Order Number 9212807

Financial distress: An evaluation of the predictive power of accrual and cash flow information using ordinal multi-state prediction models

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The University of Tennessee, 1991

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FINANCIAL DISTRESS: AN EVALUATION OF THE PREDICTIVE POWER OF ACCRUAL AND CASH FLOW INFORMATION USING ORDINAL MULTI-STATE PREDICTION MODELS

A Dissertation

Presented for the

Doctor of Philosophy

Degree

The University of Tennessee, Knoxville

Terry J. Ward

August, 1991

To the Graduate Council:

I am submitting herewith a dissertation written by Terry J. Ward entitled "Financial Distress: An Evaluation of the Predictive Power of Accrual and Cash Flow Information Using Ordinal Multi-State Prediction Models." I have examined the final copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirement for the degree of Doctor of Philosophy with a major in Business Administration.

Jan R. Williams, Major Professor

We have read this dissertation
and recommend its acceptance:

Accepted for the Council:

Associate Vice Chancellor
and Dean of The Graduate School

DEDICATION

This dissertation is dedication to the memory of my father

Jarvey Ward

and

to my newborn son

Scott Keenan Ward

The circle remains unbroken

ACKNOWLEDGEMENTS

I would like to thank my major professor, Dr. Jan R. Williams, for his patience and guidance over the past three years. I would also like to thank the other committee members, Dr. James M. Reeve, Dr. Keith G. Stanga, and Dr. Esteban Walker for their comments and assistance over the past three years. I would like to express my thanks to my wife, Cheryl, for her love and understanding during those times when things appeared the most bleak. Finally, I would like to thank Ben Foster and Tina Mills for their friendship and companionship over the past three years; the two of you made the program almost enjoyable.

ABSTRACT

The primary stream of research testing the importance of cash flow information has concerned the ability of accounting information to predict financial distress. Most prior financial distress studies have primarily used a dichotomous bankrupt/nonbankrupt response for financial distress. These dichotomous distress studies suffered from many limitations. The primary objective of this study was to better evaluate the ability of cash flows to predict financial distress by correcting for many of these limitations through the use of ordinal multi-state prediction models. Another purpose of this study was to test the feasibility of using ordinal multi-state models to predict financial distress and the appropriateness of the multi-state scale as stated in this study.

Separate models for lag periods from one to three years prior to financial distress were constructed to test the predictive ability of cash flows and accrual ratios. These models (cash flows, accrual, and mixed models) were constructed using ordinal logistic regression (OLR), thus taking into consideration the ordinal response scale of financial distress. The ordinal response variable in this study was financial distress with the following four states of distress: (1) financially healthy, (2) dividend reduction/elimination, (3) debt accommodation and/or loan/interest default, and (4) bankruptcy. The predictor variables were the relevant cash flows and accrual ratios. Rank probability scores and classification accuracy were both used to test the predictive strength of the models.

The results of this study were consistent with the theoretical model developed in this study and the opinions expressed by the FASB. Cash flows are useful in predicting financial distress when combined with accrual data; however, cash flows are not more

useful by themselves than accrual ratios in predicting financial distress.

Proportional odds tests also indicated that the ordinal scale used in this study may not fit the data very well for the accrual ratios tested. Further analyses indicated that the scaling problem occurred because the bankrupt firms, overall, were not as financially distressed as the loan interest/principal default and/or debt accommodation firms. This finding calls into question the use of a simple dichotomous bankrupt/nonbankrupt response as a proxy for financial distress.

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CHAPTER 1

INTRODUCTION

The 1970s and 1980s saw an increased interest in the importance of cash flow information. This increased interest was generated by a number of economic occurrences such as business failures, financial difficulties, and severe economic conditions [Chastain and Cianciolo, 1986] and eventually led to the creation of the statement of cash flows by the FASB [1987].

Catalysts Leading to the Creation of a Statement of Cash Flows

Together, the following three occurrences have been the primary catalysts leading to the creation of the statement of cash flows: (1) the increased interest in solvency analysis, (2) the development of the funds flow concept, and (3) the creation of future cash flows as a criterion for evaluating the usefulness of accounting information.

Early in the twentieth century, accountants and researchers placed primary importance on the liquidity and solvency of a business entity. This emphasis on solvency resulted from the fact that firms during this period obtained funding primarily from bank loans. However, accountants eventually shifted their attention to the needs of long-term equity investors. Thus, attention was shifted to the income statement. However, many accounting researchers and accounting information users still maintained the importance of funds flow information in evaluating the solvency of a company. The profession eventually yielded to the pressures from the advocators of information for solvency analysis and issued Accounting Principles Board Opinion No. 19, requiring the presentation of a "funds" statement.

Advocates of accounting information for solvency evaluation primarily recommended techniques based on a simple concept from organic theory called the "flow" concept. This concept basically states that analyzing the flows of an entity provides information concerning the survival of the entity. The "funds flow" concept assumes that funds are the lifeblood of a company; thus, a sufficient level of funds must be maintained in order for the company to pay its debts when due. Any transaction affecting the level of funds is considered an inflow or outflow of funds. A primary element of this concept is the need to identify the distinct units (activities) which create the inflow or outflow of funds. Provided the inflow (outflow) valves are connected with distinct units or activities, the possibility exists for determining a pattern as to the uses of the funds flowing out, and the funds used to replenish the fund of resources, thus enabling one to predict future inflows and outflows of funds. Accountants were left to develop their own definition of funds. APB Opinion No. 19 allowed numerous definitions of funds, including working capital and cash. However, most companies presented statements using the working capital basis. The working capital basis was later found to not be the best measure of funds from operations.

The renewed interest in cash flow information was also a direct result of the development of a conceptual framework by the Financial Accounting Standards Board (FASB). The FASB adopted the "funds flow" concept in the development of the conceptual framework; however, the FASB incorporated the cash definition of funds in the conceptual framework rather than the working capital definition. The conceptual framework established the ability to help investors and creditors predict future cash flows as the primary criterion for evaluating the usefulness of accounting information.

With predicting future cash flows as the primary criterion for evaluating the usefulness of accounting information, many accounting researchers and accounting information users naturally stressed the benefits of a cash flow statement. This opinion was consistent with the funds flow concept which states that observing present cash flows by activities should provide information in predicting future cash flows. Many researchers believed that, when considered with accrual information, present cash flow information had incremental value in predicting future cash flows, while other researchers believed that present cash flows were better predictors of future cash flows than accrual ratios.

The FASB responded to the need for cash flow information by issuing Statement of Financial Accounting Standards (SFAS) No. 95 [FASB, 1987] which required that companies prepare a statement of cash flows. In Statement No. 95, the FASB stresses the incremental importance of cash flow information while still maintaining the primacy of accrual information. The FASB stated that when taken together with additional information in the other financial statements the statement of cash flows should:

> help investors, creditors, and others to (a) assess the enterprise's ability to generate positive future net cash flows; (b) assess the enterprise's ability to meet its obligations, its ability to pay dividends, and its needs for external financing; (c) assess the reasons for differences between net income and associated cash receipts and payments; and (d) assess the effects on an enterprise's financial position of both its cash and noncash investing and financing transactions during the period [FASB, 1987, paragraph 5].

Empirical Financial Distress Research

Researchers used the predictive ability paradigm [Beaver, Kennelly, and Voss, 1968] and the future cash flow criterion to test competing accounting methods. Since future cash flows are constructs, researchers developed proxies for future cash flows. Financial distress was chosen by a number of researchers as an acceptable proxy. The assumption is that firms experiencing financial distress have negative, or less positive cash flows than financially healthy companies. Thus, the accounting information which best distinguishes between distressed and healthy companies is considered most useful to investors and creditors. Prior researchers primarily used a dichotomous response variable to proxy for financial distress; this dichotomous response variable was normally bankrupt/nonbankrupt.

The results of empirical research concerning the ability of cash flow information to predict financial distress have been disappointing. Overall, researchers have found that cash flows do not have greater predictive usefulness than accrual ratios in predicting financial distress, nor do cash flows appear to have incremental predictive usefulness when combined with accrual ratios. However, these studies suffer from a number of limitations which could be confounding the results. These limitations are discussed in the following paragraphs.

Few researchers attempted to develop a theoretical framework for selecting the cash (funds) flow variables to test; thus, few researchers developed hypotheses to test. A theoretical framework of the financial distress process is needed to better understand the timing and usefulness of accounting information.

Previous financial distress studies often violated many of the assumptions of the statistical techniques used. Studies using multiple discriminant analysis (MDA) tended to violate the assumption that the populations (predictor variables) are normally distributed; financial ratios tend not to be normally distributed. Subsequent researchers used logistic (also probit) techniques because of their advantages over MDA [Press and Wilson, 1978]. However, most of these studies violated two important assumptions of logistic regression concerning the response variable. By nature of the methods used to select the distressed and nondistressed firms, researchers violated the assumption that the response variables are randomly drawn. However, most prior researchers failed to adjust for this bias by using weighted logit models or by sampling a larger percentage of healthy firms. These researchers also sampled such a small sample of firms in relation to the number of predictor variables that sampling bias was likely present in their parameter estimates [Noreen, 1988; Stone and Rasp, 1991].

