the firms which are least likely to produce complete financial data. Consequently, some firms with a very high probability of failure may be excluded from the sample. However, the same study has shown that this bias "does not appear to affect the statistical inferences or overall classification rates" (p. 80). While a larger sample would have been preferable, other bankruptcy studies have utilized much smaller samples. Figure 1 details the bankrupt firms used in the study. Of this sample, 80% (43 firms) were randomly selected to be used in the development of the model and the remaining 20% (11 firms) were assigned to the validation subsample.

## FIGURE 1

## SAMPLE OF BANKRUPT FIRMS

| Company | SIC Code | Filing Date | Statement Date Used |
|---|---|---|---|
| Allied Stores* | 5311 | 1/90 | 1/89 |
| Amdura Corporation | 3420 | 4/90 | 12/89 |
| Ames Department Stores, Inc. | 5331 | 4/90 | 1/90 |
| Bank Building & Equipment* | 1540 | 5/90 | 10/89 |
| Big Sky Transportation | 4512 | 5/90 | 6/89 |
| Braniff | 4512 | 9/89 | 1/89 |
| Calumet Industries* | 2911 | 2/90 | 9/89 |
| Caribbean Select | 2033 | 12/90 | 12/89 |
| CCAir* | 4512 | 7/90 | 6/89 |
| Chyron* | 3861 | 9/90 | 6/89 |
| Circle K Corporation | 5412 | 5/90 | 4/89 |
| Continental Airlines, Inc. | 4512 | 12/90 | 12/89 |
| Continental Airlines Holding | 4512 | 12/90 | 12/89 |
| CPT Holding Corporation | 7373 | 10/90 | 6/90 |
| Crazy Eddie, Incorporated | 5371 | 6/89 | 2/89 |
| Dexon, Incorporated | 3564 | 10/89** | 3/89 |
| Digicon, Incorporated | 1382 | 1/90 | 7/89 |
| Doskocil Companies | 2013 | 3/90 | 12/89 |
| Eagle-Picher Industries | 3714 | 1/91 | 11/89 |
| Eastern Airlines | 4512 | 3/89 | 12/88 |
| Equitec Financial Group* | 6282 | 8/90 | 12/89 |
| Fairfield Communities, Inc. | 1531 | 10/90 | 12/89 |
| General Homes Corporation | 1531 | 8/90 | 9/89 |
| Hills Department Stores | 5331 | 1/91 | 1/90 |
| Insilco Corporation | 3585 | 1/91 | 12/89 |
| International American Homes | 1531 | 4/90 | 3/89 |
| Kurzweil Music | 3931 | 4/90 | 12/89 |
| Lone Star Industries | 3241 | 12/90 | 12/89 |
| MMR Holding Corporation | 1731 | 3/90 | 6/89 |
| National Enterprise* | 2452 | 10/90** | 12/89 |
| National Gypsum Company | 1540 | 10/90 | 12/89 |
| New Star Entertainment | 7812 | 10/89** | 3/89 |
| Overmyer | 3320 | 6/90 | 12/89 |
| Pan Am Corporation | 4512 | 1/91 | 12/89 |
| Pharmakinetics Labs, Inc. | 8734 | 11/90 | 6/90 |
| Photo-marker Corporation | 3861 | 10/89** | 6/89 |
| Priam Corporation | 3572 | 10/89 | 6/89 |
| Prime Motor Inns, Inc. | 7011 | 9/90 | 6/89 |
| Professional Care, Inc.* | 7363 | 10/88** | 9/88 |
| Raytech Development Corp. | 3290 | 3/89 | 12/88 |
| Resorts International | 7990 | 12/89 | 12/88 |
| Robertson Companies, Inc. | 5211 | 8/90 | 12/89 |
| Scat Hovercraft, Inc.* | 3790 | 5/90 | 12/89 |
| Silk Greenhouse, Inc. | 5990 | 12/90 | 1/90 |

**FIGURE 1 continued**

**SAMPLE OF BANKRUPT FIRMS**

| Company | SIC Code | Filing Date | Statement Date Used |
|---|---|---|---|
| SIS Corporation | 5812 | 6/90 | 12/89 |
| Southland Corporation | 5412 | 10/90 | 10/89 |
| Sportsman's Guide, Inc.* | 5961 | 4/89 | 12/88 |
| Telecalc, Incorporated | 3661 | 12/89 | 1/89 |
| TGX Corporation | 5172 | 2/90 | 12/88 |
| TS Industries | 3086 | 8/89 | 9/88 |
| Ultimap Corporation* | 7373 | 12/90 | 1/90 |
| United Merchants & Mfg. | 2200 | 11/90 | 6/90 |
| U.C.I. Medical Affiliates | 8093 | 10/88** | 9/88 |
| W. Bell & Company, Inc. | 5399 | 12/90 | 1/90 |

* - Firm randomly assigned to validation subsample. All other firms assigned to model development subsample.

** - Month of Chapter 11 filing could not be determined. Date listed is the start of the SEC fiscal quarter in which the company filed Chapter 11 proceedings.

Two samples of nonfailed firms were selected from the COMPUSTAT Current and Research files. The first sample consists of 500 nonfailed firms randomly selected from the two-digit SIC codes from which the failed firms were drawn. The second sample consists of 100 nonfailed firms randomly selected from across all SIC codes regardless of whether any failed firms were selected from the same SIC code. This second sample is used to evaluate the generalizability of the study to firms in SIC codes other than those which include failed firms.

Data for each failed firm was collected based on the year of failure. The data for the samples of nonfailed firms was drawn from the same time periods. Consequently, the samples of nonfailed firms were split so that data for the same proportion of nonfailed firms was collected from a given year as for failed firms. That is, if data for 15% of the failed firms came from fiscal years ending in 1990, then data for 15% of the firms in the nonfailed samples was also collected from fiscal years ending in 1990. The number of nonfailed firms selected from each year for the first (second) sample is as follows: 1988 - 75 (15); 1989 - 350 (70); and 1990 - 75 (15). Once the appropriate number of firms to be drawn from each year was determined, the samples of nonfailed firms representative of each year were randomly selected. If adequate data was not available for a particular firm, the firm was excluded from the study and a replacement was randomly selected.

The first sample of nonfailed firms was split into two subsamples, with 400 of the firms (80%) to be used in the development of the model, and the remaining 100 (20%) to be used to validate the model. Of the 400 nonfailed firms assigned to the development sample, 57 with 1988 fiscal year ends, 276 with 1989 year ends and 66 with 1990 year ends were randomly selected. The composition of this resulting sample is in keeping with the proportion of failed firms from each year in the development sample.

The second sample of nonfailed firms, those chosen from across all SIC codes, was only used as a validation sample to assess the model's effectiveness across all industry groups, not to develop the model. Consequently, the second sample did not need to be as large as the first.

The inclusion of several nonfailed firms for each failed firm results in a larger sample than a one-to-one match and is more representative of mix of failed and nonfailed firms in the population. Poor approximation of population proportions has been shown to be a shortcoming in earlier bankruptcy studies. In a 1984 study, Zmijewski showed that the approximation of the population characteristics with regard to the proportion of failed firms is necessary to reduce the bias inherent in choice-based samples. Choice-based samples are those in which the value of the dependent variable, in this case failure or nonfailure, is known prior to the selection of the sample, and the sample is selected based on that knowledge.

Zmijewski showed that previous bankruptcy studies which used a one-to-one match of failed and nonfailed firms produced coefficients for the independent variables which were biased. These coefficients were quite different from those produced when an appropriate technique to adjust for the difference between the sample and population characteristics was used. The bias makes assessment of the effect of individual variables more difficult. The bias was much less when the proportion of failed firms in the sample approached the proportion of failed firms in the population. Zmijewski also showed that the bias does not significantly effect overall classification rates for the models (Zmijewski, 1984).

The use of 500 nonfailed firms and 54 failed firms results in a sample proportion of approximately 10% failed and 90% nonfailed firms. These proportions are deemed adequate to reduce the inherent bias to an acceptable level. Consequently, no adjustments need be made to the statistical estimation techniques.

## RESPONSE AND PREDICTOR VARIABLES

The response (dependent) variable in the study is a dichotomous indicator of failure. A firm is deemed to have failed if the firm had filed for protection under Chapter 11 of the bankruptcy code during the period October 1, 1988 to January 31, 1991. A firm is deemed to be nonfailed if no such filing has occurred in the year following the issuance of the most recent financial statements used in the study.

The predictor (independent) variables for the cash-based model are measures of cash position and performance. The variables comprise ratios derived from data from the cash flow statement or such items in combination with data from the income statement and balance sheet.

Few ratios have been developed by previous researchers for the analysis of the cash flow statement. Giacomino and Mielke (1988) and Carslaw and Mills (1991) present some useful ratios for the analysis of cash flows. Additional ratios were developed specifically for this study to measure various operating, financing and investing activities of the firms. The ratios were developed through consideration of the interrelationships of information contained in the cash flow statement as well as the income statement and balance sheet, and their perceived ability to measure facets of financial performance which may distinguish between failed and nonfailed firms. Some of the ratios are cash-based equivalents of accrual-based ratios found to be significant in previous studies of business failure or bond ratings.

Figure 2 lists the forty ratios selected for analysis in this study. These ratios are grouped into a priori categories according to their presentation on the statement of cash flows and the activities they are perceived to measure. The list of ratios used in this study is not intended to be an exhaustive list of all possible cash-based ratios which may be useful in the prediction of business failure. An unbound list of these ratios for convenient reference is located in Appendix B.

# FIGURE 2

## LIST OF RATIOS TESTED

### OPERATING PERFORMANCE

R1) $\dfrac{\text{CFFO}}{\text{Sales}}$

R2) $\dfrac{\text{CFFO}}{\text{Net income}}$ (note a)

R3) $\dfrac{\text{CFFO}}{\text{Total cash flow}}$ (note a)

R4) $\dfrac{\text{CFFO}}{\text{Average total assets}}$

R5) $\dfrac{\text{Cash from sales}}{\text{Average total assets}}$

R6) $\dfrac{\text{Cash from sales}}{\text{CFFO}}$

R7) $\dfrac{\text{Cash paid for inventory}}{\text{CFFO}}$

### ABILITY TO SERVICE DEBT

R8) $\dfrac{\text{CFFO before interest}}{\text{Cash paid for interest}}$

R9) $\dfrac{\text{Cash paid for interest}}{\text{Interest expense}}$

R10) $\dfrac{\text{CFFO - preferred dividends}}{\text{Average current liabilities}}$

R11) $\dfrac{\text{CFFO}}{\text{Interest paid + reduction in LT debt + other fin. uses}}$

R12) $\dfrac{\text{Total cash flow}}{\text{Interest paid + reduction in LT debt + other fin. uses}}$

(See page 84 for explanations of abbreviations and note.)

**FIGURE 2 continued**

**LIST OF RATIOS TESTED**

**ABILITY TO SERVICE DEBT CONTINUED**

R13) $$\frac{\text{Proc. from Issuance of LT debt + other financing sources}}{\text{Interest paid + reduction of LT debt + other fin. uses}}$$

R14) $$\frac{\text{Reduction in LT debt + other financing uses}}{\text{Average LT debt}}$$

**ABILITY TO RAISE CAPITAL**

R15) $$\frac{\text{Proceeds from sale of stock}}{\text{CFFF}}$$

R16) $$\frac{\text{Proceeds from sale of stock}}{\text{Total cash flow}}$$

R17) $$\frac{\text{Proceeds from issuance of LT debt}}{\text{CFFF}}$$

R18) $$\frac{\text{Proceeds from issuance of LT debt}}{\text{Total cash flow}}$$

R19) $$\frac{\text{Proceeds from issuance of LT debt}}{\text{Average LT debt}}$$

R20) $$\frac{\text{Proc. from sale of stk + iss. of LTD + other fin. sources}}{\text{Total cash flow}}$$

**REPLACEMENT AND EXPANSION**

R21) $$\frac{\text{Capital expenditures + acquisitions + other invest. uses}}{\text{CFFI}}$$

R22) $$\frac{\text{Incr in invest. + cap. exp. + acquis. + other invest uses}}{\text{CFFI}}$$

R23) $$\frac{\text{Incr in invest. + cap. exp. + acquis. + other invest uses}}{\text{CFFO}}$$

(see page 84 for explanations of abbreviations and note.)

**FIGURE 2 continued**

**LIST OF RATIOS TESTED**

**REPLACEMENT AND EXPANSION CONTINUED**

R24) $$\frac{\text{Incr in invest. + cap. exp. + acquis. + other invest uses}}{\text{Total cash flow}}$$

R25) $$\frac{\text{Cap. exp. + acquis. - sale of PP\&E + other invest. act.}}{\text{Average property, plant and equipment}}$$

**SELF-CANNIBALIZATION**

R26) $$\frac{\text{Cash paid for inventory}}{\text{Cost of goods sold}}$$

R27) $$\frac{\text{Proceeds from sale of PP\&E + other investing sources}}{\text{CFFI}}$$

R28) $$\frac{\text{Proceeds from sale of PP\&E + other investing sources}}{\text{Total cash flow}}$$

R29) $$\frac{\text{Proceeds from sale of PP\&E + other investing sources}}{\text{Average PP\&E}}$$

R30) $$\frac{\text{Pr. from sale of invest. and PP\&E + other invest. sources}}{\text{CFFI}}$$

R31) $$\frac{\text{Pr. from sale of invest. and PP\&E + other invest. sources}}{\text{Total cash flow}}$$

R32) $$\frac{\text{Pr. from sale of invest. and PP\&E + other invest. sources}}{\text{Average total assets}}$$

R33) $$\frac{\text{CFFI}}{\text{Average total assets}}$$

R34) $$\frac{\text{CFFI}}{\text{Average PP\&E}}$$

(see page 84 for explanations of abbreviations and note.)

**FIGURE 2 continued**

**LIST OF RATIOS TESTED**

**OTHER CASH FLOW ACTIVITIES**

R35) $\dfrac{\text{Purchase of stock}}{\text{CFFF}}$

R36) $\dfrac{\text{Payment of dividends}}{\text{CFFO}}$

R37) $\dfrac{\text{Payment of dividends}}{\text{CFFF}}$

**CASH POSITION**

R38) $\dfrac{\text{Cash}}{\text{Current liabilities}}$

R39) $\dfrac{\text{Cash}}{\text{Total liabilities}}$

R40) $\dfrac{\text{Cash}}{\text{Total assets}}$

**KEY TO ABBREVIATIONS:**

CFFF = Cash flow from financing activities
CFFI = Cash flow from investing activities
CFFO = Cash flow from operating activities

**Note a** - Ratio contains a numerator and denominator which may be either positive or negative, allowing for misleading interpretation of the ratio value. The numerator is the item of primary interest. Consequently, the ratio value is entered as positive if numerator is positive, negative if numerator is negative.

## INTERPRETATION OF INDEPENDENT VARIABLES

The ratios used as independent variables are divided into seven categories: operating performance, ability to service debt, ability to raise capital, replacement and expansion, self-cannibalization, other financing activities, and cash position. These categories are derived from the major sections of the cash flow statement and are intended to measure various aspects of a firm's sources and uses of cash. This section describes the aspects the ratios are intended to measure and the anticipated differences between the ratio values for failed and nonfailed firms.

### OPERATING PERFORMANCE RATIOS

The operating performance ratios are designed to measure various aspects of a firm's ability to generate cash flows from operations and the uses of cash for operating activities. Healthy firms typically exhibit good cash flow from operations and consequently have to place less reliance on other sources of cash. Poor operating cash flows may be indicative of firms which are more likely to fail.

Ratios R1 (CFFO/Sales) and R2 (CFFO/Net income) measure quality of revenues and income by relating operating cash flow measures to accrual-based revenue and income measures. These ratios are cash-based modifications to Elam's (1975) net income/sales and NIPD/sales ratios. Increased use of accruals and deferrals have acted to reduce the correlation between accrual-based income measures and cash flows. These ratios are designed to measure the extent of correlation between the two types of measures. It is anticipated that a firm is less likely to declare bankruptcy if operating cash flows are adequate, regardless of the reported income figure. Consequently, firms with negative operating cash flow measures (ie., negative values for these ratios) will be more likely to fail than firms with positive values.

Ratio R3 (CFFO/Total cash flow) states CFFO as a percentage of total cash flows. Again, a negative CFFO figure is expected to be more indicative of impending failure than is a positive CFFO figure. Failing firms are expected to be more likely to exhibit negative values for this ratio than are nonfailing firms.

Ratios R4 (CFFO/Average total assets) and R5 (Cash from sales/Average total assets) measure the ability to use assets to generate operating cash flows. Nonfailing firms are expected to be more efficient at using assets to generate operating cash flows than are failing firms. Failing firms are expected to be more likely to exhibit low or negative values for these ratios than are nonfailing firms. These ratios are similar to the accrual-based ratios relating sales and net income to total assets which were found to be significant in studies by Beaver (1966), Altman (1968) and Deakin (1972).

The magnitude of ratio R6 (Cash from sales/CFFO) measures the proportion of CFFO generated by cash collections from customers. The ability to raise cash through sales and collections from customers is believed to be indicative of a firm which is not as likely to fail as one which does not generate much cash from sales or suffers from collection problems. This ratio is essentially the cash-based reciprocal of the net income/sales and NIPD/sales ratios found to be significant by Elam (1975).

Ratio R7 (Cash paid for inventory/CFFO) yields the amount of cash paid for inventory. The magnitude of this ratio is presumed to indicate the ability or willingness of a firm to acquire inventory. A nonfailing firm is expected to exhibit a greater ability or willingness to use cash to acquire and pay for inventory than is a failing firm. By contrast, a failing firm may be inclined to not replace inventory.

**ABILITY TO SERVICE DEBT RATIOS**

The ability to service debt ratios are believed to be particularly important to the prediction of business failure. Boritz (1991) contends that defaults on principal and interest payments are one of the late stages in the process of business failure and signal a state of insolvency. These ratios measure the firm's ability to make interest payments and to repay debt principal.

Ratio R8 (CFFO before interest/cash paid for interest) is an interest coverage ratio measuring the ability of the firm to make interest payments from operating cash flows. A value greater than one indicates the ability to make interest payments from operating cash flows. A value less than one indicates an inability to make interest payments from such cash flows. This inability may, in turn, reflect an increased likelihood of failure. Similar accrual-based ratios were found to be significant by Pogue and Soldofsky (1969) and Pinches and Mingo (1973) in bond rating studies.

Ratio R9 (Cash paid for interest/interest expense) measures the portion of interest expense paid in cash. A value less than one may indicate an inability to pay off accruing interest, which may be caused by debt service problems associated with failing firms.

Ratio R10 [(CFFO - preferred dividends)/average current liabilities] is similar to Beaver's (1966) net income/total debt ratio except that R10 focuses on current debt rather than total debt and is intended to measure the sufficiency of operating cash flows to cover current debt levels. A relatively high value may indicate an increased ability to make debt payments from operating cash flows. A low or negative value may imply a need to use other sources of cash to meet current debt payments.

The ability of the firm to meet all debt service requirements out of operating cash flows is measured by ratio R11 [CFFO/(int. paid + red. in LTD + other fin. uses)]. A firm which is able to meet a large portion of its debt service requirements out of operating cash flows would presumably exhibit a relatively high value for this ratio. Such a firm is presumed to have a lower probability of failing than a firm which does not have the ability to meet debt service requirements from operating cash flows.

Ratio R12 [Total cash flow/(int. paid + red. in LTD + other fin. uses)] is similar to the previous ratio except that R12 measures the ability to make debt service payments from total cash flows. The interpretation is similar to that of R11. A higher value is consistent with a greater ability to meet debt service obligations and hence a lower likelihood of failure.

The firm's ability to refund debt that has matured is measured by ratio R13 [(Proc. from iss. of LTD + other fin. sources)/(int. paid + red. of LTD. +other fin. uses)]. A relatively high value is presumed to indicate that the firm has the ability to borrow additional funds to repay debt which is maturing. A firm which cannot repay or refund its maturing debt would be more likely to fail than one which does have the ability to refund debt.