Most prior financial distress studies pooled firms across a large period of time to obtain a sufficient sample of bankrupt firms. These researchers also selected holdout samples from the same period of time as the sample used to generate the statistical models. Sampling across years introduces additional variation and lowers the likelihood of finding significant results. Also, selecting the holdout sample from the same period as the original sample results in *ex post* discrimination. These *ex post* discriminations are true only if stationarity exists. Since Mensah [1984] found that accounting models are not stationary across time, *intertemporal* validation is needed; one should draw the holdout sample from a future period distinct from the original sample period.

Another limitation of prior financial distress studies is the use of bankruptcy as the criterion to operationalize financial distress. The use of a dichotomous classification of distress is an overly simple representation of the financial distress process and is unlikely to capture the true underlying construct. Firms are not simply bankrupt or healthy but possess certain degrees of distress which vary from day to day and period to period. Many events indicate different degrees of financial distress. The use of bankruptcy as a proxy for financial distress can also be criticized on the grounds that bankruptcy is a legal event rather than an economic event. Financial distress results from economic occurrences. Only economic events should truly capture the level of financial distress of a firm. The economic conditions of bankruptcy are probably different than the economic conditions of other types of distressed firms. Thus, using a legal event as a proxy for economic conditions may produce misleading results. Even the firms selected by legal status may form a heterogeneous set because some firms voluntarily choose bankruptcy, and others do not. Thus, their economic conditions may be quite different [Dietrich, 1984].

Finally, studies have found indirect evidence that cash flows may be more useful in the more recent years. Otherwise, cash flow information should have become more useful as the profession moved closer to the all-inclusive definition of income [Gombola and Ketz, 1983; Franz and Thies, 1988]. However, prior studies have tested the predictability of accounting information from pre-1983 data only; post-1982 data may produce different results.

Multi-State Financial Distress Studies

Lau [1982 and 1987] corrected for many of the methodological limitations of the above corporate failure predictive models by using a five-state response model to approximate the continuum of corporate financial health instead of the conventional bankrupt/nonbankrupt dichotomy. However, Lau's studies also suffered from a number of limitations, mostly related to the limitations of the logistic technique available to her at this point in time.

Lau generated multinomial logit (MLA) analysis models using the QUAIL program [Berkman *et al.*, 1979]. Even though Lau treated the response variable as an ordinal scaled variable, her statistical models were nominal and not ordinal models. Agresti [1984] stresses the many advantages of ordinal logistic models over nominal models when the response scale is ordinal. Ordinal models are easier to use because of the similarity between ordinal multi-state logistic models and simple ordinary regression. One can develop the same types of tests as in simple regression and ordinal models are more powerful in cases where the response is truly ordinal. The nominal model used by Lau did not allow direct testing of the individual independent variables because the nominal model produced five parameter estimates for each independent variable. Also, the nominal model used by Lau apparently did not provide overall test statistics for the goodness of fit of the overall model. Current ordinal logistic techniques are not affected by these limitations.

Lau also only tested one cash flow variable, operating cash flow, in her dissertation [1982]. However, she did test various funds flow definitions and reported the working capital model in the published study from her dissertation [1987].

Third, Lau sampled most of her loan default firms using a retrospective sampling scheme. She selected the firms with potential loan interest/principal defaults by identifying those firms that had either filed for bankruptcy or had C-rated bonds during 1977 to 1980. She then used the firms' SEC 10-K reports to identify which of the firms had also defaulted on interest and/or principal payments during 1976 and 1977. This retrospective sampling technique likely interjects additional bias in the sample; the sampling scheme undersamples those firms which recover from distress after loan/interest default (less distressed firms). Although there is evidence that many (if not most) bankrupt firms previously experienced loan/interest default [Gioux and Wiggins, 1984], most firms which experience loan interest/default do not eventually become bankrupt [Flagg, 1988].

Objectives of the Study

The primary objective of this study is to better evaluate the ability of cash flow information to predict financial distress by: incorporating different sampling techniques, using a different sampling period (post-1982), developing a theoretical framework of financial distress to select the cash flow variables to test, and developing ordinal multi-state prediction models of financial distress. Another purpose of this study is to test the feasibility of using ordinal multi-state models to predict financial distress and the appropriateness of the multi-state ordinal response as stated in this study. Of special interest is the use of bankruptcy as the final state of financial distress.

This study tests the usefulness of cash flow information by extending the methodology of prior financial distress studies. Similar to Lau, this study is based on multi-state distress models. However, ordinal logistic regression (OLR) using the proportional odds model is used to generate the statistical models of interest. Thus, this study differs from prior financial distress studies as follows:

(1) A theoretical representation of the failure process is used to select the cash flow variables to test.

(2) Sufficient sample sizes are obtained for all models tested to lower the amount of sampling bias in the logistic models. A larger sample of healthy firms is also obtained to limit the effects of choice-based sample bias.

(3) A multi-state financial distress variable is used as the proxy for financial distress; thus, this study is not limited by the weaknesses of using a dichotomous bankrupt/nonbankrupt proxy as the dependent variable.

(4) Firms used to generate the predictive models are not pooled across a large time frame but are selected from one year; holdout firms are obtained from a year other than the year used to generate the models in this study.

(5) The data for this study are obtained from the post-1982 period.

(6) Ordinal logistic regression (proportional odds model), rather than MDA or MLA, is used to generate the multi-state models in this study, thus correcting for the limitations of using MDA or MLA. This procedure enabled the author to test the incremental predictive ability of cash flow variables using multi-state prediction models. OLR also takes advantage of the ordinal scale of the financial distress variable and is an extension of prior multi-state financial distress research.

(7) Various steps were taken to obtain the best sample possible. Loan/interest default and debt restructure firms include firms which recover from financial distress after loan/interest default and/or debt restructure. Financially distressed firms are also sampled to enable the author to check for other confounding problems.

Summary of Findings

The results of this study are consistent with the theoretical model developed in this study and the opinions expressed by the FASB. Cash flows are useful in predicting financial distress when combined with accrual data; however, cash flows are not more useful by themselves than accrual ratios in predicting financial distress. Also, cash flows appear to be more useful in the short-run than in the long-run. In fact, adding cash flows to accrual ratios three years prior to financial distress decreases the predictive power (classification accuracy) of the model when compared to the model with only the accrual ratios.

This study also uncovered other interesting results. First, the naive cash flow variable (NOF) tested in early financial distress studies (net income plus depreciation and amortization) is still a very powerful predictor of financial distress even when included in models with a better measure of operating cash flow. Further analysis indicates that the reason NOF is still a significant predictor of financial distress is because NOF is an alternative measure (and better measure for predicting financial distress than net income) of income and not because NOF is a measure of operating cash flow.

Second, the OLR accrual and mixed (both accrual and cash flows together) models always reject the proportional odds assumption, indicating that the ordinal scale used in this study may not fit the data very well for the variables tested in this study. Further analysis indicated that the scaling problems occurred because the bankrupt firms, overall, were not as financially distressed as the loan interest/principal default and/or debt accommodation firms, based on the financial variables tested in this study (especially the accrual ratios). This finding questions the use of a simple dichotomous bankrupt/nonbankrupt response as a proxy for financial distress and indicates the advantage of using multi-state prediction models.

Organization of the Study

Chapter 2 reviews the historical development of the statement of cash flows with special emphasis on the reasoning behind requiring a statement of cash flows and demonstrates why cash flow information should be beneficial in predicting financial distress. Chapter 3 contains a review of the empirical research literature and the motivation for the study. This chapter contains two main sections. Section one addresses the following three areas of empirical research: (1) the ability of current cash flow information to predict future cash flows, (2) the association of cash flow information with stock prices and returns, and (3) the usefulness of cash flows in predicting financial distress. Section two discusses the motivation for the study and covers the following three areas of interest: (1) the limitations of prior dichotomous financial distress (bankruptcy) studies and the methodology literature addressing these limitations, (2) Lau's multi-state prediction studies and the limitations not addressed by these multi-state studies, and (3) a summary of how the author's study differs from prior financial distress cash flow studies.

Chapter 4 discusses of the methodology used in this study and the hypotheses tested. This chapter is divided into five sections. Section one provides a discussion of the theoretical model of financial distress. Section two discusses the development of the independent variables used in this study based on the theoretical model of financial distress. Section three discusses the hypotheses tested in this study. Section four contains a discussion of OLR and the comparisons and statistical tests used to test the hypotheses. The final section contains a discussion of the sampling procedures used to obtain samples of firms for 1988 and 1989.

Chapter 5 presents the empirical results and is divided into seven main sections. Section one discusses the selection of a scaling measure for the cash flows and section two reviews the means and standard deviations for the variables used in this study. Section three discusses the testing of the five main hypotheses. Section four contains an analysis of the tendency of accrual and mixed models to reject the parallel lines assumption. Section five discusses the predictive power of OLR models (and selected nominal logistic models) using a rank order scoring rule (RPS) and section six reviews the predictive power of these models using classification accuracy. Finally, section seven discusses the results for the two-state logistic models with only loan default/accommodation firms and bankrupt firms included and illustrates the primary reason why the proportional odds assumption is rejected for the accrual and mixed models.

This study concludes with Chapter 6. This chapter summarizes the findings and contributions of this study, the limitations of this study, and offers recommendations for future research.

CHAPTER 2

HISTORICAL DEVELOPMENT OF THE STATEMENT OF CASH FLOWS

Chapter 2 contains an overview of the historical development of the statement of cash flows and the impact of a renewed interest in solvency analysis on this development. The purposes of this chapter are (1) to illustrate the reasoning behind requiring a statement of cash flows and (2) to demonstrate why cash flow information should be beneficial in predicting financial distress.

Together, the following three occurrences have been the primary catalysts leading to the creation of the statement of cash flows: (1) the renewed interest in solvency analysis, (2) the development of the funds flow concept, and (3) the creation of future cash flows as a criterion for evaluating the usefulness of accounting information. Thus, special emphasis is placed on the funds flow concept for solvency analysis when future cash flows is used as a criterion for evaluating the usefulness of accounting information.

This chapter is divided into three sections. Section one describes the funds flow concept for solvency analysis. Section two demonstrates the development of a cash flow criterion for evaluating the usefulness of cash flow information and how this criterion contributed to a renewed interest in cash flow information. Finally, the last section describes the statement of cash flows, as required by SFAS 95.

Solvency and the Funds Flow Concept

In recent years, both financial statement users and accounting researchers have expressed the need for additional information about cash flows. However, this interest in cash flow information is not unique to the 1970s and 1980s. Thomas [1982] found that users emphasized cash flow information as early as the 1400s.

Cash flow information was also stressed during the early part of the 1900s. According to Heath [1978], "during the first three decades of this century, the emphasis was clearly on solvency" [p. 4]. For example, in 1902, U.S. Steel Corporation presented cash flow information in a format similar to the "indirect" format used today [Rosen and DeCoster, 1969].[1] The emphasis on solvency during this period resulted from the fact that bankers were the primary users of financial statements. Since most loans of this period were short-term loans, the profitability of a company was not considered relevant in evaluating loans; the creditors focused their attention on the current financial position of the company. This balance sheet approach was accompanied by an emphasis on liquidity and solvency.[2]

According to Anton [1962], original funds analysis techniques made use of a simple concept from organic theory called the "flow" concept. This concept basically states that analyzing the flows of the lifeblood of an entity provides information concerning the survival of the entity. The timing and speed of the flows are of primary importance, especially when multiple inflow and outflow valves exist.

Accountants, and accounting researchers, applied this concept to the solvency analysis of business entities. Figure A-1 illustrates this concept.[3] The "funds flow" concept assumes that funds are the lifeblood of a company; thus, a sufficient level of

[1] Although users commonly emphasized the usefulness of cash flow information, the information requested was normally a funds flow form of information other than cash flows.

[2] Even though both concepts are balance sheet oriented, solvency is a much broader concept than liquidity. According to Heath, *liquidity* is defined either as the nearness to cash of a company's asset holdings or as a description of the relationship between a company's current assets and current liabilities. *Solvency*, however, is the ability of the company to "raise cash by whatever means available to the company in relation to the company's need for cash" [p. 2].

[3] All figures and tables are shown in the Appendices.

funds must be maintained in order for the company to pay its debts when due. Any transaction affecting the level of funds is considered an inflow or outflow of funds.

A primary element of this concept is the need to identify the distinct units (activities) which create the inflow or outflow of funds. Provided the inflow (outflow) valves are connected with distinct units or activities, the possibility exists for determining a pattern as to the uses of the funds flowing out, and the funds used to replenish the fund of resources, thus enabling one to predict future inflows and outflows of funds.[4] Simply observing the inflows and outflows would indicate manipulation of the valves, but one cannot determine patterns unless the distinct units (activities) causing the inflows and outflows are also identified.

Accountants were left to develop their own definition of funds. Many different approaches were taken, some of which were: funds as cash, funds as total resources, funds as working capital, funds as current assets, funds as money assets, and funds as net money assets [Anton, pp. 31-36]. This broad definition of funds has created confusion among researchers over the years. Many users and accountants have interchangeably used the phrases funds, changes in working capital, cash flows, and so forth. However, cash flows and changes in working capital are simply different approaches to operationalize the funds flow concept.

By the 1930s, accountants had shifted their attention to the needs of long-term equity investors. As a result, attention was shifted to the income statement, earnings, and earnings per share. In 1953, Arthur Stone Dewing stated that "... for the last thirty-five years, ... there has been a steady drift among accountants ... toward recognition of the fundamental nature of the income account" [Dewing, 1953, pp. 519-520].

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[4]Vatter [1947] developed a theoretical framework for a funds theory approach. However, he advocated the replacement of proprietary and entity theories, with the fund as the basic accounting unit.

Earnings replaced funds flow in importance because earnings were perceived as better surrogates for future cash flows [Ijiri, 1980]. This emphasis on the income statement became so strong that suggestions by financial statement users that cash flows were useful in solvency evaluation were often met by verbal hostility. Cash flow information was seen as a challenge to the supremacy of the income statement. The following comment in 1961 by J.S. Seidman, who later became president of the American Institute of Certified Public Accountants (AICPA), was typical of this anti-cash flow bias:

> Instead of studying various ways and terminology for presenting cash flow statements, I think the profession is called upon to report to companies, to analysts, to stockholders, and the exchanges that cash flow figures are dangerous and misleading and the profession will have no part of them [Heath, p. 6].

However, many researchers (accounting and finance) and accounting information users continued to emphasize the importance of funds flow information. Although many different concepts of funds continued to be advocated by accountants, by 1960 the primary concept of funds advocated was based on the working capital concept.

The profession eventually yielded to pressures by financial statement users for funds flow information and issued Accounting Principles Board (APB) Opinion No. 19 [APB, 1971], requiring the presentation of a "funds" statement. Opinion No. 19 required that a statement of changes in financial position be presented. The primary purpose of the statement of changes in financial position was to show the change in a company's funds for the period reported. This change in funds was the difference between the total sources of funds and total uses of funds. Preparers were required to "prominently disclose working capital or cash provided from or used in operations for the period" [paragraph 10]. The company could use either a direct or indirect approach to show the working capital or cash provided or used from operations.

Each company was given great latitude in selecting the means to present the statement. Thus, many different definitions of working capital or cash were adopted. As a result, the funds statement suffered from a number of limitations [Cappel, 1990]:

> (1) The ambiguity of the term "funds" led companies to express changes in financial position in a variety of ways, such as changes in quick assets, changes in cash, and changes in working capital. As a result, funds flow from operating activities differed depending on the basis of the statement.
> (2) Although companies presented statements using different bases, the most common basis used was working capital. However, working capital was later found to not be the best measure of funds from operations.
> (3) Some statements were presented in a sources and uses format while others followed an activity format.
> (4) In some cases, the same items were classified into different categories on different statements among firms using the activity format.
> (5) Frequently, the changes in the amounts of assets and liabilities were reported at net amounts rather than gross amounts, resulting in the incomplete presentation of information [p. 75].

Future Cash Flows Criterion

In 1961, Staubus stated that "a major objective of accounting is to provide quantitative economic information that will be useful in making investment decisions" [p. iii]. According to Staubus, the ideal information needed by investors is "future cash transfers" [p. 17]. This concept was later expressed by the report of the American Institute of Certified Public Accountants Study Group on the Objectives of Financial Statements in 1973 [AICPA]. In this report, Objective No. 3 states that "an objective of financial statements is to provide information useful to investors and creditors for predicting .... potential cash flows." The Statement of Financial Accounting Concepts (SFAC) No. 1 [FASB, 1978] broadened this by stating that "financial reporting should provide information to help in assessing .... prospective net cash inflows" [paragraph 37].

The establishment of a stated objective of accounting information led to the testing of accounting information using a predictive ability approach advocated by Beaver, Kennelly, and Voss [1968]. The validity of predictors (accounting models being an example) can be assessed by determining the correlation of such predictors with an established criterion. With future cash flows representing the established criterion (as stated by the FASB), researchers could empirically determine which accounting methods or models were more useful. The accounting method(s) or model(s) which best predict(s) future cash flows would be the most valid (based on a decision usefulness perspective).

The emphasis on future cash flows as the criterion for evaluating the usefulness of accounting information naturally led many accounting researchers to advocate the need for additional cash flow information [Staubus, 1961; Chambers, 1966; Revsine, 1973; Sorter, 1967 and 1982]. Some researchers not only stressed the need for additional cash flow information, but even suggested that cash flow information may be more useful than traditional accrual information [Carson, 1965; Ijiri, 1978; Lee, 1972, 1978, 1981, and 1985; Lawson, 1978 and 1985; Ferrara, 1981].[5] These researchers claim accrual information is distorted because of certain deficiencies in the current reporting system, and that these distortions are more severe during periods of inflation. They believe that the promulgation of certain accounting methods such as accounting for deferred taxes, pension liabilities, and leases makes accrual information a poor predictor of future cash flows, especially future short-term cash flows. Justifications for requiring a greater emphasis on cash flow information (either alone or in addition to accrual information) are based on the belief that cash flows are "harder" than accrual information; cash flow information is more objective, simple, and easier to understand; and cash flow information may capture the impact of inflation better than accrual information [Ismail and Kim, 1989].