Ratio R14 [(Red. in LTD + other fin. uses)/average LTD] measures the portion of average long-term debt paid off. This ratio is intended to reflect a firm's ability to reduce its outstanding long-term debt. This ability may be indicative of a relatively healthy firm. However, interpretation of this ratio may be confounded by healthy companies which are expanding through the issuance of additional long-term debt.

**ABILITY TO RAISE CAPITAL RATIOS**

The ratios in this category are intended to measure the firm's ability to raise financing through the issuance of stock or debt, or through other financing sources. Firms perceived as failing may have more trouble raising additional financing than would healthy, expanding firms. These ratios seek to measure those differences. Stephens and Govindarajan (1990) suggest that the type of financing may have a significant effect on future cash flows and, correspondingly, liquidity. Debt financing requires periodic interest payments and ultimate principal repayment, whereas equity financing has no such requirements. Consequently, the type of financing raised may exacerbate liquidity problems. To determine if this occurs in the short run, some of the ratios in this section are devoted to debt financing while others assess equity financing.

Ratios R15 (Proceeds from sale of stock/CFFF) and R16 (Proceeds from sale of stock/total cash flow) measure the proportion of financing cash flows and total cash flows accounted for by the issuance of stock. A firm perceived as nonfailing should exhibit a greater ability to issue new shares than would a firm believed to be failing. Consequently, a nonfailing firm is expected to have values of greater magnitude than would a failing firm.

The interpretation of ratios R17 (Issuance of LTD/CFFF), R18 (Issuance of LTD/total cash flow) and R19 (Issuance of LTD/average LTD) is similar to that of the previous two ratios. R17 through R19 measure the ability of the firm to obtain long-term debt financing. A firm with the ability to obtain such financing may be better able to resist failure in the short run that would a firm which cannot obtain financing. Boritz (1991) suggests that a firm facing liquidity problems may attempt to borrow its way out of financial trouble. As such, attempts to issue new borrowings may signal a recognized liquidity problem. Of course, the acquisition of too much long-term debt may be a precursor of bankruptcy in the long run.

Ratio R20 [(Proc. from sale of stock and issuance of LTD + other fin. sources)/total cash flow] measures the portion of total cash flows accounted for by financing sources. The ability to raise financing may be indicative of a healthy, expanding firm or, at least, of a firm which has the ability to raise financing to stave off bankruptcy in the short run. Firms not on the verge of failure are expected to have a greater magnitude for this ratio than are firms which are failing. Conversely, in the long run, consistently high values for this ratio may indicate an inability of the firm to finance operations through operating cash flows. This scenario may be indicative of impending failure if debt loads become too burdensome.

**REPLACEMENT AND EXPANSION RATIOS**

This category includes ratios which are intended to measure the firm's willingness and ability to replace assets and to expand the asset base. Expansion is often characteristic of healthy firms, while troubled firms are more likely to postpone asset replacement or expansion.

Ratios R21 [(Capital exp. + acquisitions + other invest. uses)/CFFI], R22 [(Incr. in invest. + cap. exp. + acquis. + other invest. uses)/ CFFI], R23 [(Incr. in invest. + cap. exp. + acquis. + other invest. uses)/CFFO] and R24 [(Incr. in invest. + cap. exp. + acquis. + other invest. uses)/total cash flow] measure the proportion of cash flows from operating and investing activities, as well as total cash flows, used to replace or expand capital assets and investments. The magnitude of these ratios reflects the firm's ability to use cash for such acquisitions. A failing firm, strapped for cash, would be expected to have difficulty making major investments in noncurrent assets without the use of external financing.

The final ratio in this category, R25 [(Cap. exp. + acquis. - sale of PP&E + other invest. act.)/average PP&E], measures the net expenditure in property, plant and equipment as a percentage of average property, plant and equipment. The net expenditure is intended to measure expansion or contraction of the asset base rather than replacement of assets. The magnitude of a positive value indicates the extent to which a firm has expanded. The magnitude of a negative value indicates the contraction, possibly due to impending failure and a desire to sell off assets.

**SELF-CANNIBALIZATION RATIOS**

Self-cannibalization ratios are intended to measure the extent to which a firm is contracting through disposal of assets or failure to replace assets. Self-cannibalization is generally considered to be more indicative of failing firms than of nonfailing firms as it may signal an extreme attempt to raise cash (Boritz, 1991).

The first self-cannibalization ratio, R26 (Cash paid for inventory/cost of goods sold), measures the extent to which the firm is replacing inventory. Values less than one would reflect a failure to replace inventory while values greater than one reflect an expansion of inventory. A failure to replace inventory, especially in significant amounts, may be indicative of a failing firm, while expansion of inventory may be indicative of a healthy, expanding firm. Interpretation of this ratio may be confounded if firms have adopted "just in time" inventory practices. Such practices attempt to minimize inventory levels in order to improve profits by reducing inventory carrying costs.

Ratios R27 [(Proc. from sale of PP&E + other invest. sources)/CFFI], R28 [(Proc. from sale of PP&E + other invest. sources)/total cash flow], R29 [(Proc. from sale of PP&E + other invest. sources)/average PP&E], R30 [(Proc. from sale of invest. and PP&E + other invest. sources)/CFFI], R31 [(Proc. from sale of invest. and PP&E + other invest. sources)/total cash flow] and R32 [(Proc. from sale of invest. and PP&E + other invest. sources)/average total assets] measure the extent to which investing activities act as sources of cash. The numerators of these ratios are measures of sources of cash from investing activities. These measures are related to net investing cash flows, total cash flows and average asset measures. The larger the magnitude of the ratio values, the greater is the disposal of assets. Failing firms may be more inclined to self-cannibalize to raise cash than would nonfailing firms. Large magnitudes for the ratios in this group may indicate a need to convert long-lived assets to cash which may, in turn, imply impending failure.

Ratios R33 (CFFI/average total assets) and R34 (CFFI/average PP&E) relate net investing cash flows to average total assets and average property, plant and equipment, respectively. These ratios are intended to measure the ability of the firm to use assets to generate investing cash flows. A positive value implies the firm was able dispose of assets to generate a net cash flow. A negative value indicates the firm expanded the asset base during the year.

**OTHER CASH FLOW ACTIVITIES**

Ratio R35 (Purchase of stock/CFFF) measures the percentage of net financing cash flows used to purchase treasury stock. Firms facing liquidity problems would probably have little inclination to use cash for such purposes. Therefore, if the magnitude of this ratio is large, it may be indicative of the amount of the firm's excess cash and, consequently, the firm's ability to resist bankruptcy.

The remaining ratios in this category, R36 (Payment of dividends/CFFO) and R37 (Payment of dividends/CFFF), measure the portion of operating and financing cash flows used to pay dividends. A failing firm may elect, or be forced, to suspend dividend payments (Boritz, 1991). Therefore, values of or near zero may indicate liquidity problems.

**CASH POSITION RATIOS**

The final three ratios used in this study, R38 (Cash/current liabilities), R39 (Cash/total liabilities) and R40 (Cash/total assets), measure the cash position of the firm. A firm with a strong cash position is generally believed to be better able to resist bankruptcy. These ratios relate cash position to current liabilities, total liabilities and total assets. The strength of a firm's cash position is indicated by the magnitude of the ratio value. Higher values are expected to be associated with firms with strong cash positions while lower values may be more indicative of firms with liquidity problems.

**VARIABLES USED IN THE REPLICATION OF PREVIOUS STUDIES**

Testing the second hypothesis involves the replication of the bankruptcy studies of Beaver (1966), Altman (1968), Deakin (1972), Ohlson (1980) and Zavgren (1985) and uses the same predictor variables included in the final models developed in these studies. Figure 3 contains a list of the ratios used in these accrual-based models. An unbound list of these ratios is also included in Appendix B for easier reference.

These same ratios are used in the test of the third hypothesis. The test of this hypothesis involves the use of

# FIGURE 3

## RATIOS USED IN ACCRUAL-BASED MODELS

### BEAVER, 1966

B1) $\frac{\text{"Cash flow"}}{\text{Total debt}}$

### ALTMAN, 1968

A1) $\frac{\text{Working capital}}{\text{Total assets}}$

A2) $\frac{\text{Retained earnings}}{\text{Total assets}}$

A3) $\frac{\text{Earnings before interest and taxes}}{\text{Total assets}}$

A4) $\frac{\text{Market value of equity}}{\text{Total debt}}$

A5) $\frac{\text{Sales}}{\text{Total assets}}$

### DEAKIN, 1972

D1) $\frac{\text{"Cash flow"}}{\text{Total debt}}$

D2) $\frac{\text{Net income}}{\text{Total assets}}$

D3) $\frac{\text{Total debt}}{\text{Total assets}}$

D4) $\frac{\text{Current assets}}{\text{Total assets}}$

D5) $\frac{\text{Quick assets}}{\text{Total assets}}$

D6) $\frac{\text{Working capital}}{\text{Total assets}}$

D7) $\frac{\text{Cash}}{\text{Total assets}}$

D8) $\frac{\text{Current assets}}{\text{Current liabilities}}$

D9) $\frac{\text{Quick assets}}{\text{Current liabilities}}$

D10) $\frac{\text{Cash}}{\text{Current liabilities}}$

D11) $\frac{\text{Current assets}}{\text{Sales}}$

D12) $\frac{\text{Quick assets}}{\text{Sales}}$

D13) $\frac{\text{Working capital}}{\text{Sales}}$

D14) $\frac{\text{Cash}}{\text{Sales}}$

**FIGURE 3 continued**

**RATIOS USED IN ACCRUAL-BASED MODELS**

**OHLSON, 1980**

O1) log(total assets/GNP price-level index)

O2) $\frac{\text{Total liabilities}}{\text{Total assets}}$

O3) $\frac{\text{Working capital}}{\text{Total assets}}$

O4) $\frac{\text{Current liabilities}}{\text{Current assets}}$

O5) $\frac{\text{Net income}}{\text{Total assets}}$

O6) $\frac{\text{Funds provided by operations}}{\text{Total liabilities}}$

O7) $\frac{(NI_t - NI_{t-1})}{(|NI_t| + |NI_{t-1}|)}$ Where $NI_t$ is net income for the most recent period

O8) Dummy variable: 1 if total liabilities exceeds total assets, 0 otherwise

O9) Dummy variable: 1 if net income was negative for the last two years, 0 otherwise

**ZAVGREN, 1985**

Z1) $\frac{\text{Total income}}{\text{Total capital}}$

Z2) $\frac{\text{Sales}}{\text{Net plant}}$

Z3) $\frac{\text{Inventory}}{\text{Sales}}$

Z4) $\frac{\text{Debt}}{\text{Total capital}}$

Z5) $\frac{\text{Receivables}}{\text{Inventory}}$

Z6) $\frac{\text{Quick assets}}{\text{Current liabilities}}$

Z7) $\frac{\text{Cash}}{\text{Total assets}}$

the ratios from the existing accrual-based models and the inclusion or substitution of variables used to develop the cash-based model as part of the test of the first hypothesis in order to determine whether such addition or substitution can improve the accrual-based models.

## FACTOR ANALYSIS OF PREDICTOR VARIABLES

The use of numerous predictor variables creates three potential problems. First, lack of a guiding theory may result in a haphazard collection of variables which are chosen because of their popularity or the intuition of the researcher. Haphazard selection of variables may result in the inclusion of two or more variables which measure essentially the same facet of financial position or performance, or the failure to include a variable which measures a particular facet of the firm not captured by other variables. Second, as the variable set is composed of a finite number of accounting measures, multicollinearity becomes a potential problem. This is especially true in the case of ratio variables, many of which may include the same accounting measures. Third, the inclusion of too many variables may result in violation of the assumptions of the statistical analysis techniques and may make the results difficult to interpret. Factor analytic techniques are used to limit these problems.

Factor analytic techniques reduce the variable set to a smaller set of underlying factors by grouping the original variables into sets, called factors, based on the amount of variance accounted for by the variables. Several benefits are gained by the use of factor analytic techniques. The factors indicate the underlying financial parameters measured by the variable set as a whole. Factor analytic results may provide some insight into the type of information contained in the variable set and may help guide the selection of variables for the final model.

Reduction of the variable set is achieved by selecting one variable from each factor. As the variables in each factor contain similar information, the use of more than one of the variables in a given factor is not necessary. Fewer predictor variables reduce multicollinearity by decreasing the likelihood that the variables included in the model are linear combinations of each other or that they exhibit a high degree of inter-correlation. In addition, fewer variables in the final model simplify the application of the model and the interpretation of the results.

The cash- and accrual-based variables for all of the failed and nonfailed firms in the study are factor-analyzed using the principal components analysis technique. The principal components analysis is of an exploratory nature - to determine whether a small number of components can account for most of the variation within the original variable set. This method is recommended by Dillon and Goldstein (1984) who state its purpose is to "determine factors (i.e. principal components) in order to explain as much of the total variation in the data as possible with as few of these factors as possible" (p. 24).

An orthogonal rotation technique is used to group the variables into principal components. Orthogonal rotation yields a set of uncorrelated (orthogonal) components which may be easier to interpret than the components derived from the original, unrotated solution. Kim and Mueller (1978b) recommend orthogonal rotation for exploratory studies.

The decision regarding the number of components to be included in the terminal solution is guided by analysis of component eigenvalues, skree test, and the criterion of substantive importance. Components with eigenvalues greater than one are generally considered to be significant. This general rule of thumb is used as a starting point in the present study. The skree test graphs the eigenvalues and suggests that the last component to be retained is the one at which the graph begins to level off. These two methods are only applicable to unrotated solutions. The criterion of substantive importance is used as a guide if the orthogonally rotated solution results in more easily interpretable components than the unrotated solution. The criterion of substantive importance is based on consideration of the amount of the total variance in the data explained by each individual component. Only those components which are deemed to explain a substantial portion of the total variance are considered significant (Kim and Mueller, 1978a).

The common method of determining which variable to select as representative of a given component is to select the variable which loads most heavily on a given component. This general rule of thumb is followed unless another heavily loading variable is more intuitively appealing or more representative of the component's interpretation. In this manner, each variable in the final model is an element of the original variable set, and no further manipulation of the variable values is necessary. This method is consistent with previous studies in this area and is used in the current study. A benefit of this method is that the final variables included in the bankruptcy model are individual financial measures or ratios and not weighted combinations of such measures and ratios. The result is a model composed of easily interpretable variables.

Principal components analysis reduces the original set of cash-based variables into a more parsimonious set of noncollinear variables which still capture most of the information contained in the original variable set. Once this is accomplished, the reduced variable set is used to develop a cash-based bankruptcy prediction model to test the first hypothesis.

**REPORTING OF RESULTS**

The significant components identified, and the variables which load heavily on those components, are reported. For purposes of this study, a variable with a component loading of 0.70 or higher is considered to load heavily on the component.

Variables with loadings of less than 0.70 are not reported. An attempt is made to interpret the underlying meaning of each component by considering the nature of the variables which load on the component. Component loadings for the individual variables are given, and the individual variable selected to represent each component is identified.

## TEST OF THE FIRST HYPOTHESIS

The first hypothesis, as stated in Chapter 1, is as follows:

$H_1$: Models based on cash flow data have no ability to distinguish firms proceeding toward bankruptcy from firms which are not proceeding toward bankruptcy.

### MODEL DEVELOPMENT

The test of the first hypothesis involves the development of a bankruptcy prediction model. The dependent variable of the model is a dichotomous indicator that the firm has failed or has not failed. The independent variables are cash-based ratios selected to represent the components identified in the previously discussed principal components analysis portion of the study.

The samples of failed and nonfailed firms are split with one part used to develop the models and the other used as a holdout sample to test the models' classification accuracy. The split between the development and holdout samples is an 80/20 ratio. This results in 443 firms (43 failed and 400 nonfailed) used to develop the models and 111 (11 failed and

100 nonfailed) used for validation. The use of a large sample to develop the model is an attempt to improve the accuracy of the estimated model coefficients and consequently improve the reliability of the resulting models. In addition, the use of a large number of observations in the development of the models is in keeping with the data requirements of the logit procedure.

Prediction models are developed through the multiple discriminant analysis (MDA) and logit procedures. Both of these methods have been used successfully in previous bankruptcy studies, as discussed in Chapter 2.

**IDENTIFICATION OF BEST MODEL**

The resulting MDA and logit models are compared to determine which performs better. Previous researchers have found little difference between the two methods and usually report the results of only one method. The determination of which model exhibits superior performance is based on the resulting classification error rates of the models. Classification error rates (number of firms incorrectly classified/total number of firms) of the models are compared and the best performing model selected. This approach is preferable to relying on the individual models' significance statistics ($R^2$, F-tests, etc.) as classification accuracy is more important to this study than is explanatory ability. The significance of the overall model indicates whether the model can successfully discriminate between failed and nonfailed firms. Therefore, the appropriate test of significance could be used to accept or reject the first hypothesis. However, this significance test is based on the model's ability to classify the same data used to develop the model. A better test is the model's ability to classify firms in the holdout sample.

Tests of the models' ability to classify the holdout samples are performed. Attention is focused on the models' ability to predict failure over the short-run - within one year from the date of the most recently issued financial statements.

The multiple discriminant analysis procedure in the SAS statistical analysis software allows for a direct test of the model's ability to classify a holdout sample. The model is developed using one set of data. The holdout sample is then classified by the resulting model. This procedure is followed in the current study to classify both holdout samples.

No such validation routine exists in the logit procedure for classifying holdout samples. Classification of the development and holdout samples with the logit model begins by using the model's intercept and coefficients to calculate scores for each firm in the sample. The scores are then arranged in numerical order. The transition point between positive and negative scores is the boundary dividing those firms which have been classified as failed from those firms classified as nonfailed. The procedure used in this study results in negative scores for firms classified as nonfailed and positive scores for firms classified as failed. The overall classification accuracy, overall error rate and type I and type II error rates are calculated for the development and holdout samples.

The classification error rates relating to the holdout samples for the MDA and logit models are compared. The best performing model is used for the remainder of the study.

**TEST OF THE FIRST HYPOTHESIS**

Rejection of the first hypothesis occurs if the cash-based bankruptcy model exhibits a classification error rate which is less than would be achieved by a random assignment to the failed or nonfailed category. A binomial test for proportions is used to determine whether the classification error rate when using the model is better than the expected classification error rate if the firms had been randomly classified. The expected classification error rate is based on the relative percentages of failed and nonfailed firms in the holdout sample. The binomial test determines whether to accept or reject the hypothesis that the use of the model does not improve on the classification error rate achieved by random assignment.

**REPORTING OF RESULTS**

The model used in the test of the first hypothesis is reported. Appropriate statistics on the overall significance of the model and of the individual predictor variables are also reported.

Overall, Type I and type II error rates are reported for both the original sample and the holdout samples. No distinction is made between the importance of Type I and Type II errors as the relative cost of each type of error would be user-specific. Consequently, attention is concentrated on the total error rate observed for the holdout sample. Results of the binomial test for proportions are reported, along with the related level of significance of the results.

## TEST OF THE SECOND HYPOTHESIS

The second hypothesis, as stated in Chapter 1, is as follows:

$H_2$: There is no difference between cash flow-based models and other models used for assessing the likelihood of bankruptcy.

### REPLICATION OF ACCRUAL-BASED STUDIES

The second hypothesis is tested by a comparison of the classification error rates of the cash-based model developed to test the first hypothesis with those experienced by replicating other, previously developed bankruptcy models.

Five models are selected for replication: (1) Beaver (1966); (2) Altman (1968); (3) Deakin (1972); (4) Ohlson (1980); and (5) Zavgren (1985). These models are chosen because of their significance in the bankruptcy literature, classification accuracy and reliance on commonly available information which increases the practical application of the models. Models which rely on sophisticated variables such as regression-derived trend variables or measures of variability within variables are excluded because the calculation of those variables may be beyond the ability of the users of financial information and consequently render such models impracticable. No cash-based models are replicated. The cash-based models developed in prior studies proved to have less predictive ability than accrual-based models. This study compares the accuracy of a new cash-based model to existing models which have proven useful in predicting bankruptcy.