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[5]This renewed interest is consistent with the funds flow concept explained earlier. This concept indicates that if future cash flows are the relevant criteria to predict, then a cash flows based funds statement will provide sufficient information to develop patterns to predict future cash flows.

However, accounting literature basically asserts that earnings, not cash flow, should be reported by accounting systems. A good example of this argument is presented by the FASB [1978] in Statement of Financial Accounting Concept No. 1:

> Information about enterprise earnings based on accrual accounting generally provides a better indication of an enterprise's present and continuing ability to generate favorable cash flows than information limited to the financial aspects of cash receipts and payments [p. ix].

The FASB stressed the incremental usefulness of cash flow information with the release of the Discussion Memorandum on funds flow reporting in December, 1980 [FASB, 1980]. Later, the Board issued an exposure draft of a proposed concepts statement which stressed that funds flow should concentrate on cash rather than working capital [FASB, 1981]. However, the Board decided not to issue a concepts statement specifically on cash flows but to consider the subject as part of its concept on recognition and measurement (SFAC No. 5). In December 1984, the Board issued SFAC No. 5, stating that "a full set of financial statements for a period should show: .... Cash flows during the period" [FASB, paragraph 13]. The FASB acknowledged the usefulness of cash flow information by proposing that the statement of changes in financial position be replaced by a cash flow statement. By a vote of four to three, the FASB issued Statement 95, Statement of Cash Flows, in November 1987, effective for fiscal years ending after July 15, 1988 [FASB, 1987].[6]

[6]The three members of the Board who dissented did not oppose the requirement of a statement of cash flows. The members basically dissented because the Board failed to follow a consistent application of the cash based definition of a funds statement for all transactions. For example, all three members dissented to the requirements that interest and dividends received and interest paid be shown as cash flows from operating activities, and two of the members dissented because the Board failed to require only the direct method of reporting net cash flow from operating activities.

SFAS 95 - Cash Flow Statement

In addressing the reasons for requiring a statement of cash flows, the FASB [1987] stated that the significance of cash flow information has "increasingly been recognized" [paragraph 2] since Opinion 19 was issued. However, the Board did not modify its assertion that accrual information better predicts future cash flows but simply indicated cash flows have incremental value, useful to investors and creditors. The FASB stated that when taken together with additional information in the other financial statements, the statement of cash flows should:

> help investors, creditors, and others to (a) assess the enterprise's ability to generate positive future net cash flows; (b) assess the enterprise's ability to meet its obligations, its ability to pay dividends, and its needs for external financing; (c) assess the reasons for differences between net income and associated cash receipts and payments; and (d) assess the effects on an enterprise's financial position of both its cash and noncash investing and financing transactions during the period [paragraph 5].

The primary purpose of the statement of cash flows is to provide information about the cash receipts and cash disbursements of an enterprise; thus, the "statement of cash flows shall classify cash receipts and cash payments as resulting from investing, financing, or operating activities" [paragraph 14]. Both the direct and indirect methods of reporting cash are allowed, but the direct method is preferred. Only the components used to calculate cash flow from operating activities (CFFO) differ under the two methods. The gross cash flows from investing and financing activities are shown under both methods.[7] According to Statement No. 95, investing, financing, and operating activities are as follows:

> (1) *Investing activities* - include making and collecting loans and acquiring and disposing of debt or equity instruments and property, plant, and equipment and other productive assets, that is, assets held for or used in the production of goods or services by the enterprise (other than materials that are part of the enterprise's inventory) [paragraph 15].

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[7]However, items considered to have quick turnover with maturities of three months or less qualify for net reporting.

(2) *Financing Activities* - include obtaining resources from owners and providing them with a return on, and a return of, their investment; borrowing money and repaying amounts borrowed, or otherwise settling the obligation; and obtaining and paying for other resources obtained from creditors on long-term credit [paragraph 18].

(3) *Operating activities* - include all transactions and other events that are not defined as investing or financing activities, and generally involve producing and delivering goods and providing services [paragraph 21].

Under the indirect method, CFFO is calculated by adjusting net income for non-cash items. The direct method shows the actual cash receipts from sales, cash disbursements, federal taxes paid, interest and dividends received, and interest paid. Even though both methods result in the same CFFO, the majority of lenders and investors who responded to the exposure draft asked the Board to require the use of the direct method.[8] These groups argued that the different inflows and outflows from operating activities are more important than a single subtotal such as CFFO. In the initial exposure draft, the FASB indicated that the Board intended to require the use of the direct method to calculate CFFO. However, the FASB later stressed this opinion by simply recommending, and not requiring, the use of the direct method. The Board stated in Statement No. 95 that "information about the gross amounts of cash receipts and cash payments during a period is more relevant than information about the net amounts of cash receipts and payments" [paragraph 11]. If the direct method is used, the company must also provide a "reconciliation of net income to net cash flow from operating activities" [paragraph 30].[9] Statement 95 also requires enterprises with foreign currency transactions or foreign operations to "report the reporting currency equivalent of foreign currency cash flows using the exchange rates in effect at the time of the cash flows," but

[8]Commercial lenders were especially vocal in their support for the direct method. However, both commercial lenders and equity analysts requested more detailed information on cash flows from operating activities.

[9]Few companies chose to use the direct method to calculate CFFO. A review of the 1990 Accounting Trends and Techniques indicated that only 17 of 600 surveyed companies presenting a statement of cash flows for 1989 used the direct method to report net cash flow from operating activities.

allows the use of a weighted average exchange rate for the period if the weighted average does not vary substantially from the actual exchange rates [paragraph 25].

Statement of Financial Accounting Standards (SFAS) No. 102 [FASB, 1989] and SFAS No. 104 [FASB, 1989] amended SFAS No. 95. SFAS 102 exempts defined benefit pension plans which adhere to Statement 35, Accounting and Reporting by Defined Benefit Pension Plans, and other benefit pension plans presenting information similar to that required under Statement 35, from having to prepare a statement of cash flows. Provided certain conditions are met [paragraph 7], Statement 102 also exempts:

> (1) investment companies subject to the requirements of the Investment Company Act of 1940; (2) investment enterprises having similar characteristics as those subject to the 1940 Act; and (3) common trust funds, variables annuity account, or similar funds maintained by a bank, insurance company, or other enterprise in its capacity as a trustee, administrator, or guardian for the collective investment and reinvestment of money [paragraph 6].

SFAS No. 102 also addresses the classification of cash flows from acquisitions and sales of certain securities and other assets. According to SFAS No. 102, "cash receipts and cash payments resulting from purchases and sales of securities and other assets shall be classified as operating cash flows if those assets are acquired specifically for resale and are carried at market value in a trading account" [paragraph 8]. Also, cash receipts and cash payments resulting from the acquisition and sales of loans "shall be classified as operating cash flows if the loans are acquired specifically for resales and are carried at market value or at the lower of cost or market value." Cash receipts from the sales of loans not specifically acquired for resale "shall be classified as investing cash inflows" [paragraph 9].

SFAS No. 104 allows banks, savings institutions, and credit unions to report certain items as net receipts and disbursements. These items are: "(a) deposits placed with other financial institutions and withdrawals of deposits, (b) time deposits accepted and repayments of deposits, and (c) loans made to customers and principal collections of loans" [paragraph 3]. If an enterprise is a part of a consolidated enterprise, then the net amounts of the cash receipts and disbursements must be shown separate from the gross amounts of cash receipts and disbursements for other investing and financing activities of the consolidated enterprise. Statement 104 also allows certain cash flows accounted for as hedges of "identifiable transactions or events, including anticipatory hedges, to be classified in the same category as the cash flows from the items being hedged provided that accounting policy is disclosed" [paragraph 6].

CHAPTER 3

REVIEW OF THE RESEARCH LITERATURE AND MOTIVATION FOR THE STUDY

A review of the relevant research literature is presented in this chapter. The chapter is organized into the following two sections. Section one provides a review of research dealing with the usefulness of cash flow information. This section illustrates the different approaches to testing cash flow information and addresses the following three areas of research: (1) the ability of current cash flow information to predict future cash flows, (2) the association of cash flow information with stock prices and returns, and (3) the usefulness of cash flows in predicting financial distress (bankruptcies).

Section two discusses the motivation for this study and is divided into three parts. The first part offers a discussion of the limitations of prior dichotomous financial distress cash flow studies and the methodology literature addressing these limitations. The second part discusses the two studies which used multi-state financial distress prediction models and the limitations not addressed by these studies. The third part contains a summary of how this study differs from prior financial distress cash flow studies.

Prior Research

The three main areas of research dealing with the usefulness of cash flow information have been: (1) the ability of current cash flows to predict future cash flows, (2) the association of cash flow information with stock prices and returns, and (3) the usefulness of cash flows in predicting financial distress (bankruptcies).

Predicting Future Cash Flows

A number of studies have attempted to predict future cash flows. The primary purpose of each of these studies was to determine whether current cash flows could predict future cash flow from operations.

Fisher [1980] used seven univariate regression models for the period 1946 to 1975 to predict cash flow from operations (defined as net income adjusted for noncash expenses and revenues and changes in noncash working capital items) for fifty companies. Each model contained one of seven independent variables (some accrual and some funds flow variables) and was developed for lag periods of one, two, three, four, and five years. Fisher found that accrual earnings were better predictors of cash flow from operations than historical cash flow from operations.

Brooks [1981] developed models using the Box-Jenkins modeling technique to forecast cash flow from operations (unadjusted for changes in current assets and current liabilities) for thirty firms. The models were developed using data obtained from the third quarter of 1964 to the fourth quarter of 1978. The author first used past cash flow from operations to predict future cash flow from operations. Then, an accrual based earnings model was added to past cash flow from operations to develop a mixed model. Results indicated that earnings information did not have predictive content above past cash flow from operations.

Using future cash flow from operations as a dependent variable, Greenberg *et al.* [1986] empirically tested whether current earnings or current cash flow from operations better predicted future cash flow from operations. Separate tests for lag periods from one to five years and for multi-lagged periods of two and three years were conducted. Results indicated (in all cases) that the earnings model (income before extraordinary items and discontinued operations) was a better predictor of future cash flow from operations.

Waldron [1988] developed two multiple regression models to predict cash flow from operations. The models were generated based on data for thirty companies from the first quarter of 1977 to the last quarter of 1986. One model was labeled the accrual model and included ten accrual and environmental ratios as predictors. The other model was labeled the cash flows model and included seven cash flows and environmental ratios as predictors. Waldron selected these variables based on theoretical reasoning. She found that the cash flows model was not superior to the accrual model in predicting future cash flow.

Bowen *et al.* [1986] investigated empirical relationships between signals provided by accrual earnings and various measures of cash flows. This study differed from the other studies in that the authors looked at multiple dependent variables for future cash flows, and in turn, multiple independent variables for the following cash flows (funds flows or naive cash flows): net income plus depreciation and amortization, cash flow from operations, cash flow after investment, and change in cash and short-term marketable securities. The authors used multiple univariate statistical models (regression, one dependent variable for each model, and correlation analyses) to predict the various cash flows. Four out of the five cash flow variables indicated that random walk models using cash flows predict future cash flows as well as, or better than, traditional accrual models. The one exception was that net income plus depreciation and amortization was the best predictor of future cash flow from operations.

The results of the above research are obviously mixed. These studies, however, suffer from a number of limitations. Determining a time frame for predicting future cash flows is very subjective; a specific event does not exist. Also, only Bowen *et al.* looked at future cash flows other than cash flow from operations, and they did so using multiple univariate models. A truer test of the ability of present cash flows to predict future cash flows would concern multivariate tests incorporating simultaneous multiple dependent variables (cash flows). As a result, the external validity of these studies is limited.

Stock Market Studies

Early empirical research in this area indicated that cash flows did not have incremental information content above earnings [Ball and Brown, 1968; Beaver and Dukes, 1972; Patell and Kaplan, 1977]. As part of their earnings study of 1968, Ball and Brown also tested the information content of operating cash flow. They used operating income as a surrogate for operating cash flow. The absolute abnormal returns for both positive and negative cash flow changes were slightly lower than the changes for earnings, thus indicating a lower association with abnormal returns for operating cash flow. Beaver and Dukes [1972] found similar results by regressing stock returns on earnings and cash flow, defined as earnings plus depreciation, amortization, and change in deferred tax account.

Patell and Kaplan [1977] tested whether operating cash flow had incremental information content above annual earnings. The authors used the Compustat variable "total funds from operations" as the surrogate for operating cash flow. They concluded that operating cash flow did not have incremental information content.

However, results in the above studies could have been affected by the surrogates used for cash flow, forms of income and working capital from operations (WCFO). Christie *et al.* [1984] presented evidence that the insignificant incremental information content may have been attributable to the problem of collinearity between WCFO (and other accrual measures) and earnings. Research by Rayburn [1986] and Bowen *et al.*

[1987] concerning the association of accrual and cash flow information with stock prices and returns indicated that cash flow information had incremental information content, relative to that contained in earnings. The authors used the indirect approach to calculate the surrogate for cash flow from operations rather than WCFO and WCFO was not found to have incremental information content.

Wilson [1987] found that the market reacts more favorably to larger cash flows. However, in research addressing the generality of Wilson's findings, Bervad and Stober [1989] found no evidence of the relation observed by Wilson. Still, Ismail and Kim [1989] found that funds and cash flow risk measures (betas) provide significant incremental explanatory power over that provided by the earnings risk measure (beta) in explaining the variability in market betas.

Overall, research in this area seems to indicate that cash flows have incremental information content above accrual information, although cash flows are not substitutes for accrual information.

Financial Distress Studies - Landmark Studies

The prediction of financially distressed (bankrupt) firms has been the subject of a substantial amount of research. However, most of the financial distress studies fall into one of two categories based on the study's primary objective. Either the primary purpose of the study is to use financial distress as a criterion variable to test the importance of accounting information or the primary purpose is to develop the most accurate model possible to help users predict bankruptcy. The two seminal works of Beaver [1966] and Altman [1968] are typical of studies in each of these two categories.

Beaver [1966] attempted to provide empirical evidence concerning the usefulness of accounting information using a predictive ability criterion. The primary purpose of studies such as Beaver's is to test the usefulness of accounting information by using financial distress as a criterion variable. The most recent cash flow studies dealing with financial distress fall under this approach. Since Beaver also tested naive cash flow variables, a discussion of his study is offered later.

Altman [1968] attempted to improve conventional ratio analysis by developing a multivariate model using multiple discriminant analysis (MDA). His famous Z-score model is still used today to predict bankruptcy. The primary objective of studies such as Altman's "landmark study" is to develop the most accurate model or tool (discriminant function) to enable users to effectively, and economically, predict bankrupt firms.[10] These researchers are primarily interested in the predictive accuracy of the model and how the model compares to a naive model. The information content of the variables is secondary.[11]

Ohlson [1980] extended Altman's methodology three ways: (1) he used multivariate logit analysis to determine probabilistic estimates of failure instead of a simple deterministic classification of a firm as bankrupt or nonbankrupt; (2) he collected a larger, and more representative, sample of 105 bankrupt firms and 2,058 nonbankrupt firms; and (3) he only included firms with published financial data released prior to the announcement of bankruptcy to reduce the amount of sampling bias. Zavgren [1985] also used logistic analysis in a similar study of 45 bankrupt and 45 nonbankrupt firms. Unlike Ohlson, Zavgren theoretically justified the inclusion of seven variables found to load highest on separate factors in a study by Pinches *et al.* [1975]. Both Zavgren and

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[10]Altman *et al.* [1981] provide a thorough discussion of what the authors consider to be the "ten landmark studies."

[11]The distinction between these two objectives was more obvious in the earlier studies because of the limited capabilities of the statistical techniques used (forms of discriminant analysis) to develop tests of significance on particular variables. Later, the implementation of logistic and probit techniques enabled researchers to address both objectives. Still, the primary objective of a financial distress study dictates the type of methodology used.

Ohlson found that their bankruptcy models could be used to predict a firm's likelihood of failure for up to five years in advance with reasonable accuracy.[12]

Financial Distress Studies - Naive Cash Flow Variables

The following studies tested cash flow variables in their predictive models and are summarized in Table B-1. However, each of these studies basically used a crude approximation of cash flow from operations, net income plus depreciation and amortization.

Beaver [1966] performed a univariate analysis of the ability of 30 ratios (four of which were cash flow ratios) to distinguish between 79 failed and 79 nonfailed firms. The failed firms were those which had failed between 1954 and 1964. The failed firms were matched with the nonfailed firms based on industry and asset size. Beaver defined a failed firm as one which had experienced one of the following events: bankruptcy, bond default, overdrawn bank account, or nonpayment of a preferred stock dividend.

Beaver primarily used simple classification techniques based on various cutoff points to distinguish between the failed and nonfailed firms. He found that: (1) accounting information can be used to predict failure as early as five years before failure; (2) different ratios predict with different degrees of accuracy; (3) accounting information predicts nonfailure better than failure; and (4) the ratio cash flow/total debt was the best performing variable, with an 87% classification rate for year one and a classification rate of 78% five years prior to failure. However, Beaver's greatest contribution was his

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[12] Predicting bankruptcy has been a long and fruitful area of research. However, for brevity's sake, the author has only described the studies by Altman, Ohlson, and Zavgren because these studies are typical of financial distress studies which did not incorporate cash flow variables into their models. Interested readers should see Ball and Foster [1982] which contains a complete listing of earlier financial distress studies.

suggestion that financial distress could be used as a framework for evaluating the usefulness (predictive ability) of accounting information [Altman *et al.*, 1981].

Deakin [1972] extended the studies by Altman [1968] and Beaver by incorporating the fourteen "strongest" variables suggested by Beaver and the multivariate methodology recommended by Altman. The author obtained a sample of 32 firms which failed between 1964 and 1970 and 32 nonfailed firms. The firms were matched based on industry, asset size, and year of financial data. Like Beaver, Deakin sampled the firms based on a failed/nonfailed classification scheme; a failed firm was one which was bankrupt, insolvent, or liquidated. Using MDA, Deakin found that the ratio cash flow/total debt was very important to the discriminant model. The fourteen variable model predicted failure as far as three years in advance with fairly high accuracy.