The test of the second hypothesis requires the replication of the previously cited models with current data in order to directly compare the error rates of the accrual-based models to the cash-based model developed for the test of the first hypothesis. Previously reported error rates for the models cannot be used because those error rates are based on data which may not be comparable to the data used to develop the cash-based model due to changes in financial reporting requirements. Consequently, all models are developed and tested using the same sample of failed and nonfailed firms. Use of the original variables with more current data also allows for the evaluation of the models' generalizability across time. Classification error rates are determined by analyzing each of the models' ability to classify the same holdout samples.

**TEST OF THE SECOND HYPOTHESIS**

The second hypothesis is tested through a series of two-sided Chi-square tests. The cash-based model is compared to each of the accrual-based models individually to determine whether significant differences exist in the models' abilities to accurately classify the holdout samples. The rows of each 2X2 contingency table are the two models being compared. The columns are the number of correct and incorrect classifications produced by each model. A significant difference, in either direction, between the cash-based model and at least one of the accrual-based models is sufficient to reject the hypothesis.

The previously described Chi-square tests only test for differences in overall accuracy, not for differences in Type I and Type II error rates. Chi-square tests can be used to determine if differences exist in these error rates by conducting separate Chi-square tests for failed and nonfailed firms. The comparative classification results for the failed firms are tested. This tests for differences in the Type I error rates. The test is then be repeated for nonfailed firms to test for differences in the Type II error rates achieved by the models.

**REPORTING OF RESULTS**

Overall classification error rates for the cash-based model and the replications of the five accrual-based models are reported. Results of the five Chi-square tests comparing the cash-based model to each accrual-based model are reported, along with the related level of significance of the results.

Type I and Type II error rates are reported for each of the five inter-model comparisons. Chi-square values and the related levels of significance are also reported for each comparison.

### TEST OF THE THIRD HYPOTHESIS

The third hypothesis, as stated in the first chapter, is as follows:

$H_3$: The inclusion or substitution of cash-based information into an existing model has no effect on the ability of the model to distinguish firms proceeding toward bankruptcy from those which are not proceeding toward bankruptcy.

### MODIFICATION OF ACCRUAL-BASED STUDIES

The third hypothesis is tested by comparing the classification error rates of four of the five accrual-based models replicated in the test of the second hypothesis with modified versions of those accrual-based models. The Beaver model is excluded from this portion of the study because, as a univariate model, it does not lend itself to the addition of more independent variables. The models are modified by adding cash-based variables selected for analysis as part of the test of the first hypothesis to the accrual-based models, and/or by substituting cash-based variables for some of the variables originally used in the accrual-based models. The scope of this study is limited to assessing the contribution, if any, of cash-based variables to existing accrual-based bankruptcy models. No attempt is made to develop a new, "best" model from all available cash- and accrual-based measures.

## SELECTION OF VARIABLES

Variables used in the modified versions of the models are carefully selected to avoid multicollinearity problems. In this regard, principal components analysis is used to analyze correlations between the variables. For each accrual-based model, the variables originally used in that model are analyzed using principal components analysis along with all of the forty variables used to develop the cash-based model for the test of the first hypothesis. Some multicollinearity is expected to occur between the variables because of the limited number of accounting measures used to calculate the entire ratio set. The results of the principal components analyses serve as a starting point to determine which variables are to be included in each of the four modified accrual-based models.

Two benefits are gained through this use of principal components analysis. First, multicollinearity problems inherent in the original models, if any, are detected. Second, the addition or substitution of cash-based variables into the accrual-based models can be done without creating new multicollinearity problems.

## TEST OF THE THIRD HYPOTHESIS

The third hypothesis is tested through a series of Chi-square tests to assess the significance of the differences in the classification abilities between the original version of the accrual-based model and its modified counterpart. The true test of the contribution of the cash-based variables is whether they improve the classification accuracy of the model to which they are added. This incremental contribution is tested by the same procedures used to test the second hypothesis. Chi-squared tests are performed on each model. The rows of the 2X2 contingency table comprise the model before and after modification by the addition or substitution of the cash-based variables. The columns are the number of correct and incorrect classifications produced by each version of the model. A significant difference, in either direction, between the two versions of any of the models is sufficient to reject the hypothesis.

Chi-square tests are also used to test for differences between the original and modified models' Type I and Type II error rates. Separate Chi-square tests are conducted for the failed and nonfailed firms. The comparative classification results for the failed firms are tested for differences in the Type I error rates. The test is repeated for the nonfailed firms to test for differences in the Type II error rates. These Chi-square tests determine whether the addition of the cash-based variables improves or weakens the overall classification accuracy as well as the Type I and Type II errors of the models.

**REPORTING OF RESULTS**

The results of the principal components analyses are reported, with attention focused on variables which exhibit significant intercorrelations. The variables to be used in each of the four modified models are identified. Modifications to the original models, in the form of additions and/or substitutions are highlighted by emphasizing which cash-based variables, if any, have entered the models and which accrual-based variables, if any, have been dropped from the models.

Overall classification error rates for the original and modified versions of the models are reported. Results of the four Chi-square tests comparing the original and modified models are reported, along with the related level of significance of the results.

Type I and Type II error rates are reported for each of the four inter-model comparisons. Chi-square values and the related levels of significance are also reported for each comparison.

**SUMMARY**

This chapter has discussed the methodology used in this study, including sample selection, data collection and variable selection. Methodological considerations for testing each of the three research hypotheses was discussed, with attention being focused on the classification error rates as the ultimate measure of a bankruptcy model's effectiveness.

Type I and Type II error rates were also emphasized for their importance to different user groups. Chapter four discusses the analysis of the data with respect to each of the research hypotheses and the resultant findings are reported.

# CHAPTER 4

## ANALYSIS OF DATA

This chapter discusses the results of the application of the methodology described in Chapter 3. This chapter is divided into four sections: (1) factor analysis of cash flow ratios; (2) test of the first hypothesis; (3) test of the second hypothesis; and (4) test of the third hypothesis.

### FACTOR ANALYSIS OF CASH FLOW RATIOS

The forty cash flow ratios outlined in Chapter 3 were factor-analyzed as a prelude to developing the cash-based model for the test of the first hypothesis. The factor analysis was performed in order to discover any underlying facets of firm performance which were measured by the ratios, to distill the variable set into a more parsimonious group with the intention of reducing the number of variables to be included in the model, and to avoid the multicollinearity problems which may be associated with the use of a multivariate model.

The factor analysis was performed using the SAS FACTOR procedure on the forty cash-based ratios for 640 of the companies in the study (54 failed and 586 nonfailed). The principal components method of extraction was used to group the variables into factors (components). Use of this method results in a principal components analysis of the variables. The initial unrotated solution resulted in few of the variables loading heavily on any of the components. A more satisfactory solution was achieved when the components were rotated using the orthogonal VARIMAX rotation procedure. VARIMAX produces a set of components which are uncorrelated with each other. The resulting rotated solution produced eleven interpretable components containing variables with component loadings of at least 0.70. These eleven components accounted for 69% of the total variation in the data set with each component accounting for between 3.3% and 10.0% of the total variation. Figure 4 lists the component loadings for the ratios loading heavily on each component.

**INTERPRETATION OF COMPONENTS**

The purpose of principal components analysis is to group variables based on the underlying attributes measured by the variables. While this is statistically possible, it is not always feasible to interpret the components. In this study, all eleven components resulting from the analysis did seem relatively easy to interpret. This section discusses the interpretation of the components and indicates which ratios were used to represent the components in the cash-based model.

The first component is composed of ratios R7 (Cash paid for inventory/CFFO), R6 (Cash from sales/CFFO), R36 (Payment of dividends/CFFO) and R23 [(Incr. in invest. + cap. exp. + acquis. + other invest. uses)/CFFO]. The common thread linking these four ratios is the denominator cash flow from operations. This emphasis on CFFO is in keeping with the

## FIGURE 4

## COMPONENT LOADINGS

| RATIO | COMP 1 | COMP 2 | COMP 3 | COMP 4 | COMP 5 | COMP 6 |
|---|---|---|---|---|---|---|
| R7* | 0.99906 | | | | | |
| R6 | 0.99839 | | | | | |
| R36 | 0.99726 | | | | | |
| R23 | 0.99685 | | | | | |
| R18 | | 0.95906 | | | | |
| R20* | | 0.94692 | | | | |
| R31 | | 0.94160 | | | | |
| R24 | | 0.93691 | | | | |
| R22* | | | 0.93889 | | | |
| R21 | | | 0.93117 | | | |
| R30 | | | 0.90240 | | | |
| R27 | | | 0.85801 | | | |
| R38* | | | | 0.96311 | | |
| R39 | | | | 0.94757 | | |
| R40 | | | | 0.89909 | | |
| R11* | | | | | 0.90091 | |
| R13 | | | | | 0.88735 | |
| R12 | | | | | 0.78336 | |
| R34* | | | | | | 0.85683 |
| R33 | | | | | | 0.81179 |
| R25 | | | | | | -0.89829 |

| RATIO | COMP 7 | COMP 8 | COMP 9 | COMP 10 | COMP 11 |
|---|---|---|---|---|---|
| R4* | 0.87315 | | | | |
| R10 | 0.85916 | | | | |
| R29* | | 0.84826 | | | |
| R32 | | 0.84820 | | | |
| R37* | | | 0.93548 | | |
| R17 | | | 0.93416 | | |
| R26* | | | | 0.91314 | |
| R19* | | | | | 0.81480 |
| R14 | | | | | 0.74424 |

* - Indicates ratio selected to represent component

factor-analytic studies of Gombola and Ketz (1983a) and Gombola, et al. (1987) which identified the existence of a separate factor representing CFFO from a set of cash- and accrual-based ratios. Given that three of the four ratios loading heavily on this component represent the use of CFFO, this component is interpreted as the magnitude of cash flows available for use by the entity.

Ratio R7 (Cash paid for inventory/CFFO) was chosen to represent this first component because it has the highest loading and because of its intuitive appeal. Cash paid for inventory is an item which may be discretionary for failing firms. A failing firm may either delay or default on payment of purchases, or may liquidate inventory without replacing it, thus lowering the payments made for inventory. A nonfailing firm would want to continue replenishing inventory and maintain good relationships with suppliers.

The common element in the second component is total cash flows, showing up in the denominators of each of the four ratios loading heavily on this component: R18 (Proc. from iss. of LTD/total cash flow), R20 [(Proc. from sale of stock and iss. of LTD + other fin. sources)/total cash flow], R31 [(Proc. from sale of invest. + sale of PP&E + other invest. sources)/total cash flow] and R24 [(Incr. in invest. + cap. exp. + acquis. + other invest. uses)/total cash flow]. The numerators of R18, R20 and R31 are all sources of cash flows, the first two being financing sources and the third being from investing activity. The numerator of R24 is a use of cash flows for investing activities. The primary implication is that this component measures the ability to raise cash from outside sources, either through financing or investing activities. This interpretation is consistent with the premise that healthy firms may be better able to raise additional financing while failing firms may not be so fortunate. R24 implies a secondary interpretation that the component measures the ability or willingness to use cash for investing purposes.

This component is represented in the cash-based model by ratio R20 even though it is not the highest loading ratio in the component. R20 [(Proc. from sale of stock and iss. of LTD + other fin. sources)/total cash flow] is very similar to the highest loading ratio, R18, but includes a broader measure of sources of external financing through the inclusion of sales of stock and other financing sources. These additional sources of financing may help to distinguish between failing and nonfailing firms.

The third component is a combination of the ability to raise and use cash flows through investing activities. All of the ratios have CFFI as denominators. The two highest loading ratios, R22 [(Incr. in invest. + cap. exp. + acquis. + other invest. uses)/CFFI] and R21 [(Cap. exp. + acquis. + other invest. uses)/CFFI], have numerators which measure the use of cash for investing purposes. R30 [(Proc. from sale of invest. +sale of PP&E + other invest. sources)/CFFI] and R27 [(Proc. from sale of PP&E + other invest. sources)/CFFI] have investing sources in the denominator. At first glance this component appears difficult to interpret, but an analysis of the ratios makes it less confusing. A healthy, expanding firm would most likely have a negative CFFI as cash is spent on investing activities. Consequently, all four of the ratios would have negative values for healthy firms. (The numerators must, by definition, be positive). The opposite is true for failing firms. Failing firms would be more likely to sell off assets to raise cash than to invest in additional expansion. This would result in positive CFFI and, therefore, positive values for the ratios. The highest loading ratio, R22 [(Incr. in invest. + cap. exp. + acquis. + other invest. uses)/CFFI], was chosen to represent this component.

The fourth component is a measure of cash position. This component corresponds to the findings of Pinches, Mingo and Caruthers (1973) and others. Ratio R38 (Cash/current liabilities), represents this factor. This ratio is a very strict measure of liquidity and is also the highest loading ratio associated with the fourth component.

The ability to service debt is the apparent underlying attribute of the fifth component. Three ratios load heavily on this component: R11 [CFFO/(int. paid + red. of LTD + other fin. sources)], R13 [(Proc. from iss. of LTD + other fin. sources)/(int. paid + red. of LTD + other fin. uses)] and R12 [Total cash flow/(int. paid + red. of LTD + other fin. uses)]. All of these ratios contain the reduction of long-term debt and other financing uses in their denominators. In addition, R11 and R12 include the amount of interest paid in the denominator. The numerators of this component's ratios are all measures of sources of cash which may be used to make the debt service payments. As such, they may be considered "debt service coverage" ratios. This component is similar to the facet of firm performance measured by Beaver's "cash flow"/total debt ratio except that Beaver emphasized debt levels and this component emphasizes reductions in debt levels.

The ratio chosen to represent this component is R11 [CFFO/(int. paid + red. of LTD + other fin. sources)]. This ratio has the highest loading on the component. R11 is also intuitively appealing because it measures the adequacy of CFFO for covering debt service payments. Companies with good operating cash flows are more likely to be able to make debt service payments from operating cash flows than are companies facing liquidity problems.

The ratios in the sixth component represent the direction of change in the firm's asset base - either expansion or contraction. Ratios R34 (CFFI/average PP&E) and R33 (CFFI/average total assets) are positively correlated with each other, but negatively correlated with R25 [(Cap. exp. + acquis. - sale of PP&E + other invest. uses)/total cash flow]. Analysis of the numerators provides an explanation for this result. The numerators in R34 and R33 would be negative for expanding firms because cash outflows for investing activities would outweigh the inflows from such activities. The numerator in R25 would be positive for expanding firms as capital expenditures and acquisitions would outweigh sales of assets. Consequently, ratios R34 and R35 would exhibit negative values for expanding firms while R25 would have a positive value for the same firms. The opposite would hold true for firms which are contracting their asset base.

R34 (CFFI/average PP&E) has been chosen to represent the sixth component. Although R34 does not load as heavily as R25 [(Cap. exp. + acquis. - sale of PP&E + other invest. uses)/total cash flow], it is more attractive because its numerator, CFFI, is a broader measure of investing activity than is the numerator of R25. This expanded measure may contain additional useful information not captured by R25.

Component seven is a measure of the magnitude of CFFO. R4 (CFFO/average total assets) represents this component because it loads higher than does R10 [(CFFO - preferred dividends)/average cur. liab.]. In addition, R4 measures the ability of the firm to use assets to generate cash flows from operations. This ability is important to the long-run liquidity of firms. R4 is identical to a ratio used by Gombola, et al. (1987).

Self-cannibalization is the attribute measured by the eighth component. Both ratios loading on this component compare the amounts of cash received from disposing of assets to a measure of average assets. Ratio R29 [(Proc. from sale of PP&E + other invest. sources)/average PP&E] has been chosen to symbolize this component.

Component nine is a measure of the magnitude of financing cash flows. Of particular interest in this component is ratio R37, payment of dividends to CFFF. Payment of dividends was found to be a significant predictor of failure in studies by Gentry, Newbold and Whitford (1985a and 1985b). R37 is used in the development of the cash-based model employed to test the first hypothesis.

Only one ratio, R26 (Cash paid for inventory/cost of goods sold), loaded heavily on the tenth component. This ratio is a measure of the replacement rate of inventory. High values may indicate an expansion of inventory while low values may be indicative of an inability or unwillingness to replace inventory items. A similar measure was used by Gentry, Newbold and Whitford (1985b) in their decomposition of CFFO into its component parts, including cash paid for inventory.

The final component includes two heavily loading ratios which are measures of debt position; R19 (Proc. from iss. of LTD/average LTD) and R14 [(Red. of LTD + other fin. uses)/average LTD]. While debt position is not a cash flow item, it is presumably useful for distinguishing between failing and nonfailing firms. Some measure of debt position has been used in almost every study of bankruptcy. See, for example, Beaver (1966), Deakin (1972), Zavgren (1985), and others. R19 was selected to represent the component. This ratio measures the ability of the firm to raise additional debt financing, given the level of long-term debt already accumulated by the firm. Those firms which are perceived as failing or which have overly burdensome debt levels would face difficulty borrowing additional funds and would consequently have a lower value for this ratio.

## SUMMARY OF FACTOR ANALYSIS OF THE ORIGINAL VARIABLE SET

The factor analysis of the forty ratios developed for this study was conducted with three goals in mind: (1) to discover whether the variable set could identify any underlying attributes in the data; (2) to reduce the variable set; and (3) to select uncorrelated variables for inclusion in the cash-based model. All of these goals were achieved.

First, eleven attributes of the data were identified: magnitude of cash flow from operations; ability to raise outside funding; magnitude of investing activity; cash position; ability to service debt; change in size of asset base; magnitude of cash flow from operations relative to assets and liabilities; self-cannibalization; magnitude of cash flow from financing activities; replacement rate of inventory; and debt position. Second, the variable set was reduced from forty ratios to the eleven selected to represent the components. Finally, the eleven selected ratios exhibit very low to insignificant correlations. These low correlations should minimize the influence of multicollinearity in the development of the failure prediction model. Figure 5 presents the correlation matrix for the eleven ratios chosen to represent the principal components.

**FIGURE 5**

**CORRELATION MATRIX**
**FOR RATIOS REPRESENTING ELEVEN COMPONENTS**

| | R4 | R7 | R11 | R19 | R20 | R22 |
|---|---|---|---|---|---|---|
| R4 | 1.00000 | 0.00458 | 0.18721 | -0.18774 | 0.00355 | -0.02252 |
| R7 | | 1.00000 | 0.00323 | 0.00042 | -0.02179 | -0.00275 |
| R11 | | | 1.00000 | -0.01555 | 0.00241 | -0.00802 |
| R19 | | | | 1.00000 | 0.00521 | 0.02933 |
| R20 | | | | | 1.00000 | -0.07725 |
| R22 | | | | | | 1.00000 |
| R26 | | | | | | |
| R29 | | | | | | |
| R34 | | | | | | |
| R37 | | | | | | |
| R38 | | | | | | |

| | R26 | R29 | R34 | R37 | R38 |
|---|---|---|---|---|---|
| R4 | -0.16009 | -0.11589 | -0.00757 | 0.01516 | -0.06595 |
| R7 | -0.00436 | 0.00877 | 0.00667 | -0.00195 | 0.01623 |
| R11 | -0.00931 | -0.02442 | -0.02644 | -0.00075 | 0.09267 |
| R19 | 0.04632 | 0.02659 | -0.02735 | -0.00624 | 0.11741 |
| R20 | -0.00363 | 0.03288 | 0.01309 | 0.00173 | -0.01573 |
| R22 | 0.01780 | 0.07663 | 0.04296 | -0.00501 | -0.01165 |
| R26 | 1.00000 | 0.10141 | 0.02946 | 0.00345 | 0.04502 |
| R29 | | 1.00000 | 0.44626 | -0.00875 | -0.03056 |
| R34 | | | 1.00000 | -0.00421 | -0.14016 |
| R37 | | | | 1.00000 | -0.01978 |
| R38 | | | | | 1.00000 |

## TEST OF THE FIRST HYPOTHESIS

The test of the first hypothesis began with the development of MDA and logit models based on the ratios selected to represent the eleven components identified in the previous section. The best of these models, based on classification accuracy, was selected. Finally, a binomial test of proportions was performed to determine whether the classification accuracy of the model is significantly better than chance.