Similar to Beaver and Deakin, Blum [1974] used a failed/nonfailed classification to determine the predictability of financial ratios. However, the primary purpose of Blum's study was to "develop a Failing-Company Model to aid the Antitrust Division of the Justice Department in assessing the probability of business failure" [Altman *et al.*, 1981, p. 227] using linear MDA. Blum defined a failed firm as any firm meeting one of the following criteria: (1) failure to pay debts when due, (2) debt accommodation agreement with creditors to reduce debts, or (3) occurrence of bankruptcy. Like Beaver, Blum based selection of the ratios to test on a "cash flow framework." The only cash flow variable in the model, cash flow/total debt, was generally ranked high in the predictive models.

The prior studies by Beaver, Deakin, and Blum were criticized because of their heterogeneous failed/nonfailed sample selection scheme. In a two-group failure classification, firms within a group should be homogeneous and representative of the population of failed enterprises [Altman *et al.*, 1981]. Thus, subsequent studies by

Altman *et al.* [1977], Norton and Smith [1979], and Mensah [1983] tested the ability of financial ratios to predict bankrupt/nonbankrupt firms. The authors used various stepwise linear and quadratic MDA models. The results of these bankruptcy studies, except for Altman *et al.*, basically validated the results of prior studies which used a broader definition of failure. Cash flow variables were not part of the best model in the study by Altman *et al.* However, Mensah found cash flow/net worth to be the most important ratio, while cash flow/total assets and cash flow/total debt were both found to be important by Norton and Smith.

Holmen [1988] compared the predictive accuracy of the Altman Z-score model [Altman, 1968] and the cash flow/total debt (.03 and .07 cutoff points) variable used by Beaver on a sample of 84 bankrupt and 84 nonbankrupt firms for the period 1977 through 1984. Thus, Holmen used a holdout sample of a separate period to test the predictive usefulness of the variables. He found that the simple cash flow/total debt univariate model predicted bankruptcy with fewer errors than the multivariate Altman Z-score model, which did not include a cash flow variable.

Financial Distress Studies - More Appropriate Cash Flow Variables

The following studies tested more appropriate cash flow variables (adjusted for changes in accounts) and are summarized in Table B-2. In each of these studies, the primary purpose was to test the usefulness of cash flow information using a predictive ability paradigm. These studies represent the state of the art in financial distress cash flow studies.

A study by Largay and Stickney [1980] of the 1975 bankruptcy of W.T. Grant was the catalyst behind the explosion of cash flow studies during the 1980s. In this study, Largay and Stickney observed the trends of certain accrual ratios (profitability, turnover, liquidity, and solvency ratios) and cash flow from operations (CFO) for ten years preceding bankruptcy. The authors found that the company's CFO provided a more accurate and timely signal of W.T. Grant's eventual failure than traditional accrual ratios.

However, two studies by Casey and Bartczak (C&B) [1984 and 1985] appeared to contradict the study by Largay and Stickney. In the 1984 study, C&B tested whether CFO or accrual ratios could best predict bankruptcy. The authors obtained a matched-pair sample (matched on industry) of bankrupt and nonbankrupt firms for the period 1971-1982. The sampling scheme resulted in a total sample of 60 bankrupt and 230 nonbankrupt firms. Half of the firms (30 bankrupt and 165 nonbankrupt firms) were used to develop the classification models, while the other firms were used as a holdout group to test the validity of the models developed.

The authors generated two groups of models with lag periods of one to five years before bankruptcy. The first group of models was composed of univariate cash flow models for each lag period. The cash flow variables tested were: CFO (working capital provided by operations, plus or minus changes in the noncash working capital accounts); CFO divided by current liabilities; and CFO divided by total liabilities. The other group of models was composed of multivariate accrual models generated from linear MDA. Each accrual model included the following six accrual ratios: net income/total assets, cash/total assets, current assets/current liabilities, net sales/current assets, current assets/total assets, and total liabilities/owners'equity. Thus, the authors basically compared the classification accuracy of each cash flow variable separately to the classification accuracy of the six combined accrual ratios. C&B found that neither cash flow variable had higher classification rates than the combined six accrual ratios. However, the authors failed to test whether the cash flow variables had incremental predictive ability.

In their subsequent study [1985], C&B attempted to determine whether CFO could increase the accuracy of accrual-based ratios to distinguish between bankrupt and nonbankrupt firms. The study was basically the same as the previous one except the approach was different; the objective was to determine if CFO had incremental predictive ability. The authors developed accrual, cash flow, and mixed (cash flow variables added to the accrual models) models for lag periods of one to five years. In order to obtain test statistics on each variable, C&B also generated mixed models using conditional stepwise logit analysis.[13] C&B concluded that operating cash flows "do not provide incremental predictive power over accrual-based ratios" [p. 395].

The research by C&B seems to validate the FASB position that accrual information better predicts future cash flows, but contradicts the FASB position that cash flow information taken together with accrual information should better predict future cash flows. However, C&B only tested CFO, and they used working capital from operations (WCFO) to calculate CFO. Drtina and Largay [1985] found that using WCFO to calculate CFO may create confounded results because of the inconsistencies among the way firms define WCFO and the diversity in reporting practices. C&B also failed to control for firm size, either by matching on size or by incorporating a size variable in the models. Ohlson [1980] found that firm size was a very significant predictor of bankruptcy.

In a study similar to the studies of Casey and Bartczak, Gentry *et al.* [1985] compared 33 bankrupt and 33 nonbankrupt firms to determine if funds flow information could predict financial distress. Firms were matched on size, industry, and sales. The

[13]Most statistical packages for MDA do not generate meaningful test statistics for each variable tested (the slopes using MDA have no intuitively practical meaning). MDA is also primarily a classification technique instead of a predictive technique; thus, MDA is not the most appropriate technique to use when the purpose is to test the ability of independent variables (cash flows and/or accrual ratios) to predict financial distress.

authors used a separate sample of 23 weak and 23 nonweak firms to validate the models instead of a separate holdout group of bankrupt/nonbankrupt firms. The weak firms were identified by the "creditwatch list issued by the Wells Fargo Bank" and "from various financial services who rate candidates for financial failure" [p. 158]. Instead of testing CFO, the authors tested seven funds flows (each scaled by total net cash flows) based on Helfert's [1982] "cash-based funds flow model" and six accrual ratios. The seven funds flows tested were operations, working capital, financial, fixed coverage expenses, capital expenditures, dividends, and other asset and liability flows. The authors used various statistical techniques to generate the models (individual and mixed models) to test the funds flow and accrual ratios (MDA, probit, and logit techniques); however, the logit models provided the best results. Gentry *et al*. found that only the dividend funds flow component was significant both one year and three years before bankruptcy. They also found that the components of CFO (funds from operations, working capital, and fixed coverage expenses) failed to improve the classification of failed and non-failed firms. However, the authors never specifically tested CFO.

In a subsequent study, Gentry *et al.* [1987] extended the 1985 study by comparing the predictability of accrual ratios and funds flow components. The authors broke up the net working capital from operations variable into five funds flow components (changes in accounts). The five funds flow components were accounts receivable, inventory, other current assets, accounts payable, and other current liabilities. Thus, the authors looked at eleven funds flow variables instead of seven, as in their prior study. Six accrual ratios most common in prior financial distress studies were also tested. The authors found that outflows of certain components indicated a healthy company. Inventories, dividends, and receivables were inversely related to bankruptcy; nonfailed companies showed net outflows for inventories, receivables, and dividends while failed companies showed inflows leading up to the bankruptcy. The dividend flow component was also a significant incremental predictor of bankruptcy. Thus, this study offers evidence that the particular inflows and outflows of funds may be more important in predicting bankruptcies than a net flow such as CFO.

Aziz *et al.* [1988] tested the predictability of six cash flow variables on a sample of 49 bankrupt and 49 nonbankrupt firms for the period 1971-82 (the models were generated with data collected from 1966-1981). The cash flows tested were operating cash flow, net capital investment, taxes paid, liquidity change, stockholders' cash flow, and lender cash flows. These cash flows were selected based on a cash flow identity developed by Lawson [1978 and 1985] and were scaled by the book value of the firm to avoid the problem of heteroscedasticity. Lawson's cash flow identity differs from Helfert's [1982] cash-based model in that Lawson's model is for "firm valuation," while Helfert's model is to provide analysis by "area of management attention" [Aziz *et al.*, pp. 419-420]. MDA and logistic regression were used to generate the models (lagged for 1-5 years) to test the cash flow variables.

The authors found that the cash flows taxes paid, operating cash flow, and lender cash flow were significant in two of the five years before bankruptcy, with taxes paid significant in all five years. A comparison with the Gentry *et al.* [1985] and Altman *et al.* [1977] (ZETA) models indicated that Lawson's model was superior to the Gentry *et al.* model for the only year compared and was superior to the Altman *et al.* model for three or more years before bankruptcy. However, Aziz *et al.* failed to test the incremental predictability of cash flows above accrual ratios alone.