### DEVELOPMENT OF CASH-BASED MODELS

Two MDA models were analyzed. The first model was composed of all eleven ratios. Analysis of the univariate test statistics for this model indicated that only two of the ratios, R29 [(Proc. from sale of PP&E + other invest. sources)/average PP&E] and R38 (Cash/cur. liab.), were significant at the .10 level. Overall, this first model was significant at the .10 level. The second model was a two-variable model composed only of those ratios found to be significant in discriminating between failed and nonfailed firms, R29 and R38. Overall, the second model was significant at the .005 level. Both of these models achieved a classification accuracy of 90.07% on the original development sample. However, the accuracy decreased slightly when classifying the holdout samples, with the two-variable model exhibiting 1-2% better accuracy than the eleven-variable model. Several other combinations of the ratios proved to be no better than the two-variable model.

Two logit models were also examined. A forced-entry procedure was used to develop a model which contained all eleven ratios. The stepwise-entry procedure, using a .10 level of significance as the criteria for variables entering or staying in the model, was used to develop the second logit model. In the eleven-variable model, only the intercept and R38 were significant and the model itself was significant at the .10 level. The stepwise procedure resulted in a model comprising the intercept, R29 [(Proc. from sale of PP&E + other invest. sources)/average PP&E] and R38 (Cash/cur. liab.). This two-variable model was significant at the .005 level. The classification accuracies of the two logit models were almost identical on the development sample, but the two-variable model classified the holdout samples with greater accuracy than did the full eleven-variable model. As with the MDA models, several other combinations of ratios were tried without achieving greater success than with the two-variable logit model. Figure 6 details the coefficients and significance statistics for the four models analyzed.

**SELECTION OF CASH-BASED MODEL**

Selection of the model to be used to test the first and second hypotheses was based on the relative abilities of the four previously described models to classify the holdout samples. Consistent with the findings of previous researchers, there was little difference between the

# FIGURE 6

## COEFFICIENTS AND SIGNIFICANCE STATISTICS OF CASH-BASED MODELS

### ELEVEN-VARIABLE MDA MODEL

| Individual Variables | | | |
|---|---|---|---|
| Variable | Coefficient | F-test | Prob > F |
| R4 | 2.2071 | 2.3083 | 0.1294 |
| R7 | 0.0009 | 0.2284 | 0.6330 |
| R11 | 0.0012 | 0.6094 | 0.4354 |
| R19 | 0.0149 | 0.3490 | 0.5550 |
| R20 | 0.0014 | 1.2504 | 0.2641 |
| R22 | 0.0669 | 1.4375 | 0.2312 |
| R26 | 0.5052 | 0.9892 | 0.3205 |
| R29 | -1.3199 | 5.0969 | 0.0245** |
| R34 | -0.1768 | 2.6462 | 0.1045 |
| R37 | 0.0077 | 0.0023 | 0.9619 |
| R38 | 0.4844 | 6.4445 | 0.0115** |

| Complete Model | | |
|---|---|---|
| Statistic | F-test | Prob > F |
| Wilks' Lambda | 1.7327 | 0.0639* |

### TWO-VARIABLE MDA MODEL

| Individual Variables | | | |
|---|---|---|---|
| Variable | Coefficient | F-test | Prob > F |
| R29 | -2.0821 | 5.0969 | 0.0245** |
| R38 | 0.6483 | 6.4445 | 0.0115** |

| Complete Model | | |
|---|---|---|
| Statistic | F-test | Prob > F |
| Wilks' Lambda | 5.5426 | 0.0042*** |

* - Significant at 0.10 level
** - Significant at 0.05 level
*** - Significant at 0.005 level

FIGURE 6 continued

COEFFICIENTS AND SIGNIFICANCE STATISTICS
OF CASH-BASED MODELS

ELEVEN-VARIABLE LOGIT MODEL

Individual Variables

| Variable | Coefficient | Wald Chi-square | Prob > Chi-square |
|---|---|---|---|
| Intercept | -1.6204 | 26.5090 | 0.0001**** |
| R4 | -0.5181 | 0.1973 | 0.6569 |
| R7 | -0.0009 | 0.1906 | 0.6624 |
| R11 | -0.0205 | 0.4143 | 0.5198 |
| R19 | -0.0396 | 0.1351 | 0.7132 |
| R20 | -0.0017 | 1.5948 | 0.2066 |
| R22 | -0.0327 | 1.8504 | 0.1737 |
| R26 | -0.2143 | 0.9514 | 0.3294 |
| R29 | 0.5534 | 1.5094 | 0.2192 |
| R34 | 0.1083 | 0.1761 | 0.6748 |
| R37 | 0.0030 | 0.0010 | 0.9753 |
| R38 | -1.6009 | 5.9149 | 0.0150** |

Complete Model

| Statistic | Chi-square | Prob > Chi-square |
|---|---|---|
| Chi-square for covariates | 18.761 | 0.0655* |

TWO-VARIABLE LOGIT MODEL

Individual Variables

| Variable | Coefficient | Wald Chi-square | Prob > Chi-square |
|---|---|---|---|
| Intercept | -1.8177 | 77.3136 | 0.0001**** |
| R29 | 0.6630 | 3.4059 | 0.0650* |
| R38 | -1.7657 | 7.1023 | 0.0077 |

Complete Model

| Statistic | Chi-square | Prob > Chi-square |
|---|---|---|
| Chi-square for covariates | 10.887 | 0.0043*** |

* - Significant at 0.10 level
** - Significant at 0.05 level
*** - Significant at 0.005 level
**** - Significant at 0.0001 level

accuracies of the MDA and logit models. However, regardless of the methodology used to develop the models, the two-variable models outperformed the models comprised of all eleven variables. Consequently, the final cash-based model was chosen from among the two-variable models.

The choice between the two-variable MDA and logit models was a virtual toss-up. The logit model was slightly better at classifying the first holdout sample, but slightly worse with regard to the second holdout sample (i.e. that comprised of companies from all SIC groups). The classification accuracies for the two models were identical when the two holdout samples were combined into one. The overall classification accuracy of the development sample was used as a tie-breaker. Based on this criteria, the two-variable logit model was selected as the cash-based model to be used for the remainder of this study. The classification accuracies, Type I and Type II error rates for each model are presented in Figure 7.

The high overall classification accuracies of the models are misleading. Analysis of the Type I and Type II error rates indicates the models are quite efficient at identifying the nonfailed firms (i.e. Type II error rates between 0 and 3%). However, the models are very poor when it comes to classifying the failed firms. Type I error rates (i.e. the probability of misclassifying a failed firm) ranged from 91 to 100%. The models appear to be classifying almost all of the firms as nonfailed. This assignment strategy will naturally result in high overall classification accuracies given the

## FIGURE 7

## CLASSIFICATION ACCURACIES AND ERROR RATES FOR CASH-BASED MODELS

| | MODEL | | | |
|---|---|---|---|---|
| | 11-var. MDA | 2-var. MDA | 11-var. Logit | 2-var. Logit* |
| **DEVELOPMENT SAMPLE** | | | | |
| Overall accuracy | 90.07% | 90.07% | 90.52% | 90.29% |
| Overall error rate | 9.93% | 9.93% | 9.48% | 9.71% |
| Type I error rate | 95.35% | 97.67% | 95.35% | 100.00% |
| Type II error rate | 0.75% | 0.50% | 0.25% | 0.00% |
| **FIRST HOLDOUT SAMPLE** | | | | |
| Overall accuracy | 87.39% | 89.19% | 88.29% | 90.09% |
| Overall error rate | 12.61% | 10.81% | 11.71% | 9.91% |
| Type I error rate | 100.00% | 90.91% | 100.00% | 100.00% |
| Type II error rate | 3.00% | 2.00% | 2.00% | 0.00% |
| **SECOND HOLDOUT SAMPLE** | | | | |
| Overall accuracy | 88.29% | 90.99% | 88.29% | 90.09% |
| Overall error rate | 11.71% | 9.01% | 11.71% | 9.91% |
| Type I error rate | 100.00% | 90.91% | 100.00% | 100.00% |
| Type II error rate | 2.00% | 0.00% | 2.00% | 0.00% |

* - Two-variable logit model selected as final model for the test of the first and second hypotheses.

high proportion of nonfailed firms in the samples. The overall error rate may be attributed to the virtually absolute misclassification of the failed firms. In essence, the overall classification accuracy appears to be largely the result of chance. The next section describes the outcome of a binomial test of proportions to determine whether the accuracies are in fact better than would have been achieved with a random assignment strategy.

**BINOMIAL TEST OF PROPORTIONS**

Binomial tests of proportions were conducted on the cash-based model's ability to classify the original development sample and each of the two holdout samples. A normal approximation to the binomial distribution was appropriate due to the sample sizes, value of p (probability of being classified as nonfailed) and value of 1 - p (probability of being classified as failed) (Rosner, 1986). A one-tailed test was used to determine whether the overall error rate achieved by the model was significantly lower than would have been achieved using a naive model in which all firms are assigned to the nonfailed class.

The hypotheses for the binomial tests took the following form:

$H_{null}$: p is greater than or equal to p*

$H_{alt}$: p is less than p*

where:

p = observed overall error rate

p* = predicted overall error rate if all observations are assigned to the nonfailed group.

The decision rule was to reject $H_{null}$ if the observed number of incorrectly classified firms was less than the value calculated in the binomial test at the 0.05 level of significance. In addition, the actual critical alpha level was calculated.

In each case, the null hypothesis could not be rejected. The observed numbers of incorrect classifications were much higher than the calculated cutoff value. This outcome is not surprising given that the number of firms incorrectly classified in each of the three trials (development sample, holdout 1 and holdout 2) was exactly equal to the number of firms which would have been incorrectly classified if all firms were intentionally assigned to the nonfailed class. The critical alpha level with respect to the development sample was 0.50, and 0.49 with respect to each of the holdout samples. Based on these results, the first hypothesis cannot be rejected. The cash-flow-based model developed has no ability to distinguish between firms heading toward bankruptcy and those not proceeding toward bankruptcy.

**SUMMARY OF THE TEST OF THE FIRST HYPOTHESIS**

Four cash-based bankruptcy models were developed. Of these four, a two-variable logit model was selected for use in the test of the first and second hypotheses because it achieved a better level of classification accuracy than any of the other three models. The final model was subjected to a series of binomial tests of proportions to determine whether the model could classify firms in the development and holdout samples with greater accuracy than a naive model which simply assigned all firms to the nonfailed class. The final cash-based model failed these tests as no difference was found between the error rates of the cash-based and naive models. Consequently, the first hypothesis could not be rejected.

## TEST OF THE SECOND HYPOTHESIS

The test of the second hypothesis began with the replication of five accrual-based bankruptcy models: Beaver (1966); Altman (1968); Deakin (1972); Ohlson (1980); and Zavgren (1985). Classification accuracies and error rates were calculated and reported for the replications of these models. The classification accuracy of each model was compared to the cash-based model developed in the preceding section. Finally, Chi-square tests were conducted to determine whether differences between the overall, Type I, and Type II error rates exist between the cash-based model and each of the accrual-based models.

**REPLICATION OF ACCRUAL-BASED MODELS**

The five accrual-based studies listed above were replicated using the same data sets as in the first hypothesis. The replications used the same variables and methodologies as in the original accrual-based studies.

Data from the 443 firms in the development sample and the 111 firms in each of the holdout samples was used to develop and test the Beaver, Deakin and Ohlson models. Thirteen failed firms were excluded from the replication of the Altman model due to the unavailability of market value of equity data. Consequently, the Altman model replication used 433, 108 and 108 firms from the development and holdout samples, respectively. Market value of total equity for the remainder of the firms was calculated as the sum of the market value of common stock plus the liquidation value of preferred stock. Liquidation value of preferred stock was used as a surrogate for the market value of preferred stock which, in most cases, was unavailable. Bowman (1980) supports the use of accounting values as surrogates for market values, stating that his research "indicates that the accounting measure may be a very good surrogate for market value" (p. 253).

Five failed firms were excluded from the replication of Zavgren's study. These five firms had zero values for inventory. Consequently, the receivables/inventory ratio for these firms was undefined. The development and holdout samples respectively supplied 440, 109 and 109 firms for the replication of Zavgren's study.

The overall classification accuracies of the five accrual-based models, shown in Figure 8, were quite good, ranging between 87% to 94%. However, as with the cash-based model developed in the previous section, these results must be viewed in the context of the proportion of failed and nonfailed firms used in the study. Approximately 90% of the firms in the study were nonfailed. Consequently, a naive model classifying all firms as nonfailed would achieve results very similar to those attained by the accrual-based models.

Analysis of the Type I and Type II error rates for the accrual-based models indicates the models' inefficiencies at identifying failed firms, and effectiveness at identifying those firms which have not failed. No model was able to correctly classify greater than half of the failed firms. The models of Ohlson and Deakin, with Type I error rates of 53.49% and 62.79% respectively, performed better than the other models on the development sample. Each of the models misclassified all of the failed firms in both of the holdout samples. However, all of the accrual-based models were quite good at properly classifying the nonfailed firms. Type II error rates ranged from a low of 0.50% for Altman's model on the development sample to a high of 3.00% for Deakin's model on the second holdout sample.

## CHI-SQUARE TESTS OF CLASSIFICATION ACCURACIES

A series of Chi-square tests was conducted to determine whether differences exist in the overall accuracies, Type I,

## FIGURE 8

### CLASSIFICATION ACCURACIES AND ERROR RATES FOR CASH AND ACCRUAL-BASED MODELS

| | MODEL | | | |
|---|---|---|---|---|
| | Cash-based | Beaver (1966) | Altman (1968) | Deakin (1972) |
| **DEVELOPMENT SAMPLE** | | | | |
| Overall accuracy | 90.29% | 90.29% | 92.38% | 91.87% |
| Overall error rate | 9.71% | 9.71% | 7.62% | 8.13% |
| Type I error rate | 100.00% | 100.00% | 93.94% | 62.79% |
| Type II error rate | 0.00% | 0.00% | 0.50% | 2.25% |
| **FIRST HOLDOUT SAMPLE** | | | | |
| Overall accuracy | 90.09% | 90.09% | 91.67% | 89.19% |
| Overall error rate | 9.91% | 9.91% | 8.33% | 10.81% |
| Type I error rate | 100.00% | 100.00% | 100.00% | 100.00% |
| Type II error rate | 0.00% | 0.00% | 1.00% | 1.00% |
| **SECOND HOLDOUT SAMPLE** | | | | |
| Overall accuracy | 90.09% | 90.09% | 91.67% | 87.39% |
| Overall error rate | 9.91% | 9.91% | 8.33% | 12.61% |
| Type I error rate | 100.00% | 100.00% | 100.00% | 100.00% |
| Type II error rate | 0.00% | 0.00% | 1.00% | 3.00% |

**FIGURE 8 continued**

**CLASSIFICATION ACCURACIES AND ERROR RATES FOR CASH AND ACCRUAL-BASED MODELS**

| | MODEL | | |
|---|---|---|---|
| | Cash-based | Ohlson (1980) | Zavgren (1985) |
| **DEVELOPMENT SAMPLE** | | | |
| Overall accuracy | 90.29% | 93.68% | 91.82% |
| Overall error rate | 9.71% | 6.32% | 8.18% |
| Type I error rate | 100.00% | 53.49% | 87.50% |
| Type II error rate | 0.00% | 1.25% | 0.25% |
| **FIRST HOLDOUT SAMPLE** | | | |
| Overall accuracy | 90.09% | 89.19% | 90.83% |
| Overall error rate | 9.91% | 10.81% | 9.17% |
| Type I error rate | 100.00% | 100.00% | 100.00% |
| Type II error rate | 0.00% | 1.00% | 1.00% |
| **SECOND HOLDOUT SAMPLE** | | | |
| Overall accuracy | 90.09% | 88.29% | 90.83% |
| Overall error rate | 9.91% | 11.71% | 9.17% |
| Type I error rate | 100.00% | 100.00% | 100.00% |
| Type II error rate | 0.00% | 2.00% | 1.00% |

and Type II error rates between the cash-based model and each of the accrual-based models. Two-sided Chi-square tests were used to ascertain whether differences occur in either direction, i.e. whether a given model performs better or worse than the one to which it is compared. Separate tests were performed for the development sample and each of the holdout samples. The results of these Chi-square tests and the related levels of significance are presented in Figure 9.

The tests for differences in the overall accuracy of the models indicated that no significant differences exist between the accuracy of the cash-based model and that of any of the accrual-based models on either the development or holdout samples. Consequently, the second hypothesis cannot be rejected.

Only one accrual-based model, Ohlson's, came close to significantly outperforming the cash-based model on overall accuracy. Ohlson's model achieved better overall accuracy than the cash-based model on the development sample. However, the difference between the two models was not significant at the 0.05 level. In regard to the holdout samples, upon which the test of the second hypothesis is based, Ohlson's model slightly underperformed the cash-based model.

No differences at all were found between Type I error rates of the cash- and accrual-based models with respect to the holdout samples. Each of the models incorrectly classified all of the failed firms in both holdout samples. Three of the accrual-based models, those of Deakin, Ohlson and

FIGURE 9

RESULTS OF CHI-SQUARE TESTS FOR COMPARISON OF CASH- AND ACCRUAL-BASED MODELS

| | SAMPLE | | |
|---|---|---|---|
| | Development | Holdout #1 | Holdout #2 |
| **OVERALL ACCURACY** | | | |
| Cash vs. Beaver | | | |
| Chi-square | 0.0000 | 0.0000 | 0.0000 |
| Significant at | > 0.9999 | > 0.9999 | > 0.9999 |
| Cash vs. Altman | | | |
| Chi-square | 1.2018 | 0.1640 | 0.1640 |
| Significant at | 0.2840 | 0.7043 | 0.7043 |
| Cash vs. Deakin | | | |
| Chi-square | 0.6810 | 0.0485 | 0.4057 |
| Significant at | 0.4336 | 0.8466 | 0.5316 |
| Cash vs. Ohlson | | | |
| Chi-square | 3.4451 | 0.0485 | 0.1869 |
| Significant at | 0.0675 | 0.8466 | 0.6879 |
| Cash vs. Zavgren | | | |
| Chi-square | 0.6343 | 0.0345 | 0.0345 |
| Significant at | 0.4470 | 0.8728 | 0.8728 |
| **TYPE I ERRORS** | | | |
| Cash vs. Beaver | | | |
| Chi-square | 0.0000** | 0.0000** | 0.0000** |
| Significant at | > 0.9999 | > 0.9999 | > 0.9999 |
| Cash vs. Altman | | | |
| Chi-square | 2.6765 | 0.0000** | 0.0000** |
| Significant at | 0.1036 | > 0.9999 | > 0.9999 |
| Cash vs. Deakin | | | |
| Chi-square | 19.6571 | 0.0000** | 0.0000** |
| Significant at | < 0.0010* | > 0.9999 | > 0.9999 |
| Cash vs. Ohlson | | | |
| Chi-square | 26.0606 | 0.0000** | 0.0000** |
| Significant at | < 0.0010* | > 0.9999 | > 0.9999 |
| Cash vs. Zavgren | | | |
| Chi-square | 5.7196 | 0.0000** | 0.0000** |
| Significant at | 0.0185* | > 0.9999 | > 0.9999 |

(see notes on next page)

**FIGURE 9 continued**

**RESULTS OF CHI-SQUARE TESTS FOR COMPARISON OF CASH- AND ACCRUAL-BASED MODELS**

| | SAMPLE | | |
|---|---|---|---|
| | Development | Holdout #1 | Holdout #2 |
| **TYPE II ERRORS** | | | |
| Cash vs. Beaver | | | |
| Chi-square | 0.0000** | 0.0000** | 0.0000** |
| Significant at | > 0.9999 | > 0.9999 | > 0.9999 |
| Cash vs. Altman | | | |
| Chi-square | 2.0050 | 1.0050 | 1.0050 |
| Significant at | 0.1761 | 0.3405 | 0.3405 |
| Cash vs. Deakin | | | |
| Chi-square | 9.1024 | 1.0050 | 3.0457 |
| Significant at | 0.0033* | 0.3405 | 0.0851 |
| Cash vs. Ohlson | | | |
| Chi-square | 5.0314 | 1.0050 | 2.0202 |
| Significant at | 0.0249* | 0.3405 | 0.1744 |
| Cash vs. Zavgren | | | |
| Chi-square | 1.0013 | 1.0050 | 1.0050 |
| Significant at | 0.3416 | 0.3405 | 0.3405 |

* - Significant at 0.05 level or better.

** - Value of Chi-square is undefined due to zero values in both the numerator and denominator of the Chi-square formula. In this case, the value of Chi-square may be defined as zero (Conover, p. 149).

Zavgren, significantly outperformed the cash-based model on the development sample. The success of these models on the development sample, along with their failure with regard to the holdout samples, seems to indicate that the models' abilities to identify failed firms do not generalize well to samples other than those from which the models were developed.

As with the Type I errors, no significant differences were found in Type II error rates of the holdout samples in the comparisons between the cash- and accrual-based models. On the development sample, the cash-based model significantly outperformed the Deakin and Ohlson models. However, the differences in the Type II error rates between the cash-based model and the other three accrual-based models were insignificant.

**SUMMARY OF THE TEST OF THE SECOND HYPOTHESIS**

The bankruptcy models of Beaver, Altman, Deakin, Ohlson and Zavgren were replicated using the models' original variables and methodologies, but with coefficients re-estimated with the data used to develop the cash-based model in the test of the first hypothesis. (See Appendix A for an analysis of the models' effectiveness when the original coefficients are applied to the present study's more recent data). Overall accuracy, and overall, Type I and Type II error rates were calculated and reported for these models. The efficacy of each of the accrual-based models was compared to the cash-based model. Comparisons were made of overall classification accuracy and Type I and Type II errors. Chi-square tests were used to determine if significant differences in these measures exist between the cash- and accrual-based models. The test results indicated that no significant differences exist between the abilities of the cash- and accrual-based models to classify the holdout samples. Consequently, the second hypothesis could not be rejected.

## TEST OF THE THIRD HYPOTHESIS

The test of the third hypothesis began with four principal components analyses. Each of the analyses included the forty ratios used to develop the cash-based model and the variables from one of the four multivariate accrual-based models: Altman (1968); Deakin (1972); Ohlson (1980); and Zavgren (1985). The results of the principal components analyses were used to identify intercorrelations between the accrual- and cash-based variables. This information was then used to develop modified versions of the accrual-based models. The best-performing modified version of each model was compared to the original version. Chi-square tests were conducted to determine whether significant differences between the overall, Type I, and Type II error rates exist between the original and modified versions of each of the four models.

### MODIFICATION OF ALTMAN'S MODEL

The principal component analysis of Altman's variables and the cash-based ratios resulted in twelve interpretable components. Figure 10 presents the composition of these components. Ten of these components corresponded to components identified in the analysis of the forty cash-based ratios. These components represent magnitude of cash flow from operations, cash position, ability to raise outside funding, magnitude of investing activities, ability to service debt, change in size of asset base, magnitude of cash flow from financing activities, self-cannibalization, replacement rate of inventory and debt-position. One component previously identified in the analysis of the forty cash-based ratios, magnitude of cash flow from operations relative to assets and liabilities, did not appear in the current analysis.

Two new components were identified. Component six measures return on assets. Two of Altman's ratios load heavily on this component. A3 relates current earnings before interest and taxes to total assets. A2 is similar except that it relates cumulative (retained) earnings to total assets. The other new component, number eight, represents asset turnover. Two ratios, A5 (Sales/total assets) and R5 (Cash from sales/average total assets), load heavily on this component. A5 relates sales to total assets. R5 is the cash-based equivalent of A5, relating cash from sales to average total assets.

Four of Altman's five ratios loaded heavily on the components. Only A1 (working capital/total assets), did not load heavily. A2 (Retained earnings/total assets) and A3 (Earnings before interest and taxes/total assets) constituted

## FIGURE 10

### COMPONENT LOADINGS: ALTMAN'S AND CASH-BASED RATIOS

| RATIO | COMP 1 | COMP 2 | COMP 3 | COMP 4 | COMP 5 | (*) COMP 6 |
|---|---|---|---|---|---|---|
| R7 | 0.9992 | | | | | |
| R6 | 0.9988 | | | | | |
| R36 | 0.9975 | | | | | |
| R23 | 0.9971 | | | | | |
| R39 | | 0.9461 | | | | |
| R38 | | 0.9426 | | | | |
| R40 | | 0.8742 | | | | |
| A4** | | 0.7691 | | | | |
| R18 | | | 0.9618 | | | |
| R20 | | | 0.9485 | | | |
| R31 | | | 0.9448 | | | |
| R24 | | | 0.9396 | | | |
| R22 | | | | 0.9300 | | |
| R21 | | | | 0.9228 | | |
| R30 | | | | 0.8851 | | |
| R27 | | | | 0.8339 | | |
| R11 | | | | | 0.9080 | |
| R13 | | | | | 0.8734 | |
| R12 | | | | | 0.7744 | |
| A3** | | | | | | 0.8449 |
| A2** | | | | | | 0.8021 |

| RATIO | COMP 7 | (*) COMP 8 | COMP 9 | COMP 10 | COMP 11 | COMP 12 |
|---|---|---|---|---|---|---|
| R34 | 0.8498 | | | | | |
| R33 | 0.8004 | | | | | |
| R25 | -0.8829 | | | | | |
| A5** | | 0.9598 | | | | |
| R5 | | 0.9592 | | | | |
| R37 | | | 0.9355 | | | |
| R17 | | | 0.9340 | | | |
| R32 | | | | 0.8294 | | |
| R29 | | | | 0.8204 | | |
| R26 | | | | | 0.8873 | |
| R1** | | | | | -0.7410 | |
| R19 | | | | | | 0.8121 |

* - New component not previously identified in analysis of cash-based ratios.

** - Ratio added to component previously identified in analysis of cash-based ratios.

the new return on assets ratio. Not surprisingly, these two ratios exhibited a moderate level of intercorrelation (0.57726). Ratio A4 (market value of equity/total debt), loaded heavily on the cash position component. There is no intuitive reason for this loading, and it may just be a statistical anomaly. Altman's final ratio, A5 (Sales/total assets) is the heaviest loading ratio on the new asset turnover component.

Several modifications to Altman's model were developed. These modifications focused on combining Altman's original variables with cash-based ratios to derive models which had better classification accuracy than Altman's original model. At the same time, attention was given to selecting a set of variables which would not present any multicollinearity problems. The most improved version of Altman's model retained A3 (Earnings before interest and taxes/total assets) and A4 (Market value of equity/total debt) and added a single cash-based ratio, R22 [(Incr. in invest. + cap. exp. + acquis. + other inv. uses)/CFFI]. Figure 11 details the coefficients, significance statistics and correlation matrix for this model.

**MODIFICATION OF DEAKIN'S MODEL**

The addition of Deakin's fourteen ratios to the forty cash-based ratios resulted in the emergence of four new components: liquidity of sales; debt to assets; asset liquidity; and proportion of interest paid. In addition, one of the components identified by the principal components analysis of the cash-based ratios disappeared. The component for the replacement rate of inventory disappeared as the ratio which defined the component, R26 (Cash paid for inventory/cost of goods sold), no longer achieved the required loading of 0.70. Figure 12 presents the component loadings of the heavily loading variables.

Component two is a new component gauging the level of liquid assets or cash flow from operations to sales. Three of Deakin's ratios, D11 (Current assets/sales), D12 (Quick assets/sales) and D14 (Cash/sales), load heavily on this component. These three ratios relate cash, quick- and current assets to sales. One cash-based ratio, R1 (CFFO/sales), also loads heavily on this component.

The ninth component is a measure of debt to assets and is composed entirely of ratios from Deakin's model. D6 (Working capital/total assets) loads positively while D3 (Total debt/total assets) loads negatively. This inverse relationship is easily understood by examining the numerator of D6. If current liabilities exceed current assets, D6 will have a negative value and will essentially be relating excess current liabilities to total assets. Therefore, a negative value for D6 carries the same connotation as a positive value for D3. Alternately, if current assets exceed current liabilities, D6 is positive and relates excess current assets to total assets. This "asset" to total assets ratio would be inversely related to D3's debt to asset measure.

One ratio loads heavily on component twelve, a new

FIGURE 11

COEFFICIENTS, SIGNIFICANCE STATISTICS
AND CORRELATION MATRIX FOR MODIFIED ALTMAN MODEL

## COEFFICIENTS AND SIGNIFICANCE STATISTICS

| Individual Variables | | | |
|---|---|---|---|
| Variable | Coefficient | F-test | Prob > F |
| A3 | 0.9651 | 3.8362 | 0.0508* |
| A4 | 0.0688 | 5.2375 | 0.0226** |
| R22 | 0.1363 | 9.7873 | 0.0019*** |

| Complete Model | | |
|---|---|---|
| Statistic | F-test | Prob > F |
| Wilks' Lambda | 6.2638 | 0.0004**** |

* - Significant at 0.10 level
** - Significant at 0.05 level
*** - Significant at 0.005 level
**** - Significant at 0.0005 level

## CORRELATION MATRIX

| | A3 | A4 | R22 |
|---|---|---|---|
| A3 | 1.00000 | -0.04846 | 0.01332 |
| A4 | | 1.00000 | 0.02042 |
| R22 | | | 1.00000 |

# FIGURE 12

## COMPONENT LOADINGS: DEAKIN'S AND CASH-BASED RATIOS

| RATIO | COMP 1 | (*) COMP 2 | COMP 3 | COMP 4 | COMP 5 |
|---|---|---|---|---|---|
| R38@ | 0.9582 | | | | |
| D10@** | 0.9582 | | | | |
| D9** | 0.9243 | | | | |
| R39 | 0.9170 | | | | |
| R40# | 0.8971 | | | | |
| D7#** | 0.8971 | | | | |
| D8** | 0.8074 | | | | |
| D11 | | 0.8871 | | | |
| D12 | | 0.8537 | | | |
| D14 | | 0.8176 | | | |
| R1 | | -0.8864 | | | |
| R7 | | | 0.9991 | | |
| R6 | | | 0.9984 | | |
| R36 | | | 0.9973 | | |
| R23 | | | 0.9969 | | |
| R18 | | | | 0.9588 | |
| R20 | | | | 0.9472 | |
| R31 | | | | 0.9410 | |
| R24 | | | | 0.9369 | |
| R22 | | | | | 0.9388 |
| R21 | | | | | 0.9312 |
| R30 | | | | | 0.9023 |
| R27 | | | | | 0.8579 |

| RATIO | COMP 6 | COMP 7 | COMP 8 | (*) COMP 9 | COMP 10 |
|---|---|---|---|---|---|
| R10 | 0.8357 | | | | |
| R4 | 0.7885 | | | | |
| D1** | 0.7763 | | | | |
| R13 | | 0.8940 | | | |
| R11 | | 0.8825 | | | |
| R12 | | 0.7938 | | | |
| R34 | | | 0.8566 | | |
| R33 | | | 0.8026 | | |
| R25 | | | -0.8950 | | |
| D6 | | | | 0.7675 | |
| D3 | | | | -0.7589 | |
| R29 | | | | | 0.8542 |
| R32 | | | | | 0.8428 |

(see notes on next page)

**FIGURE 12 continued**

**COMPONENT LOADINGS: DEAKIN'S AND CASH-BASED RATIOS**

| RATIO | COMP 11 | (*) COMP 12 | COMP 13 | (*) COMP 14 |
|---|---|---|---|---|
| R17 | 0.9347 | | | |
| R37 | 0.9336 | | | |
| D4 | | 0.7346 | | |
| R14 | | | 0.7605 | |
| R19 | | | 0.7383 | |
| R9 | | | | 0.9472 |

* - New component not previously identified in analysis of cash-based ratios.
** - Ratio added to component previously identified in analysis of cash-based ratios.
@ - Ratios R38 and D10 are identical.
\# - Ratios R40 and D7 are identical.

component measuring asset liquidity. D4 relates current assets to total assets. Intuitively, it seems as though this ratio should belong in component nine, described in the previous paragraph. While D4 loads on a separate component, it has, as may be expected, a positive correlation (0.54424) with D6 (Working capital/total assets) and a slightly negative correlation (-0.14356) with D3 (Total debt/total assets).

Component fourteen is the final new component to emerge. This component, comprising one heavily loading variable, R9 (Cash paid for interest/interest expense), is the proportion of accrual-based interest expense actually paid in cash during the year. This component is the only new component which does not include any of Deakin's ratios.

Three of Deakin's ratios, D2 (Net income/total assets), D5 (Quick assets/total assets), and D13 (Working capital/sales), did not load heavily on any factor. More significantly, each of Deakin's fourteen ratios was found to be intercorrelated at a level exceeding 0.50 with at least one of the other variables in his model. In some cases, individual variables were found to be moderately to highly intercorrelated with as many as five to seven of his other variables. Further evidence of this intercorrelation is provided by the principal components analysis which resulted in several of Deakin's ratios loading on the same factors. This finding raises immediate questions about the possibility of multicollinearity problems in Deakin's original study.

Deakin's model proved difficult to modify because of the number of variables involved. Various attempts were made to improve the model. The attempts centered on various combinations of the ratios which loaded highly on the components or which the models' significance statistics indicated to be meaningful. These trials frequently resulted in models which contained ratios intercorrelated at a level of 0.50 or above and which produced little, if any, improvement over the classification accuracy of the original model. One bright spot did appear in these early attempts - the addition of cash-based variables resulted in a slight improvement to the model's ability to classify the failed firms in the holdout sample.

Attention shifted to selecting a variable set which would not contain any correlations greater than 0.40 among the variables. This approach resulted in a five-variable model which did show some improvement over Deakin's original model and also avoided the original model's multicollinearity problems. The altered version retains four of Deakin's original ratios: D1 ("Cash flow"/total debt), D3 (Total debt/total assets), D4 (Current assets/total assets) and D10 (Cash/current liabilities). A cash-based ratio representing self-cannibalization, R29 [(Proc. from sale of PP&E + other invest. sources)/average PP&E], was included in this final modified version. Details of this model are shown in Figure 13. As the correlation matrix reveals, bi-variate correlations are low to moderate among the variables selected for this model.

**MODIFICATION OF OHLSON'S MODEL**

Twelve components were identified by the principal components analysis conducted on the forty cash-based ratios and Ohlson's nine variables. These twelve components represent the eleven identified among the cash-based ratios and one new component representing a debt/asset measure.

Component five, the debt to asset component, is composed entirely of ratios from Ohlson's model. O2 (Total liabilities/total assets) and O4 (Current liabilities/current assets) are direct measures of debt levels to assets. O3 (Working capital/total assets), loading negatively on the component, relates working capital to total assets. This ratio is an indirect measure of debt to assets as working

# FIGURE 13

## COEFFICIENTS, SIGNIFICANCE STATISTICS AND CORRELATION MATRIX FOR MODIFIED DEAKIN MODEL

### COEFFICIENTS AND SIGNIFICANCE STATISTICS

| Individual Variables | | | |
|---|---|---|---|
| Variable | Coefficient | F-test | Prob > F |
| D1 | 0.2034 | 5.9349 | 0.0152* |
| D3 | 3.3100 | 102.2599 | 0.0001*** |
| D4 | -0.8287 | 7.9910 | 0.0049** |
| D10 | 0.1693 | 6.4445 | 0.0115* |
| R29 | 0.5042 | 5.0969 | 0.0245* |

| Complete Model | | |
|---|---|---|
| Statistic | F-test | Prob > F |
| Wilks' Lambda | 21.8874 | 0.0001*** |

* - Significant at 0.05 level
** - Significant at 0.005 level
*** - Significant at 0.0001 level

### CORRELATION MATRIX

| | D1 | D3 | D4 | D10 | R29 |
|---|---|---|---|---|---|
| D1 | 1.00000 | -0.26920 | -0.06521 | -0.14616 | -0.05846 |
| D3 | | 1.00000 | -0.14356 | -0.39969 | 0.09150 |
| D4 | | | 1.00000 | 0.24787 | -0.00308 |
| D10 | | | | 1.00000 | -0.03056 |
| R29 | | | | | 1.00000 |

capital is a function of current liabilities. The other ratio loading on this component, O7, is a measure of change in income over the previous year. There is no clear intuitive reason why O7 loads on this component. O7's loading may just be a statistical anomaly. The results of the principal components analysis are reported in Figure 14.

One of the remaining five variables from Ohlson's model, O6 (Funds provided by operations/total liabilities), loaded on the component representing the magnitude of cash-flows from operations relative to assets and liabilities. The remaining four variables, O1 [log(total assets/GNP price-level index), O5 (Net income/total assets), O8 (Dummy variable for negative equity) and O9 (Dummy variable for two years of negative net income), did not load heavily on any component.

The fact that four ratios from Ohlson's model loaded on the same component suggests that some multicollinearity problem may have existed in his original study. Care was taken in the attempts to modify the Ohlson model in order to minimize multicollinearity. Numerous attempts were made to improve on Ohlson's model using both stepwise procedures and forced-entry of selected variables. As with the modification of Deakin's model, the best combination of variables was one which focused on eliminating variables which were highly correlated. The modification which resulted in the most improvement in classification accuracy was composed entirely of variables from Ohlson's original model. No improvement could be gained by adding cash-based variables.

## FIGURE 14

### COMPONENT LOADINGS: OHLSON'S AND CASH-BASED RATIOS

| RATIO | COMP 1 | COMP 2 | COMP 3 | COMP 4 | (*) COMP 5 | COMP 6 |
|---|---|---|---|---|---|---|
| R7 | 0.9990 | | | | | |
| R6 | 0.9983 | | | | | |
| R36 | 0.9972 | | | | | |
| R23 | 0.9969 | | | | | |
| R10 | | 0.8484 | | | | |
| R4 | | 0.8446 | | | | |
| O6** | | 0.8269 | | | | |
| R18 | | | 0.9589 | | | |
| R20 | | | 0.9462 | | | |
| R31 | | | 0.9417 | | | |
| R24 | | | 0.9376 | | | |
| R22 | | | | 0.9378 | | |
| R21 | | | | 0.9299 | | |
| R30 | | | | 0.9029 | | |
| R27 | | | | 0.8582 | | |
| O2 | | | | | 0.8360 | |
| O4 | | | | | 0.7903 | |
| O7 | | | | | 0.7372 | |
| O3 | | | | | -0.8345 | |
| R38 | | | | | | 0.9299 |
| R39 | | | | | | 0.9200 |
| R40 | | | | | | 0.8671 |

| RATIO | COMP 7 | COMP 8 | COMP 9 | COMP 10 | COMP 11 | COMP 12 |
|---|---|---|---|---|---|---|
| R11 | 0.8925 | | | | | |
| R12 | 0.8889 | | | | | |
| R13 | 0.7899 | | | | | |
| R34 | | 0.8550 | | | | |
| R33 | | 0.8059 | | | | |
| R25 | | -0.8938 | | | | |
| R29 | | | 0.8399 | | | |
| R32 | | | 0.8294 | | | |
| R37 | | | | 0.9346 | | |
| R17 | | | | 0.9336 | | |
| R26 | | | | | 0.8824 | |
| R19 | | | | | | 0.8101 |

* - New component not previously identified in analysis of cash-based ratios.