Aziz and Lawson [1989] extended the research of Aziz *et al.* two ways: (1) they tested the incremental usefulness of cash flow information by combining the cash flow variables with the five accrual ratios in Altman's Z-score model and (2) they used a holdout sample of 26 bankrupt and 67 nonbankrupt firms to test the validity of the models generated. The authors also extended prior research by incorporating formal hypothesis testing. Based on classification accuracy, Aziz and Lawson confirmed the results of Casey and Bartczak and Gentry *et al.*, concluding that cash flow based models do not improve on the existing model's (accrual) overall accuracy. However, concerning the holdout sample, cash flow based and mixed models exhibited superior predictive accuracy, thus indicating cash flows may be more stable across time.

A recent unpublished study [Rujoub, 1989] found that cash flow ratios recommended by Mielke and Giacomino [1988] have incremental predictive content. The authors used MDA and multivariate logit analysis to generate cash flow models, accrual models, funds flow models, and mixed models for lag periods of one, two, and three years prior to bankruptcy. The cash flow models contained eight cash flow ratios, the accrual models contained six accrual ratios, and the funds flow models contained eight ratios based on the old statement of changes in financial position. The mixed models were composed of only the cash flow and accrual ratios.

However, this study has limited external validity. Tests of the normality assumption for MDA indicated that all 22 ratios tested were significantly nonnormal, with 20 of the ratios significantly nonnormal at a p-value of less than .01. The authors also violated one of the most important assumptions of logit analysis when they used a very small sample (33 bankrupt and 33 nonbankrupt firms) to test a large number of variables in each model (eight, eight, and sixteen variables for the cash flow, accrual, and mixed models, respectively). A thorough discussion of this limitation is offered in the next section of this chapter.

The results of the above studies are disappointing in that they provide little evidence suggesting that cash flows have incremental content above accrual information in predicting financial distress. These results are surprising, since the main stated benefit of cash flows is their incremental usefulness in helping accrual information to predict insolvency [Staubus, 1989]. The one published study indicating cash flow based components have incremental predictive content [Gentry *et al.*, 1987] really found that certain changes in accounts that make up working capital have predictive content.

Motivation for Study

This part of Chapter 3 contains a discussion of the limitations of prior financial distress studies which tested the predictability of cash flows. Where appropriate, methodology studies addressing subjects related to these limitations are also discussed. These methodology studies are summarized in Table B-3.

Limitations of Prior Financial Distress Cash Flow Studies

The previous financial distress cash flow studies suffer from a number of limitations which could be confounding the results. Table B-4 contains a summary of these limitations.

Lack of Theoretical Framework of Financial Distress

Only Gentry *et al.* [1985 and 1987], Aziz *et al.* [1988], and Aziz and Lawson [1989] developed a theoretical framework for selecting the cash (funds) flow variables to test, and only Aziz and Lawson [1989] developed hypotheses. None of these studies attempted to develop a theoretical representation of the failure process.

Violations of Statistical Assumptions

Each study violated important assumptions of the statistical techniques used. MDA assumes that the predictor variables are randomly drawn and normally distributed, and linear MDA also assumes equal variance/covariance matrices for each group [Altman *et al.*, 1981]. Many researchers failed to test these assumptions. Those researchers who did test for violations of MDA assumptions found that these two assumptions were almost always violated; financial ratios do not tend to be normally distributed.

Logistic procedures are not restricted by assumptions concerning the predictor variables. Thus, they are generally preferred over MDA [Press and Wilson, 1978]. However, logistic procedures assume that the response variables are randomly drawn [Altman *et al.*, 1981] and require sample sizes of at least 10(S+1) to generate unbiased estimates, where S is the number of predictor variables in the model [McFadden, 1974; Freeman, 1987].

Noreen [1988] used simulations to compare the performance of probit and ordinary least squares regression (OLS) models in predicting bankruptcy. The models contained four independent variables and were based on sample sizes of 50 and 100.[14] Thus, the lower sample size barely met the requirement of 10(S+1). Noreen found that, for a sample size of 50, probit incorrectly rejected the null hypothesis of no effect at a rate twice the normal level and greater than OLS. However, the results basically reversed when the sample size was increased to 100 (OLS incorrectly rejected the null hypothesis more than probit). These results suggest that: (1) probit and logit techniques would be no better than OLS regression for small sample sizes; (2) an appropriate sample size for

[14]Since probit and logistic techniques are so similar, both require basically the same statistical assumptions. Thus, the results from this study for probit analysis should also hold true for logistic techniques.

using probit or logistic techniques may be closer to 20(S+1) than 10(S+1); and (3) using probit and logit techniques in bankruptcy studies with small samples could lead to the researcher incorrectly concluding that a variable is a significant predictor of financial distress when, in reality, the variable is not a significant predictor of financial distress.

Stone and Rasp [1991] subsequently extended the research of Noreen by using simulated data and actual data to compare the performance of OLS regression models and logit regression models. The authors tested the effect of sample size, number, correlation, and distribution of predictor variables on logit error rates. Like Noreen, the authors found that a sample size of 10(S+1) led to biased logistic estimators; these logistic estimators were also more biased than the OLS estimators. However, the authors found that the chi-square statistics for the overall models tended to incorrectly reject the null hypothesis of no effect while the individual parameter test statistics (t-test statistics) tended to be conservatively biased against rejecting the null hypotheses. The authors also found that: (1) skewed data tended to increase the biases of the test statistics, (2) unequal response group sizes did not appear to increase the biases provided sufficient overall sample sizes were used, and (3) moderate multicollinearity ($\rho = .50$) failed to increase the biases in the parameter estimates.

Even though the logistic estimators were more biased than the OLS estimators, the OLS models resulted in significantly higher Type 1 error rates (lower classification accuracy for identifying the firms receiving consistency qualified opinions). The authors concluded that: "even for sample sizes as small as 50 (with four predictor variables), logit rather than OLS still may be the preferable model for accounting choice studies" [p. 171] and "sample sizes of 200 (four to six predictors and skewed data) or more will be needed to ensure that logit test statistics will be properly calibrated" [p. 184]

The prior bankruptcy studies also suffered from stratification bias because the researchers nonrandomly selected the bankrupt and nonbankrupt firms. Instead of randomly selecting a sample of firms from the population and then identifying the bankrupt and nonbankrupt firms researchers were forced to identify the bankrupt firms first in order to obtain a sufficient sample size of these firms. Then, the bankrupt firms were matched with nonbankrupt firms, normally on a one to one basis. Consequently, the sample was not representative of the population (bankrupt firms were oversampled). Thus, the biased logistic or probit estimators will overclassify bankrupt firms and underclassify nonbankrupt firms. This sample bias is often referred to as "choice-based sampling bias" [Manski and Lerman, 1977].

Zmijewski [1984] empirically demonstrated the existence of choice-based sampling bias in a predictive study of financial distress. He also showed that a weighted probit model eliminated most of the sampling bias and that sampling a larger percentage of nonbankrupt firms lessened the bias. Zmijewski also found that the bias did not change the statistical results or overall accuracy of the model.[15]

All of the cash flow studies which used logistic procedures, except the studies of Casey and Bartczak [1984 and 1985], violated the requirement of a sufficient sample size for some, if not all, of their logistic models. The violations were especially severe for the two studies [Gentry *et al.*, 1987; Rujoub, 1989] which found that cash flows (funds flows) were significant predictors of bankruptcy. Gentry *et al.* and Rujoub needed minimum sample sizes of 190 and 150, respectively, to meet the minimum sample size requirement of 10(S+1) for their mixed models, and all the models for both studies used samples sizes significantly below the sample size of 200 recommended by Stone and Rasp.

[15]Manski and McFadden [1981] and Cosslett [1981] illustrate weighted procedures to correct for choice-based bias in binary logit models.

Based on Noreen's results, Gentry *et al.* and Rujoub needed sample sizes of 20(S+1), 380 and 300 firms, respectively, to eliminate this bias. Since their sample sizes are substantially below these recommended samples sizes, their results could be affected by the bias caused by using small sample sizes to generate the logistic parameter estimates.

Due to stratified sampling, all the studies using logistic procedures also violated the assumption of random selection of the response variables. However, none of the studies used weighted adjustments to correct for the choice-based sample bias, and only Casey and Bartczak [1984 and 1985] sampled a more appropriate percentage of nonbankrupt firms.

Pooling of Firms Across Time and Selection of Holdout Sample

A third limitation of the above studies is that the researchers pooled firms across a large time frame to obtain a sufficient number of bankrupt firms. Conditions probably are not stable across the different years used to develop the samples. Thus, sampling across years would tend to increase the variation in the sample, resulting in a lower likelihood of finding significant results. Also, studies which used holdout samples to verify the predictive accuracy of their models selected the holdout group of firms from the same period used to develop the models. These *ex post* discriminations are true predictions only if *stationarity* exists. Otherwise, one should draw the holdout sample from a future period distinct from the original sample period. Evidence of *ex ante* predictive power requires *intertemporal* validation and not just *cross* validation [Joy and Tollefson, 1975].

Mensah [1984] tested the stationarity of multivariate bankruptcy models for the years 1970 to 1978 for firms which failed during the period from January 1972 to June

1980. The author chose this time frame because he believed the time frame covered four separate economic periods. The four periods were: (1) steady growth phase (expansionary period - January 1972 to January 1973), (2) recessionary conditions (February 1973 to March 1975), (3) steady growth phase (recovery phase - April 1975 to December 1977), and (4) stagflation and recession (January 1978 to June 1980). The author sampled four separate groups of bankrupt/nonbankrupt firms from these four separate economic periods and developed two-year classification models for each group based on ten factor scores obtained through a factor analysis of 38 ratios.