** - Ratio added to component previously identified in analysis of cash-based ratios.

# FIGURE 15

## COEFFICIENTS, SIGNIFICANCE STATISTICS AND CORRELATION MATRIX FOR OHLSON'S MODIFIED MODEL

### COEFFICIENTS AND SIGNIFICANCE STATISTICS

| Individual Variables | | | |
|---|---|---|---|
| Variable | Coefficient | Wald Chi-square | Prob > Chi-square |
| Intercept | -3.0081 | 100.5359 | 0.0001** |
| O1 | 0.8986 | 18.6262 | 0.0001** |
| O5 | 0.2197 | 0.3877 | 0.5335 |
| O7 | 2.4285 | 23.3037 | 0.0001** |
| O8 | 1.5936 | 12.6293 | 0.0004* |
| O9 | -1.5135 | 16.1453 | 0.0001** |

| Complete Model | | |
|---|---|---|
| Statistic | Chi-square | Prob > Chi-square |
| Chi-square for covariates | 91.253 | 0.0001** |

* - Significant at 0.0005 level
** - Significant at 0.0001 level

### CORRELATION MATRIX

| | O1 | O5 | O7 | O8 | O9 |
|---|---|---|---|---|---|
| O1 | 1.00000 | 0.28426 | -0.07606 | -0.37555 | 0.02926 |
| O5 | | 1.00000 | -0.34538 | -0.37135 | 0.22129 |
| O7 | | | 1.00000 | 0.25407 | -0.06535 |
| O8 | | | | 1.00000 | 0.00421 |
| O9 | | | | | 1.00000 |

However, some improvement was gained by reducing the number of variables in the model. O2 (Total liab./total assets), O3 (Working capital/total assets), O4 (Cur. liab./cur. assets) and O6 (Funds provided by operations/total liab.) were dropped from the model, leaving O1 (Total liab./Total assets), O5 (Net income/total assets), O7 (Measure of change in net income), O8 (Dummy variable for negative equity) and O9 (Dummy variable for two years of negative net income). The coefficients, significance statistics and correlation matrix for the modified model are presented in Figure 15. It should be noted that four of the five variables retained in the model did not load heavily on any of the components. This suggests these four variables may contain unique information not contained in the variables which did load heavily.

**MODIFICATION OF ZAVGREN'S MODEL**

Principal components analysis of Zavgren's seven ratios and the forty cash-based ratios yielded fourteen interpretable components. As shown in Figure 16, three of these components are the result of the addition of Zavgren's ratios to the analysis. The remaining eleven components were identified in the analysis of the cash-based ratios by themselves.

The first new component in this analysis, component eleven, measures asset turnover. Z2 (Total income/total capital) and R5 (Cash from sales/average total assets), load heavily on this component. This component coincides with the "capital turnover" ratio identified by Pinches, et al (1973).

**FIGURE 16**

**COMPONENT LOADINGS: ZAVGREN'S AND CASH-BASED RATIOS**

| RATIO | COMP 1 | COMP 2 | COMP 3 | COMP 4 | COMP 5 |
|---|---|---|---|---|---|
| R38 | 0.9646 | | | | |
| R39 | 0.9294 | | | | |
| Z7@** | 0.9254 | | | | |
| R40@ | 0.9254 | | | | |
| Z6** | 0.9150 | | | | |
| R7 | | 0.9991 | | | |
| R6 | | 0.9984 | | | |
| R36 | | 0.9973 | | | |
| R23 | | 0.9971 | | | |
| R18 | | | 0.9611 | | |
| R20 | | | 0.9481 | | |
| R31 | | | 0.9424 | | |
| R24 | | | 0.9378 | | |
| R22 | | | | 0.9384 | |
| R21 | | | | 0.9308 | |
| R30 | | | | 0.9021 | |
| R27 | | | | 0.8570 | |
| R13 | | | | | 0.8990 |
| R11 | | | | | 0.8890 |
| R12 | | | | | 0.7892 |

| RATIO | COMP 6 | COMP 7 | COMP 8 | COMP 9 | COMP 10 |
|---|---|---|---|---|---|
| R34 | 0.8597 | | | | |
| R33 | 0.7858 | | | | |
| R25 | -0.9059 | | | | |
| R10 | | 0.8587 | | | |
| R4 | | 0.8404 | | | |
| Z3** | | | 0.8016 | | |
| R26 | | | 0.7963 | | |
| R1 | | | -0.8446 | | |
| R29 | | | | 0.8588 | |
| R32 | | | | 0.8504 | |
| R37 | | | | | 0.9352 |
| R17 | | | | | 0.9340 |

(see notes on next page)

FIGURE 16 continued

COMPONENT LOADINGS: ZAVGREN'S AND CASH-BASED RATIOS

| RATIO | (*) COMP 11 | (*) COMP 12 | COMP 13 | (*) COMP 14 |
|---|---|---|---|---|
| Z2 | 0.7980 | | | |
| R5 | 0.7464 | | | |
| Z4 | | 0.8482 | | |
| Z1 | | -0.8463 | | |
| R19 | | | 0.8005 | |
| R14 | | | 0.7591 | |
| Z5 | | | | 0.7205 |

* - New component not previously identified in analysis of cash-based ratios.

** - Ratio added to component previously identified in analysis of cash-based ratios.

@ - Ratios Z7 and R40 are identical.

Component twelve is the second newly identified component. This component is composed of ratios Z4 (Debt/total capital) and Z1 (Total income/total capital). Z4 is a financial leverage ratio comparing debt to capital. Z1 represents return on investment, relating income to capital. Pinches, et al. identified the financial leverage and return on investment factors in their 1973 factor-analytic study. In their 1975 follow-up study on higher order factors, Pinches, et al. defined the combination of these two factors as representative of return on invested capital. The twelfth component in this study is given the same interpretation.

The final component in this study is composed of one heavily loading ratio, Z5 (Receivables/inventory). This ratio defines the component as a measure of receivable turnover. The receivable to inventory ratio was also the highest loading ratio on the "receivables turnover" factor identified by Pinches, et al. (1973).

The seven ratios used in Zavgren's model were selected because they had the highest loadings on each of the seven factors identified by Pinches, et al. in their 1973 study. Zavgren contended that since the ratios loaded on separate factors, there would be little correlation between the ratios. The current study, for the most part, confirms the lack of correlation. Each of Zavgren's seven ratios loaded heavily on some component. However, the seven ratios were spread out among five of the components. Three of the ratios loaded on separate components. Two pairs of ratios, Z1 (Total income/total capital) and Z4 (Debt/total capital); and Z6 (Quick assets/cur. liab.) and Z7 (Cash/total assets), showed moderate to high intercorrelations. As might be expected, each of these pairs of ratios loaded on the same component.

Coaxing any improvement out of Zavgren's model was nearly impossible. As with all of the models in this study, proper classification of the failed firms proved to be an elusive goal. Only one version of the model could be found which could accurately classify even one of the failed firms in the holdout samples. However, the cost of being able to properly classify one failed firm turned out to be an increase in the number of nonfailed firms misclassified, resulting in a lower overall classification accuracy.

A two-variable model was finally selected as the modified version of Zavgren's model to be used in the test of the third hypothesis. The two variables composing the model are Z6 (Quick assets/cur. liab.) and R29 [(Proc. from sale of PP&E + other invest. sources)/average PP&E). This model, the details of which are shown in Figure 17, achieves a slightly higher overall classification accuracy than the original model. In addition, it offers the simplicity of a two-variable model over one with seven variables.

**SUMMARY OF THE MODIFICATION OF THE ACCRUAL-BASED MODELS**

Numerous variations of the bankruptcy prediction models of Altman, Deakin, Ohlson and Zavgren were developed. The variants were generated by systematically selecting different combinations of each model's original variables and the cash-based ratios developed for this study. Models using the selected variables were then fitted using the same modelling technique used in the original model, i.e. MDA or logit.

The results of the modifications of the four accrual-based models proved to be disappointing. The modifications to the models improved the overall classification accuracies with respect to the holdout samples in each case but one (Zavgren's model on the second holdout sample). However, as Figure 18 indicates, the improvements were minor. Ohlson's model showed the most improvement, with one additional firm properly

FIGURE 17

**COEFFICIENTS, SIGNIFICANCE STATISTICS AND CORRELATION MATRIX FOR ZAVGREN'S MODIFIED MODEL**

## COEFFICIENTS AND SIGNIFICANCE STATISTICS

Individual Variables

| Variable | Coefficient | Wald Chi-square | Prob > Chi-square |
|---|---|---|---|
| Intercept | -0.8485 | 7.3685 | 0.0066** |
| Z6 | -1.8576 | 19.1116 | 0.0001*** |
| R29 | 0.6533 | 2.9585 | 0.0854* |

Complete Model

| Statistic | Chi-square | Prob > Chi-square |
|---|---|---|
| Chi-square for covariates | 19.720 | 0.0001*** |

* - Significant at 0.10 level
** - Significant at 0.01 level
*** - Significant at 0.0001 level

## CORRELATION MATRIX

| | Z6 | R29 |
|---|---|---|
| Z6 | 1.00000 | -0.03817 |
| R29 | | 1.00000 |

classified on the first holdout sample and three additional firms in the second holdout sample properly classified. The modified versions of Altman's, Deakin's and Zavgren's models each showed an improvement of one additional firm properly classified on the first holdout sample and one, two and zero firms, respectively, on the second holdout sample.

A particular weakness of all of the models in this study, cash-based and accrual alike, has been the inability of the models to properly classify the failed firms. As previously reported in the test of the second hypothesis, the cash-based model and the five accrual-based models were unable to properly classify any of the failed firms in the holdout samples. This situation improved somewhat with the modification of the accrual-based models. The modified versions of Deakin's and Ohlson's models did properly classify one and two failed firms, respectively, in each of the holdout samples. This improvement is not spectacular by any means, but the proper classification of at least some of the failed firms is a moral victory if nothing else. No improvements in the Type I error rates could be coaxed from modifying the Altman or Zavgren models.

Reduction in the Type II error rates also met with little success. Altman's model improved from one misclassification of a nonfailed firm to zero in each of the holdout samples. The modified versions of Deakin's and Ohlson's models each had one fewer misclassification of nonfailed firms on the second holdout sample. Deakin's modification showed no improvement

FIGURE 18

CLASSIFICATION ACCURACIES AND ERROR RATES FOR ORIGINAL AND MODIFIED ACCRUAL-BASED MODELS

| | MODEL - ORIGINAL (MODIFIED) | | | |
|---|---|---|---|---|
| | ALTMAN | DEAKIN | OHLSON | ZAVGREN |
| **DEVELOPMENT SAMPLE** | | | | |
| Overall accuracy | 92.38% (92.38%) | 91.87% (91.42%) | 93.68% (91.65%) | 91.82% (91.14%) |
| Overall error rate | 7.62% (7.62%) | 8.13% (8.58%) | 6.32% (8.35%) | 8.18% (8.76%) |
| Type I error rate | 93.94% (96.97%) | 62.79% (72.09%) | 53.49% (76.74%) | 87.50% (97.50%) |
| Type II error rate | 0.50% (0.25%) | 2.25% (1.75%) | 1.25% (1.00%) | 0.25% (0.00%) |
| **FIRST HOLDOUT SAMPLE** | | | | |
| Overall accuracy | 91.67% (92.59%) | 89.19% (90.09%) | 89.19% (90.09%) | 90.83% (91.74%) |
| Overall error rate | 8.33% (7.41%) | 10.81% (9.91%) | 10.81% (9.91%) | 9.17% (8.26%) |
| Type I error rate | 100.00% (100.00%) | 100.00% (90.91%) | 100.00% (81.82%) | 100.00% (100.00%) |
| Type II error rate | 1.00% (0.00%) | 1.00% (1.00%) | 1.00% (2.00%) | 1.00% (0.00%) |
| **SECOND HOLDOUT SAMPLE** | | | | |
| Overall accuracy | 91.67% (92.59%) | 87.39% (89.19%) | 88.29% (90.99%) | 90.83% (90.83%) |
| Overall error rate | 8.33% (7.41%) | 12.61% (10.81%) | 11.71% (9.01%) | 9.17% (9.17%) |
| Type I error rate | 100.00% (100.00%) | 100.00% (90.91%) | 100.00% (81.82%) | 100.00% (100.00%) |
| Type II error rate | 1.00% (0.00%) | 3.00% (2.00%) | 2.00% (1.00%) | 1.00% (1.00%) |

on the first holdout sample and the modified Ohlson model actually had one additional misclassification on the first holdout sample. The modified version of Zavgren's model achieved one fewer misclassification on the first holdout sample but showed no improvement on the second holdout sample. The next section reports the results of Chi-square tests conducted to determine whether the improvements obtained by modifying the four models are statistically significant.

## CHI-SQUARE TESTS OF CLASSIFICATION ACCURACIES

The four pairs of original and modified models were subjected to two-sided Chi-square tests to determine whether statistically significant differences existed within the classification accuracies of each pair. Separate analyses were performed on the models' abilities to classify all firms, the failed firms, and the nonfailed firms in the development, first holdout and second holdout samples. The results of these Chi-square tests and the related levels of significance are reported in Figure 19.

The tests for differences in the overall classification accuracy of the models indicated that no statistically significant differences exist between the accuracy of any of the original accrual-based models and its modified version. These results were consistent across the development and both holdout samples. Based on these results, the third hypothesis cannot be rejected. The addition or substitution of cash-based ratios into this set of existing accrual-based models

## FIGURE 19

## RESULTS OF CHI-SQUARE TESTS FOR COMPARISON OF ORIGINAL AND MODIFIED ACCRUAL-BASED MODELS

| | SAMPLE | | |
|---|---|---|---|
| | Development | Holdout #1 | Holdout #2 |
| **OVERALL ACCURACY** | | | |
| Altman vs. M-Alt. | | | |
| Chi-square | 0.0000 | 0.0638 | 0.0638 |
| Significant at | > 0.9999 | 0.8179 | 0.8179 |
| Deakin vs. M-Deak. | | | |
| Chi-square | 0.0590 | 0.0485 | 0.1743 |
| Significant at | 0.8269 | 0.8466 | 0.6969 |
| Ohlson vs. M-Ohlson | | | |
| Chi-square | 1.3448 | 0.0485 | 0.4365 |
| Significant at | 0.2473 | 0.8466 | 0.5096 |
| Zavgren vs. M-Zav. | | | |
| Chi-square | 0.1312 | 0.0577 | 0.0000 |
| Significant at | 0.7277 | 0.8293 | > 0.9999 |
| **TYPE I ERRORS** | | | |
| Altman vs. M-Alt. | | | |
| Chi-square | 0.3492 | 0.0000*** | 0.0000*** |
| Significant at | 0.5720 | > 0.9999 | > 0.9999 |
| Deakin vs. M-Deak. | | | |
| Chi-square | 0.8473 | 1.0476 | 1.0476 |
| Significant at | 0.3858 | 0.3283 | 0.3283 |
| Ohlson vs. M-Ohlson | | | |
| Chi-square | 5.1190 | 2.2000 | 2.2000 |
| Significant at | 0.0241* | 0.1550 | 0.1550 |
| Zavgren vs. M-Zav. | | | |
| Chi-square | 2.8829 | 0.0000*** | 0.0000*** |
| Significant at | 0.0923** | > 0.9999 | > 0.9999 |

(see notes on next page)

**FIGURE 19 continued**

**RESULTS OF CHI-SQUARE TESTS FOR COMPARISON OF ORIGINAL AND MODIFIED ACCRUAL-BASED MODELS**

| | SAMPLE | | |
|---|---|---|---|
| | Development | Holdout #1 | Holdout #2 |
| **TYPE II ERRORS** | | | |
| Altman vs. M-Alt. | | | |
| Chi-square | 0.3346 | 1.0050 | 1.0050 |
| Significant at | 0.5824 | 0.3405 | 0.3405 |
| Deakin vs. M-Deak. | | | |
| Chi-square | 0.2551 | 0.0000 | 0.2051 |
| Significant at | 0.6392 | > 0.9999 | 0.6749 |
| Ohlson vs. M-Ohlson | | | |
| Chi-square | 0.1124 | 0.3384 | 0.3384 |
| Significant at | 0.7411 | 0.5797 | 0.5797 |
| Zavgren vs. M-Zav. | | | |
| Chi-square | 1.0013 | 1.0050 | 0.0000 |
| Significant at | 0.3416 | 0.3405 | > 0.9999 |

* - Significant at 0.025 level.

** - Significant at 0.10 level.

*** - Value of Chi-square is undefined due to zero values in both the numerator and denominator of the Chi-square formula. In this case, the value of Chi-square may be defined as zero (Conover, p. 149).

has no effect on the model's ability to distinguish failing firms from nonfailing ones.

The modification of the models also did not significantly affect the models' abilities to properly classify the failed firms in the holdout samples. While the modified Deakin and Ohlson models did outperform their original counterparts on the holdout samples, the differences were not statistically significant. Ironically, the modified Ohlson model actually performed much worse than the original version on the development sample. The difference was significant at the 0.025 level. However, as previously stated, performance with respect to the development sample is not as consequential as is performance on the holdout samples.

The differences in the Type II error rates also proved to be insignificant. In every case but one (Ohlson on the first holdout sample), the modified variant performed equal to or better than the original. However, the differences were not nearly great enough to be considered significant.

**SUMMARY OF THE TEST OF THE THIRD HYPOTHESIS**

The accrual-based models of Altman, Deakin, Ohlson and Zavgren were modified by adding cash-based ratios and/or removing the models' original variables. The aim of the modifications was to develop variants of each model which would exhibit improvements over the original model with respect to overall classification accuracy. The variant which showed the most improvement over the original model was selected and compared to the original model. Comparisons were made on overall classification accuracy, Type I and Type II errors. Chi-square tests were conducted to determine whether the differences between the original and modified models were statistically significant. The results of the Chi-square tests indicated that no significant differences exist between the abilities of the original and modified models to classify the holdout samples. Therefore, the third hypothesis could not be rejected.

## SUMMARY

This chapter presented the results of statistical analyses into whether cash-based ratios are useful as predictors of impending financial failure. The chapter began with a principal components analysis of forty cash-based financial ratios. The purpose of this analysis was three-fold: (1) to determine the underlying attributes of firm performance measured by these ratios; (2) to reduce the variable set from forty ratios to a more manageable number; and (3) to reduce the possibility of multicollinearity problems in the final bankruptcy prediction model developed with these ratios. The analysis showed that the ratios measure eleven aspects of firm performance: Magnitude of cash-flow from operations; ability to raise outside funding; magnitude of investing activity; cash position; ability to service debt; change in size of asset base; magnitude of cash flow from operations relative to assets and liabilities;

self-cannibalization; magnitude of cash flow from financing activities; replacement rate of inventory; and debt position.

One ratio was selected to represent each of the eleven components. These ratios were then used to develop MDA and logit models of failure prediction. The best-performing model, a two-variable logit model, was tested to determine whether its classification accuracy was better than would be achieved by a naive model classifying all firms as nonfailed. The prediction model failed this test. Consequently, the first hypothesis could not be rejected.

The chapter continued with the replication of the failure prediction models developed by Beaver, Altman, Deakin, Ohlson and Zavgren. The variables and methodologies used in these original models were applied to current data and the resulting classification accuracies were noted. The accuracies of each of these models was then compared to that of the cash-based model developed earlier in the study. Chi-square tests of the differences in classification accuracies indicated that no significant differences existed between the abilities of the cash- and accrual-based models to distinguish between failing and nonfailing firms. As a result, the second hypothesis could not be rejected.

The final section of the chapter concerned the modification of the models of Altman, Deakin, Ohlson and Zavgren. Modified versions of these models, which included both accrual- and cash-based variables, were developed. The accuracy of best-performing variant of each model was then compared to that of the original version. The outcome of Chi-square tests of the differences in accuracy indicated that the modified models performed no better than the original models. This lack of significant differences prevented the rejection of the third hypothesis.

The fifth chapter presents the summary and conclusions of this study. Implications of the study are discussed, as are its limitations. Finally, some possibilities for future research are considered.

## CHAPTER 5

## SUMMARY AND CONCLUSIONS

This chapter is composed of five primary sections. The first section presents a summary of the study and the results obtained. The conclusions to be drawn from this research, and possible explanations, are presented in the second section. The third section discusses the implications of the study. The inherent limitations are reviewed in the fourth section. Finally, the last section considers some possible extensions of the study which may provide a basis for future research in this area.

### SUMMARY AND RESULTS

This research study began with a review of the literature on bankruptcy prediction and factor analysis of financial measures. Early studies into the prediction of business failure concentrated on using accrual-based ratios as predictors of failure. These studies achieved impressive results when attempting to predict failure in the short-term. The emphasis began to shift to the use of cash-based measures, particularly cash-flows from operations, in the 1980s as the cash flow statement gained acceptance. The cash-based models achieved mixed, often disappointing results. Many of these studies, accrual- and cash-based alike, drew criticism because of a lack of guiding theory in the selection of predictor variables. Factor-analytic studies showed that variable sets could be selected which would minimize multicollinearity problems and still capture a wide range of information on firm performance. The review of the literature in these areas lead to the formation of the three research hypotheses discussed in the following sections.

**HYPOTHESIS ONE**

The first hypothesis was developed in response to the earlier cash-based studies. None of the earlier studies utilized ratios based on the components of total cash flows. For this study, a set of forty cash flow- and cash position-based ratios was developed to measure various aspects of firm performance. Eleven aspects of cash-flow performance, cash position, and debt position were identified by a principal components analysis of this variable set.

One ratio was chosen to represent each of the eleven components. These noncollinear ratios were then used as a basis for the development of a failure prediction model. A sample of 443 firms, of which approximately 90% were nonfailed and 10% failed, was used to develop MDA and logit models. The resulting two-variable logit model was used to test the hypothesis that such a model could predict failure in the near term. The model, when applied to two holdout samples, was found to be no more accurate than a naive model which classified all firms as nonfailed. The model was quite good at properly classifying the nonfailed firms. However, it proved completely incapable of identifying the failed firms in any of the samples. This finding precipitated a failure to reject the first hypothesis.

**HYPOTHESIS TWO**

The second hypothesis was based on two questions. First, was the cash-based model developed in this study better or worse at classifying failing and nonfailing firms than some of the existing accrual-based models? Second, do the impressive accuracies of the accrual-based models stand the test of time when the same variables are used on more current data?

The accrual-based models of Beaver (1966), Altman (1968), Deakin (1972), Ohlson (1980) and Zavgren (1985) were used in the test of this hypothesis. Each of the models was replicated by using its original variables and methodology, but with recent data. This was intended to give an indication of whether the variables used in these models remain as useful predictors today. The classification accuracies of these models were compared to that of the cash-based model. Only minor differences were found between the classification abilities of the cash-based model and each of the accrual-based models. Chi-square tests showed that the differences in overall accuracy were not significant. Some significant differences were found in the Type I and Type II error rates achieved on the development sample, but not on those relating to the holdout samples. In fact, none of the models properly classified any of the failed firms in the holdout samples, implying that they are not useful in predicting bankruptcy.

These results indicate that the cash-based model is no better or worse than the accrual-based models. Consequently, the second hypothesis could not be rejected. In addition, the results showed that the variables used in the accrual-based models do not generalize well to data from other time periods. This finding implies that changes in accounting methods which have occurred since these studies were originally performed may have rendered these variables useless for predicting bankruptcy, pointing to a need for the development of other predictor variables.

**HYPOTHESIS THREE**

The recent emphasis on, and availability of, the cash flow statement formed the basis for the third hypothesis. The question at hand was whether the accrual-based models of Altman, Deakin, Ohlson and Zavgren could be improved if cash flow-based variables were added to the models or substituted for some of the original variables in the models.

This portion of the study began with principal components analyses. A separate principal components analysis was conducted for each of the four models. Each analysis included the original variables in the accrual-based model plus the forty cash-based variables. The results indicated that the accrual- and cash-based ratios were, in many cases, highly correlated. Furthermore, some significant correlations existed between at least some of the original variables in each of the accrual-based models. The second finding raises the question of whether the accrual-based models experienced multicollinearity problems which may have lead to instability in their coefficients.

The results of the principal components analyses were used as a guide for developing modified versions of the accrual-based models. The original methodology used in each of the four models, logit or MDA, was retained. However, different combinations of cash- and accrual-based variables were analyzed in an attempt to arrive at models which would show a greater ability to classify the firms and would not be subject to multicollinearity problems.

Some, albeit minor, success was achieved in improving the classification accuracy of each of the models. In each case, the most improved version of the model contained fewer variables than the original. Additionally, each model except Ohlson's was improved through the addition of a cash-based variable. The accuracies of the modified variants were compared to their original counterparts. Minor improvements in accuracy were attained by the modified models. However, Chi-square tests demonstrated that the improvements were not significant. As a result of these tests, the third hypothesis, like the first two, could not be rejected.

## CONCLUSIONS

Despite the failure to reject any of the hypotheses, this study still provides useful information. To that end, several worthwhile conclusions can be drawn from the results and some possible explanations can be offered.

The results of the principal components analysis provided the first conclusion. The 1973 study of Pinches, et al. showed that accrual-based ratios essentially measured seven facets of firm performance. Likewise, the principal components analysis of the forty cash-based ratios showed that nine facets of cash flow performance can be identified (along with the cash position and debt position components). No previous study has been done on the underlying aspects of cash flows. Therefore, the conclusions of this portion of the study may act as a guide to future researchers in selecting variables for studies.

The foremost conclusion to be drawn from the test of the first hypothesis is that the cash flow-based model developed in this study is not particularly useful in distinguishing failing firms from nonfailing ones. The results of previous cash-based bankruptcy studies have been mixed, and the results of this study tend to support those studies which questioned the efficacy of cash flows as predictors of failure. The exceptionally poor performance in regard to identifying failing firms leads one to conclude that the differences between failing and nonfailing firms with respect to the cash flow ratios tested does not differ enough to discriminate between the two states.

The results of the study, however feeble, did generalize well to other industries. Comparison of the accuracy and error rates of the two holdout samples shows that, in all cases, the results obtained on the second holdout sample (firms drawn from all industry groups) did not differ materially from those achieved on the first holdout sample (firms drawn only from industries which supplied bankrupt firms for the development sample). These results were consistent across the cash-based, accrual-based and modified accrual-based models. The large number of industry groups used in the development sample may explain this level of generalizability. Alternately, the results may indicate that the industry group to which a firm belongs may have no effect on how that firm will be classified. Furthermore, this may indicate that cash-flow patterns and accrual measures may not differ greatly across industries.

The replication of the accrual-based models showed that these models are not generalizable across time. The variables which proved useful from the mid-1960s to the mid-1980s did not prove useful when applied to data from the late 1980s and 1990. Several explanations are possible.

First, changes in accounting standards have altered the way in which some items are measured and reported. These changes may cause inconsistencies between what exactly was included in a ratio in 1970 and what was included in the same ratio in 1990. General economic conditions may be a second explanation of why these models have not withstood the test of time. One possible example is that, during the late 1980s, bankruptcy may have been viewed as more palatable than in previous years. This perception may have lead firms which by previous standards had seemed fairly healthy, to file for Chapter 11 protection from creditors.

A third explanation is the change in debt levels of firms. The 1980s saw a great increase in the amount of debt carried by firms. This debt, amassed as the result of leveraged buyouts or a simply willingness to increase financial leverage, is uncharacteristic of earlier decades when financial management was much more conservative. Whereas successful firms used to be characterized by low debt levels and rising indebtedness implied failing health, the 1980s saw many firms successfully increase their debt levels without undue consequences (Kopcke, 1989). This tendency is consistent with financial theory which predicts that debt may be perceived as a valuable substitute for equity financing (Clark, 1993). Correspondingly, from a debt perspective, the line between failing and nonfailing firms became increasingly blurred. This clouding of the significance of debt levels would tend to render ratios based on debt levels less useful as predictors of failure.

The failure to coax significant improvements from the accrual-based models implies that these models may not be improved through the inclusion of cash-based variables or the deletion of some of the accrual-based ones. This failure is not surprising considering that both the cash-based model and all of the accrual-based ones are, individually, ineffective. Combining variables which apparently have little predictive power by themselves is not likely to lead to a superior predictive model.

The final conclusion to be drawn from this study, given the poor performance of all models tested, is that accurate prediction of failure may not be possible - at least for the time period covered by the study and with the variables which were used. Several explanations for this conclusion have already been advanced: changing measurement rules for accounting information, changing attitudes toward debt and bankruptcy, similarities in cash-flow patterns between failed and nonfailed firms, etc. One additional explanation is proffered. There is a wide degree of variability in the data, especially among the nonfailed firms. This variability makes any neat distinction between failed and nonfailed firms difficult to draw.

Despite the failure of this study to advance the effectiveness of bankruptcy prediction, the study does have some important implications for researchers and users of failure prediction models. The next section discusses these implications.

## IMPLICATIONS OF THE STUDY

The results of this study should sound a warning to the users of failure prediction models. The present study has shown the difficulty of properly identifying failing firms. This problem exists in both the cash-based model and, more importantly, in the accrual-based models which have been relied upon for years. Users should be cautioned that the models developed over the past several decades do not continue to exhibit a useful level of accuracy.

The failure of bankruptcy models to generalize across time raises a question about the ratios used in the models. If accounting standards have altered the data used to calculate the ratios to the point where the ratios are no longer useful for failure prediction, then are the individual ratios still useful for analysis of other areas of firm performance? For example, as stated earlier, a high debt to asset ratio no longer has the same connotation as it did prior to the 1980s. A related question is whether trends exhibited by the ratios over a period of time can be interpreted or whether some adjustment is necessary for changes in reporting requirements.

The final implication comes from the principal components analyses conducted as part of this study. These analyses have shown that various aspects of cash flow performance can be identified. This finding should be of interest to researchers investigating other uses of cash flow information. Finally, the addition of accrual-based ratios to the principal components analysis indicated that some accrual-based ratios measure the same facets of firm performance as do the cash-based ratios, while other accrual-based ratios measure unique facets.

## LIMITATIONS OF THE STUDY

Several limitations are recognized in the current study.

The first of these limitations results from limited data. The study could not utilize several years of data because the necessary cash flow information was not available until the late 1980s. Consequently, observations could not be drawn from earlier years. At the other end of the time spectrum, at least one year must have passed after the issuance of the financial data to judge whether the firm should be placed in the failed or nonfailed category. It is possible that different results could have been obtained with a larger sample or with samples from different time periods.

The study's reliance on large publicly-traded firms is a second limitation. The firms used in the study were drawn from Compustat's data base of firms listed on the major national and regional exchanges. Generalizations of the results cannot be made to smaller firms, privately held corporations, partnerships or proprietorships.

The third limitation is the reliance on a cross-section of industries. The models appear to be generalizable to industries other than the ones used to develop the models. However, different and conceivably more accurate industry-specific models may be possible if enough data could be gathered from separate industries.

Questions also arise about the models' generalizability across time. These questions stem from the stability of the information in the variables. The cash-flow information should not be subject to manipulation by changes in accounting standards. The same cannot be said about the accrual information also used in the ratios. Changes in reporting requirements may change the content of these ratios. Such changes may affect the usefulness of the ratios.

The final limitation relates to the user groups. This study focused on overall classification accuracy. No assumption was made about the cost of Type I and Type II errors. These relative costs would be specific to the individual user of the models. The models did not perform well with respect to limiting Type I errors. Consequently, a user with a high cost attached to Type I errors would find the models to be much less useful than would a user with a low Type I error cost.

## FUTURE RESEARCH POSSIBILITIES

Several avenues of future research are opened by this study. Elimination of some of the limitations will become possible as more data becomes available through the passage of time. More data would allow for expanding the time horizon over which the study is conducted. Another possibility would be to develop industry-specific models as more firms fail within each industry.

A second possibility is the development of better variables for predicting failure. For example, decomposing the cash-flow ratios into their component parts may prove useful. Using trend variables as more years of data become available, or using deviations from some type of baseline value may also prove useful. Additionally, the use of dummy variables to represent nonfinancial events such as pending lawsuits or attempts to avoid hostile takeovers may provide insights into why firms fail.

Finally, the stability of the cash-flow components over time warrants some study. The studies of Pinches, et al. (1973, 1975) indicated that factors based on accrual measures were stable over time. Gombola, et al. (1987) found that factors composed of ratios based on cash flow from operations were not stable across time. To date, no one has examined the stability of components based on cash flow measures other than cash flow from operations.

## CONCLUDING REMARKS

This research has extended the debate over whether financial accounting information is useful in the prediction of business failure. Empirical studies in this area date back to William Beaver in 1966. The empirical accrual-based studies in the years that followed achieved impressive accuracy and widespread acceptance by the financial community, although this study implies that these models may not be as accurate using current data. The results of cash-based studies have met with less success and acceptance. The present study examined new cash-based ratios and improved methodology to assess the usefulness of cash-based predictors of bankruptcy. Such ratios were not found to be useful. Additionally, the model based on these ratios was found to be no better or worse than some of the accrual-based models developed by other researchers. Attempts to improve accrual-based models through the addition of cash-based ratios also proved to be without merit. Given that bankruptcy is often the result of inadequate cash flows, these results appear to lend support to the FASB's long-held belief that accrual-basis accounting information is more useful in predicting future cash flows than is cash-based information.

# APPENDIX A

## APPLICATION OF ORIGINAL ACCRUAL-BASED MODELS TO RECENT DATA

The test of the second hypothesis in this study involved the use of recent data to re-estimate the coefficients of the variables employed by other bankruptcy models. These re-estimated models were then used to classify holdout samples and the results were compared to the results of the cash-based model developed as part of the test of the first hypothesis. The findings indicated that the re-estimated models performed no better than the cash-based model which, in turn, performed no better than a naive model which classified all firms as nonfailed. Given that the previous researchers reported superior results, compared to the findings of this study, further investigation seems warranted. The results imply that either the accounting data has changed over time, or companies themselves have changed rendering these models ineffective as bankruptcy prediction models. This appendix reports the results of an investigation into how well the original accrual-based models, using their original coefficients and variables, work when applied to recent data.

### BEAVER'S MODEL

The model developed by William Beaver in 1966 comprised a single ratio, "Cash flow"/total debt. Beaver used a dual split-half sample to determine the accuracy of his model. His original sample was split into two subsamples. The optimal cutoff point was found for each subsample, i.e. the point which resulted in the fewest misclassifications of the firms in the given subsample. Cutoff points of 0.03 and 0.07 were determined to be the optimal cutoffs for each of the two subsamples, respectively. The cutoff point from each subsample was then used to classify the firms in the other subsample. The results of these two validation procedures were then added to arrive at the total number of misclassifications. In this manner, an overall classification accuracy of 86.71% was determined.

Four tests were conducted to assess the continued utility of Beaver's model. The same 443 firms (43 failed and 400 nonfailed) used to re-estimate Beaver's model in the test of the second hypothesis were classified using Beaver's cutoff point of 0.03. The same sample was again classified with the cutoff point of 0.07. The accuracies achieved were then compared to Beaver's combined accuracy figure of 86.71%. The accuracies achieved using Beaver's two cutoff points were then compared to a naive model which categorizes all firms as nonfailed.

The results of these tests, summarized in Figure A1, indicate that Beaver's model may not generalize well to other time periods. At the 0.03 cutoff level, only 68.40% of the firms were properly classified. Only 65.46% were correctly classified using the 0.07 cutoff. The naive model scored an overall accuracy of 90.29%. The differences between the original model and the model applied to the more recent data,

**FIGURE A1**

**CLASSIFICATION ACCURACIES AND RESULTS OF CHI-SQUARE TESTS: ORIGINAL BEAVER MODEL WITH RECENT DATA**

**OVERALL CLASSIFICATION ACCURACY**

| | As orig. reported | W/recent data |
|---|---|---|
| Cutoff point = 0.03 | 86.71% | 68.40% |
| Cutoff point = 0.07 | 86.71% | 65.46% |

**CHI-SQUARE TESTS**

| Accuracy as orig. reported vs. recent data w/0.03 cutoff | |
|---|---|
| Test statistic | -4.462 |
| Significant at | < 0.0001 |

| Accuracy as orig. reported vs. recent data w/0.07 cutoff | |
|---|---|
| Test statistic | -5.055 |
| Significant at | < 0.0001 |

| Naive model (90.29% accuracy) vs. recent data w/0.03 cutoff | |
|---|---|
| Test statistic | -8.050 |
| Significant at | < 0.0001 |

| Naive model (90.29% accuracy) vs. recent data w/0.07 cutoff | |
|---|---|
| Test statistic | -8.903 |
| Significant at | < 0.0001 |

and between the model applied to the more recent data and the naive model, were tested using one-sided Chi-square tests.

In each of the four tests, the null hypothesis (that the accuracy achieved by the original model applied to recent data is at least as high as than that achieved by either the original model applied to the original data or by the naive model) is rejected. This finding implies that the model does not classify recently failed and nonfailed firms as well it had classified the original firms Beaver used to develop the model. In addition, it appears that the original model does not classify recent data as well as does a naive model which assumes no firm will fail. A possible explanation for these results is that the cutoff points used by Beaver are too high to recognize the higher debt levels which are more common among contemporary firms. Higher debt levels would obviously reduce the value of the "Cash flow"/total debt ratio for contemporary firms. Another possible explanation is that the propensity in recent years for firms to increase their debt levels in general may have rendered this variable a poor indicator for bankruptcy prediction. Finally, Beaver's definition of failure differed from that used in this study. Beaver defined failure as the filing of Chapter 10 or 11 bankruptcy, failure to make preferred dividend payments or default on a loan payment, whereas this study defined failure as the filing of a Chapter 11 petition. The discrepancy in the definition of failure may be another possible explanation for the difference in results.

**ALTMAN'S MODEL**

Altman's 1968 five-ratio MDA model achieved an overall classification accuracy of 95.45% when a cutoff point (Z-score) of 2.675 was used. At this point, the total number of misclassified firms was minimized.

This appendix reports the results of two tests that were conducted to determine whether Altman's model with the original coefficients generalizes well to more recent data. First, the 433 firms (33 failed and 400 nonfailed) used in the re-estimation of Altman's model in the test of the second hypothesis were classified using the original form of Altman's model. First, the accuracy of the re-estimated model was compared to the accuracy rate originally achieved by Altman. Second, the accuracy of Altman's model when applied to recent data was compared to the naive model which assumes all firms are nonfailing. One-sided Chi-square tests were used to assess the significance of the differences in the classification accuracies exhibited by the two groups in each of the two tests.

The findings of these tests strongly support the conclusion that Altman's model does not generalize well to more recent data. Only 64 of the 433 firms (14.78%) were properly classified by the original Altman model. This compares very poorly with the 95.45% accuracy achieved in Altman's original study and the 92.38% accuracy achieved by the naive model. As shown in Figure A2, the Chi-square tests of these differences conclusively reject the null hypothesis that the accuracy rate when applied to the more recent data is as least as good as the accuracy of the original model or that of the naive model. This supports the conclusion that Altman's model is not as efficient at classifying contemporary

**FIGURE A2**

**CLASSIFICATION ACCURACIES AND RESULTS OF CHI-SQUARE TESTS: ORIGINAL ALTMAN MODEL WITH RECENT DATA**

**OVERALL CLASSIFICATION ACCURACY**

| | As orig. reported | W/recent data |
|---|---|---|
| Cutoff point = 2.675 | 95.45% | 14.78% |

**CHI-SQUARE TESTS**

**Accuracy as orig. reported vs. recent data w/2.675 cutoff**

| | |
|---|---|
| Test statistic | -14.016 |
| Significant at | < 0.0001 |

**Naive model (92.38% accuracy) vs. recent data w/2.675 cutoff**

| | |
|---|---|
| Test statistic | -22.894 |
| Significant at | < 0.0001 |

failed and nonfailed firms as it was with the firms used in the original 1968 study. Nor is it as effective at classifying recent data as is the naive model. The explanation of these findings appears to imply a fundamental change in the ratio values across time. For the recent data on the nonfailed firms, the means of all of Altman's ratios, except the Market value of equity/book value of debt ratio, were lower than for Altman's original sample of nonfailed firms. The increase in the Market value of equity/book value of debt may be attributed to the large increases in stock prices during the 1980s which may have more than overshadowed the increase in debt levels during the same period. The result of the changes in the ratios is that the average "Z-score" for the nonfailed firms in the recent data is approximately 23% lower than for the nonfailed firms in the original data. The failed firms did not exhibit as much change in Z-scores. The mean Z-score exhibited by the failed firms in the more recent data set was only about 3.6% lower than that of the failed firms in the original data set.

**DEAKIN'S MODEL**

In his 1972 study, Edward Deakin used probabilities of group membership to classify the firms in his samples into the failed or nonfailed group. Unlike other MDA models, no cutoff score, similar to Altman's Z-score, derived from the regression coefficients was used. Deakin's methodology makes a comparison between the original and recent data difficult.

While Z-scores derived from the regression coefficients can be derived for a secondary sample (the recent data in this case), the calculation of the probabilities of group membership cannot be calculated as easily. Consequently, no directly comparable test of Deakin's model with original and recent data is possible. However, a reasonable test may still be conducted. Given that the Z-scores from the regression coefficients are related to the probabilities, finding the Z-score representing the optimal cutoff to minimize total errors will yield results which are at least as good as using the probabilities of group membership. In fact, finding the probability of group membership which minimizes total misclassifications would yield the same results as would using the optimal score. In addition, since Deakin's original model achieved an overall accuracy of 96.88%, which is better than any possible classification scheme would achieve with the recent data, the most stringent test for Deakin's model is to compare his original results to the optimal classification accuracy for the more recent data. For this reason, one comparison was made between Deakin's original model results and the overall accuracy which would be achieved by the using the optimal classification of the recent data, which, as it turned out, was the naive model.

As previously mentioned, Deakin's model properly classified 96.88% of the firms in his original sample. The naive model, assuming all firms are nonfailing, properly classified 90.29% of the 443 firms (43 failed, 400 nonfailed) tested. The difference in the classification accuracies of the model on the two samples is significant at the 0.05 level. This result indicates that Deakin's model may not generalize very well to the time period used in this study. However, it should be noted that the results of the test are just barely within the significant range. Had Deakin's original model misclassified one additional firm, the difference between the accuracies on the original data set and the recent data set would have been insignificant. The results of the test of Deakin's model are shown in Figure A3.

## FIGURE A3

**CLASSIFICATION ACCURACIES AND RESULTS OF CHI-SQUARE TESTS: ORIGINAL DEAKIN MODEL WITH RECENT DATA**

**OVERALL CLASSIFICATION ACCURACY**

| | As orig. reported | W/recent data |
|---|---|---|
| Optimal cutoffs | 96.88% | 90.29% |

**CHI-SQUARE TEST**

**Accuracy as orig. reported vs. rec. data w/opt. (naive) cutoff**

| | |
|---|---|
| Test statistic | -1.731 |
| Significant at | 0.0418 |

**OHLSON'S MODEL**

No comparison was made between the reported accuracy of Ohlson's original model and the same model applied to a more recent sample of failed and nonfailed firms. Ohlson's original study did not seek to minimize the total number of misclassified firms. Instead, Ohlson located the probability of failure which resulted in the lowest total error rates for both groups. The difference in terminology is significant. Ohlson found that the lowest total error rates occurred when 12.4% of the failed firms and 17.4% of the nonfailed firms were misclassified. However, Ohlson's sample was composed of 105 failed firms and 2,058 nonfailed firms. Therefore, at his "optimal" cutoff point, 13 failed firms and 358 nonfailed firms were misclassified. Correspondingly, Ohlson's overall accuracy was only 82.84%. Examination of Ohlson's tables of relative error rates for the two groups at various probabilities of failure indicated that a better overall accuracy could have been achieved if he had chosen a cutoff probability which would have minimized total error as opposed to trying to minimize the sum of the error rates.

**ZAVGREN'S MODEL**

Christine Zavgren's 1988 model performed quite well with recent data. In fact, the model achieved a higher classification accuracy with the more recent data than it had with Zavgren's original data set. Zavgren reported an overall error rate of 82.22%. This error rate was calculated based on the number of errors that occurred when a probability of failure which minimized total errors was selected as the cutoff point. Based on a review of Zavgren's bar charts, it can be determined that 0.50 was the optimal cutoff point.

Two different tests of the difference in classification accuracy were performed to determine whether Zavgren's model could be successfully applied to more recent samples of failed and nonfailed companies. First, her original classification accuracy was compared to the accuracy achieved when the original model was applied to 440 (40 failed and 400 nonfailed) firms and the cutoff probability of 0.50 was used. The second test compared the results achieved by applying the original model (and cutoff probability) and a naive model to the more recent data. The results of the comparisons are reported in Figure A4.

Zavgren's model performed better with the more recent data than it did with her original data set. Overall accuracy was 85.68% on the more recent data, and 82.22% on the original data. However, a one-sided Chi-square test indicated that the difference was not significant at the 0.05 level. A significant difference was found between the accuracy of Zavgren's model applied to the recent data and a naive model applied to the same data. In this comparison, the naive model outperformed Zavgren's model. The overall accuracies were 90.91% and 85.68% for the naive model and Zavgren's model, respectively.

The results of these tests suggest that Zavgren's model was not significantly better at classifying the sample of more firms. More importantly, unlike the other accrual-based models, it was not significantly worse at classifying the more recent data set. It is important to note that, while Zavgren's model appears to be generalizable to a more recent time period, it is still not as effective as a simple naive model.

**CONCLUSION**

Four accrual-based models were tested for their ability to classify more recent data sets. The models of Beaver, Altman, Deakin and Zavgren were employed in their original form and the original cutoff points used for distinguishing

**FIGURE A4**

**CLASSIFICATION ACCURACIES AND RESULTS OF CHI-SQUARE TESTS: ORIGINAL ZAVGREN MODEL WITH RECENT DATA**

**OVERALL CLASSIFICATION ACCURACY**

| | As orig. reported | W/recent data |
|---|---|---|
| Cutoff probability of 0.50 | 82.22% | 85.68% |

**CHI-SQUARE TESTS**

**Accuracy as orig. reported vs. recent data w/0.50 cutoff**

| | |
|---|---|
| Test statistic | 0.840 |
| Significant at | 0.2005 |

**Naive model (90.91% accuracy) vs. recent data w/0.50 cutoff**

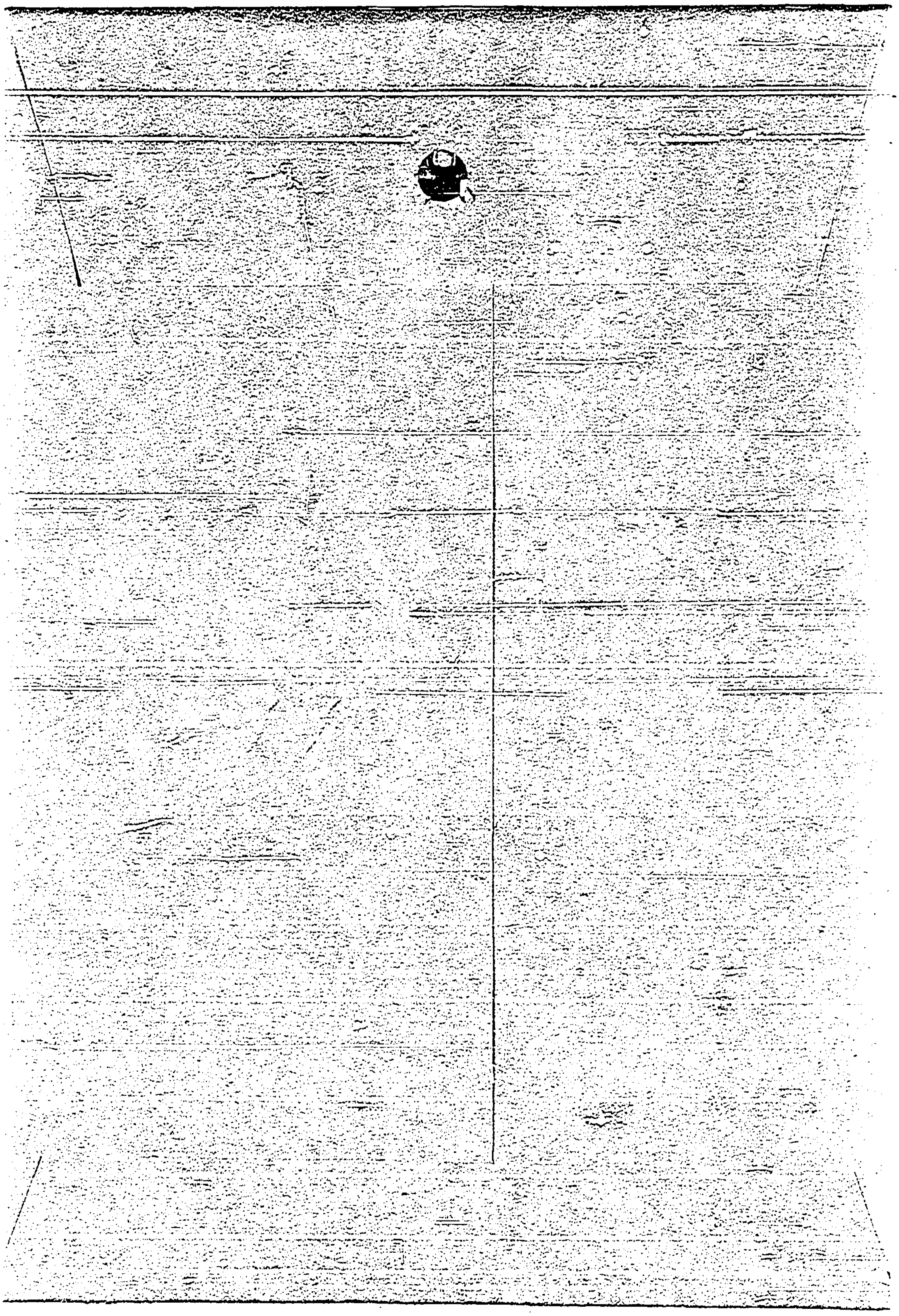
| | |
|---|---|
| Test statistic | -2.412 |
| Significant at | 0.0079 |

between failed and nonfailed firms were used.

The models of Beaver, Altman and Deakin were found to have significantly lower classification accuracy rates on the more recent data than they achieved on the original sample of firms used in their development. Additionally, the results obtained with the more recent data sets were significantly worse than the results achieved with a simple naive model which classified the entire data set as nonfailed. These results suggest that the models of Beaver, Altman and Deakin may not be generalizable to the period from which the data for these tests was collected.

Zavgren's model did appear to generalize well across time. The results obtained by applying her model to more recent data were marginally better than the results achieved on her original data set. One possible explanation for this finding is that Zavgren used more recent data than had been used in the other bankruptcy studies examined. Her data, drawn from 1972 to 1978, was current enough to have included several of the FASB's changes in accounting principles which are still in effect at the time of this study. On the other hand, the other models were based on data from as early as 1946 - well before current accounting principles had evolved. Despite the apparent ability of Zavgren's model to handle recent data, it was found that her model was outperformed by a naive model. Therefore, it appears as though Zavgren's model, like the other three accrual-based models tested, is of limited use for the prediction of business failure.

APPENDIX B



## APPENDIX B

## REFERENCE SHEETS OF RATIOS USED IN THE STUDY

### OPERATING PERFORMANCE

R1) $\dfrac{\text{CFFO}}{\text{Sales}}$

R2) $\dfrac{\text{CFFO}}{\text{Net income}}$ (note a)

R3) $\dfrac{\text{CFFO}}{\text{Total cash flow}}$ (note a)

R4) $\dfrac{\text{CFFO}}{\text{Average total assets}}$

R5) $\dfrac{\text{Cash from sales}}{\text{Average total assets}}$

R6) $\dfrac{\text{Cash from sales}}{\text{CFFO}}$

R7) $\dfrac{\text{Cash paid for inventory}}{\text{CFFO}}$

### ABILITY TO SERVICE DEBT

R8) $\dfrac{\text{CFFO before interest}}{\text{Cash paid for interest}}$

R9) $\dfrac{\text{Cash paid for interest}}{\text{Interest expense}}$

R10) $\dfrac{\text{CFFO - preferred dividends}}{\text{Average current liabilities}}$

R11) $\dfrac{\text{CFFO}}{\text{Interest paid + reduction in LT debt + other fin. uses}}$

R12) $\dfrac{\text{Total cash flow}}{\text{Interest paid + reduction in LT debt + other fin. uses}}$

## APPENDIX B

## REFERENCE SHEETS OF RATIOS USED IN THE STUDY

**ABILITY TO SERVICE DEBT CONTINUED**

R13) $\dfrac{\text{Proc. from Issuance of LT debt + other financing sources}}{\text{Interest paid + reduction of LT debt + other fin. uses}}$

R14) $\dfrac{\text{Reduction in LT debt + other financing uses}}{\text{Average LT debt}}$

**ABILITY TO RAISE CAPITAL**

R15) $\dfrac{\text{Proceeds from sale of stock}}{\text{CFFF}}$

R16) $\dfrac{\text{Proceeds from sale of stock}}{\text{Total cash flow}}$

R17) $\dfrac{\text{Proceeds from issuance of LT debt}}{\text{CFFF}}$

R18) $\dfrac{\text{Proceeds from issuance of LT debt}}{\text{Total cash flow}}$

R19) $\dfrac{\text{Proceeds from issuance of LT debt}}{\text{Average LT debt}}$

R20) $\dfrac{\text{Proc. from sale of stk + iss. of LTD + other fin. sources}}{\text{Total cash flow}}$

**REPLACEMENT AND EXPANSION**

R21) $\dfrac{\text{Capital expenditures + acquisitions + other invest. uses}}{\text{CFFI}}$

R22) $\dfrac{\text{Incr in invest. + cap. exp. + acquis. + other invest uses}}{\text{CFFI}}$

R23) $\dfrac{\text{Incr in invest. + cap. exp. + acquis. + other invest uses}}{\text{CFFO}}$

## APPENDIX B

## REFERENCE SHEETS OF RATIOS USED IN THE STUDY

### REPLACEMENT AND EXPANSION CONTINUED

R24) $$\frac{\text{Incr in invest. + cap. exp. + acquis. + other invest uses}}{\text{Total cash flow}}$$

R25) $$\frac{\text{Cap. exp. + acquis. - sale of PP\&E + other invest. act.}}{\text{Average property, plant and equipment}}$$

### SELF-CANNIBALIZATION

R26) $$\frac{\text{Cash paid for inventory}}{\text{Cost of goods sold}}$$

R27) $$\frac{\text{Proceeds from sale of PP\&E + other investing sources}}{\text{CFFI}}$$

R28) $$\frac{\text{Proceeds from sale of PP\&E } \div \text{ other investing sources}}{\text{Total cash flow}}$$

R29) $$\frac{\text{Proceeds from sale of PP\&E + other investing sources}}{\text{Average PP\&E}}$$

R30) $$\frac{\text{Pr. from sale of invest. and PP\&E + other invest. sources}}{\text{CFFI}}$$

R31) $$\frac{\text{Pr. from sale of invest. and PP\&E + other invest. sources}}{\text{Total cash flow}}$$

R32) $$\frac{\text{Pr. from sale of invest. and PP\&E + other invest. sources}}{\text{Average total assets}}$$

R33) $$\frac{\text{CFFI}}{\text{Average total assets}}$$

R34) $$\frac{\text{CFFI}}{\text{Average PP\&E}}$$

## APPENDIX B

## REFERENCE SHEETS OF RATIOS USED IN THE STUDY

**OTHER CASH FLOW ACTIVITIES**

R35) $\dfrac{\text{Purchase of stock}}{\text{CFFF}}$

R36) $\dfrac{\text{Payment of dividends}}{\text{CFFO}}$

R37) $\dfrac{\text{Payment of dividends}}{\text{CFFF}}$

**CASH POSITION**

R38) $\dfrac{\text{Cash}}{\text{Current liabilities}}$

R39) $\dfrac{\text{Cash}}{\text{Total liabilities}}$

R40) $\dfrac{\text{Cash}}{\text{Total assets}}$

**KEY TO ABBREVIATIONS:**

CFFF = Cash flow from financing activities
CFFI = Cash flow from investing activities
CFFO = Cash flow from operating activities

**Note a -** Ratio contains a numerator and denominator which may be either positive or negative, allowing for misleading interpretation of the ratio value. The numerator is the item of primary interest. Consequently, the ratio value is entered as positive if numerator is positive, negative if numerator is negative.

## APPENDIX B

## REFERENCE SHEETS OF RATIOS USED IN THE STUDY

**BEAVER, 1966**

B1) $\frac{\text{"Cash flow"}}{\text{Total debt}}$

**ALTMAN, 1968**

A1) $\frac{\text{Working capital}}{\text{Total assets}}$

A2) $\frac{\text{Retained earnings}}{\text{Total assets}}$

A3) $\frac{\text{Earnings before interest and taxes}}{\text{Total assets}}$

A4) $\frac{\text{Market value of equity}}{\text{Total debt}}$

A5) $\frac{\text{Sales}}{\text{Total assets}}$

**DEAKIN, 1972**

D1) $\frac{\text{"Cash flow"}}{\text{Total debt}}$

D2) $\frac{\text{Net income}}{\text{Total assets}}$

D3) $\frac{\text{Total debt}}{\text{Total assets}}$

D4) $\frac{\text{Current assets}}{\text{Total assets}}$

D5) $\frac{\text{Quick assets}}{\text{Total assets}}$

D6) $\frac{\text{Working capital}}{\text{Total assets}}$

D7) $\frac{\text{Cash}}{\text{Total assets}}$

D8) $\frac{\text{Current assets}}{\text{Current liabilities}}$

D9) $\frac{\text{Quick assets}}{\text{Current liabilities}}$

D10) $\frac{\text{Cash}}{\text{Current liabilities}}$

D11) $\frac{\text{Current assets}}{\text{Sales}}$

D12) $\frac{\text{Quick assets}}{\text{Sales}}$

D13) $\frac{\text{Working capital}}{\text{Sales}}$

D14) $\frac{\text{Cash}}{\text{Sales}}$

## APPENDIX B

## REFERENCE SHEETS OF RATIOS USED IN THE STUDY

**<u>OHLSON, 1980</u>**

O1) log(total assets/GNP price-level index)

O2) $\dfrac{\text{Total liabilities}}{\text{Total assets}}$

O3) $\dfrac{\text{Working capital}}{\text{Total assets}}$

O4) $\dfrac{\text{Current liabilities}}{\text{Current assets}}$

O5) $\dfrac{\text{Net income}}{\text{Total assets}}$

O6) $\dfrac{\text{Funds provided by operations}}{\text{Total liabilities}}$

O7) $\dfrac{(NI_t - NI_{t-1})}{(|NI_t| + |NI_{t-1}|)}$ Where $NI_t$ is net income for the most recent period

O8) Dummy variable: 1 if total liabilities exceeds total assets, 0 otherwise

O9) Dummy variable: 1 if net income was negative for the last two years, 0 otherwise

**<u>ZAVGREN, 1985</u>**

Z1) $\dfrac{\text{Total income}}{\text{Total capital}}$

Z2) $\dfrac{\text{Sales}}{\text{Net plant}}$

Z3) $\dfrac{\text{Inventory}}{\text{Sales}}$

Z4) $\dfrac{\text{Debt}}{\text{Total capital}}$

Z5) $\dfrac{\text{Receivables}}{\text{Inventory}}$

Z6) $\dfrac{\text{Quick assets}}{\text{Current liabilities}}$

Z7) $\dfrac{\text{Cash}}{\text{Total assets}}$

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# VITA

## DAVID M. BUKOVINSKY

**Born**

July 6, 1959, Youngstown, Ohio, USA

**Education**

University of Kentucky - 1988 to 1993
Doctor of Philosophy.

Youngstown State University - 1983 to 1985
Master of Business Administration.

Youngstown State University - 1977 to 1981
Bachelor of Science in Business Administration.

**Professional Experience**

Teaching Assistant, University of Kentucky - 1990 to 1992. Taught courses in Principles of Financial and Managerial Accounting and Intermediate Accounting.

Adjunct Instructor, University of Toledo - 1985 to 1988. Taught courses in Principles of Financial and Managerial Accounting and Financial Statement Analysis.

Teaching Assistant, Youngstown State University - 1984 to 1985. Taught courses in Principles of Financial and Managerial Accounting.

Alexander Grant & Company, Youngstown, Ohio - 1981 to 1983. Staff Accountant, audit staff.

**Scholastic and Professional Accomplishments**

Certified Public Accountant, Ohio.

American Accounting Association Doctoral Consortium Fellow - 1990.

Presidential Fellowship, University of Kentucky - 1989 through 1991.

Open Fellowship, University of Kentucky - 1988 through 1989.

American Accounting Association Doctoral Fellowship - 1988.

David M. Bukovinsky

David M. Bukovinsky