Mensah found that the models were not stationary across time, thus questioning the practice of pooling bankrupt firms across wide periods of time, as in prior studies. These results also indicate that one must obtain the holdout sample from outside the time frame used to develop the model to obtain an accurate picture of the predictive ability of the model.

Use of Bankruptcy/Nonbankruptcy as Proxy for Financial Distress

Another limitation of prior financial distress studies is the use of bankruptcy as the criterion to operationalize financial distress. The primary objective of financial distress cash flow studies is to determine the ability of cash flow information to predict financial distress which is surrogating for future cash flows. The use of a dichotomous classification of distress is an overly simple representation of the financial distress process and is unlikely to capture the true underlying construct. The financial distress of a firm is an unobservable continuum. Firms are not simply bankrupt or healthy, but possess certain degrees of distress which vary from day to day and period to period. However, since researchers do not have the capability to observe this continuum, they select events to operationalize this construct. The finance literature stresses the belief that many events indicate different degrees of financial distress, and companies may go through many of these events before bankruptcy occurs [Guthmann and Dougall, 1940; Dewing, 1953; Gordon, 1971; Newton, 1975].

Recent empirical research by Gioux and Wiggins [1984] and Flagg [1988] concerning the events leading to bankruptcy indicates that firms do indeed go through different levels (events) of financial distress. A truer test of the usefulness of a financial distress model would be the model's ability to distinguish between firms that are marginally distressed, not just between firms fairly healthy and in very serious financial distress [Jones, 1987]. Events such as loan/interest default and failure to pay dividends may be of more interest to investors and creditors because the ability to predict these events one year in advance would provide the users with an earlier warning signal than predicting bankruptcy one year in advance.

Researchers have also questioned the use of bankruptcy as a proxy for financial distress on the grounds that bankruptcy is a legal event rather than an economic event [Dietrich, 1984]. Financial distress results from economic occurrences. Only economic events should truly capture the level of financial distress of a firm. Legal recognition of bankruptcy may occur some time after the firm is economically insolvent, or occur even though the company is not economically insolvent. Also, the economic conditions of bankrupt firms are likely not similar to other types of distressed firms. Thus, using a legal event as a proxy for economic conditions may produce misleading results. Even the firms selected by legal status may form a heterogeneous set because some firms voluntarily choose bankruptcy, and others do not. Thus, their economic conditions may be quite different [p. 84].

Flagg [1988] also found that many of the firms listed on the Compustat tape as bankrupt had never experienced a previous signal of distress (defined as a net loss).

Upon further investigation he found that these firms were smaller firms, and that most would have shown a distress signal if not for management error or fraudulent activities. If researchers failed to adjust their samples for these firms, their results would be confounded. This problem primarily occurs when the researcher uses Compustat to select the bankrupt/nonbankrupt firms, and fails to verify whether management is under investigation for irregularities.

Gilbert *et al.* [1990] addressed the appropriateness of using a bankruptcy/nonbankruptcy response scale to test the importance of accounting information by replicating the studies of Casey and Bartczak [1985] and Altman [1968] using two separate samples of firms. The two samples of firms were: (1) a sample of 76 bankrupt and 304 randomly selected firms and (2) a sample of 76 bankrupt and 304 distressed firms (firms that had negative cumulative earnings over any consecutive three year period between 1972 and 1983). The authors divided the samples into two halves, one half was used to develop the models and the other half was used as holdout firms (52 bankrupt firms and 208 random or 208 distressed firms formed the model estimation groups and the rest of the firms represented the holdout groups).

Using logistic regression, the authors found that CFO (either alone or scaled by current liabilities or total liabilities) had significant incremental predictive ability when added to accrual ratios in predicting bankruptcy (unlike Casey and Bartczak), especially in the bankrupt/distressed models. The authors also found that the bankruptcy models performed poorly when used to distinguish bankrupt firms from distressed firms for the holdout sample. Thus, the results indicate that cash flow variables may be more useful in distinguishing between other events of distress and raise questions about the use of the bankrupt/nonbankrupt proxy of financial distress used in prior studies. However, Gilbert *et al.* failed to: (1) look at other economic events of distress such as loan defaults and failure to pay dividends; (2) develop multi-state models of distress to better capture the predictive ability of cash flow and accrual information; and (3) control for the size of the firms, either by matching the firms on size or by including size as an independent variable.

Period Used to Obtain Data to Generate the Models

The period of time used to generate the predictor models is also very important. Cash flows and accruals differ because various accrual methods create a difference in the timing of the recognition of revenues and expenses. These differences should have grown as the profession has moved closer to the all-inclusive definition of income.

Using factor analysis, Gombola and Ketz [1983] found that cash flow variables scaled by total debt, total assets, and equity loaded on a separate factor from accrual variables after the mid 1970s, thus suggesting that cash flow variables provided information not in other financial data. However, cash flow variables scaled by total debt generally had weaker factor loadings. Gombola *et al.* [1987] subsequently tested whether the failure of prior studies to obtain sampling data points after the mid 1970s could be confounding the results of these studies. The authors divided their sample into pre-1972 and post-1972 sampling groups. They concluded that cash flow variables were not more relevant in the post-1972 model. However, their samples may have been too small to detect a difference, and the authors failed to develop models from the post-1981 period.

In a study concerning the intertemporal divergency among cash flow, working capital, and income from operations, Franz and Thies [1988] found that income and working capital from operations had diminished as a percentage of cash flow over the period from 1967 to 1985. Their results also indicated that most of the decrease in income as a percentage of cash flow occurred from 1981 to 1985 (decrease from .5099 to

.3493 versus a decrease of .5519 to .5099 for the period from 1967 to 1981) [p. 24]. This increasing gap between income and cash flow suggests that cash flows may provide additional information in predicting financial distress, and that models developed from the post-1981 period are more likely to detect the incremental usefulness of cash flows as predictors of financial distress. However, all of the previous cash flow studies generated models with at least half of the data points falling before 1975, and all of the studies' models were developed from data primarily occurring prior to 1982.

Lau's Financial Distress Studies

Lau [1987] corrected for many of the methodological limitations of the above corporate failure predictive models by using a five-state model to approximate the continuum of corporate financial health instead of the conventional bankrupt/nonbankrupt dichotomy. The states were: financial stability, omitting or reducing dividend payments, default of loan interest and/or principal payments, protection under Chapter X or XI of the Bankruptcy Act, and bankruptcy and liquidation.

The financial distress prediction models were constructed using "multinomial logit analysis" (MLA). This technique provided estimates of the probabilities that a firm will enter each of five financial states instead of "classifying" a firm into a certain financial state. Lau developed one, two, and three year models for firms falling into the five states during 1976 (1974/75, 1973/4 and 1972/73 financial data were used to predict 1976's financial distress). A holdout sample was used to test the models' abilities to predict 1977 distress. Thus, Lau's models are developed over the same period of time for all firms, firms are not pooled across different years, and the holdout sample is from a different year.

Lau based the selection of predictor variables on theoretical reasoning. The ten variables tested were based on Donaldson's "financial mobility" concept of financial distress [1986]. Two of the variables were "funds flow" variables (of which one was a trend variable). Working capital flow variables were used as the two funds flow variables in this study. Lau found that, when compared to a MDA model, the MLA model performed well for one, two, and three years prior to financial distress.

Lau also attempted to test the predictive ability of four different definitions of "funds flow," one of which was cash flow from operations, in her related dissertation [1982]. However, because of limitations in her models, statistical inferences were difficult to obtain, and the results differed depending on the method used. MDA ranked cash flow from operations as the best funds flow variable, while MLA ranked cash flow from operations as the lowest.

Limitations of Lau's Studies

Lau's studies represented a substantial advancement in the methodology of financial distress prediction models. Still, Lau had a number of limitations in her studies. First, she used MLA [Nerlove and Press, 1973; McFadden, 1974] to develop the models to determine the probability of a firm occurring in one of the five states in a given period. Assuming a model with 10 predictor variables, and defining p_i as the probability that a firm is in state i, this logit model postulates that the p_i can be estimated as follows:

$$Z_i = b_{i1}X_1 + \dots + b_{i10}X_{10}$$
$$\text{for each state } i = 1 \text{ to } 5,$$
$$\text{then } p_i = \exp(Z_i) / \sum_{i=1}^{I} \exp(Z_i)$$

This model is a nominal based model and does not assume that the Y levels are ordinal in nature. Thus, Lau's model develops a logit for each financial state; the model has five parameter estimates, and five test statistics, for each variable in the model.

However, the levels of distress used by Lau obviously represent an ordinal scale of distress; the levels of distress are proxies for the continuous construct, financial distress. Lau even considered the distressed firms to be on an ordinal scale. She stated that "we view these states as being on a continuum" [1982, p. 27] and "states one to four are states of increasing severity of financial distress" [1987, p. 128]. Even though the nominal MLA is an improvement over MDA, the model is inferior to ordinal logistic procedures for ordinally scaled response variables. According to Agresti [1984], ordinal procedures have the following advantages over nominal procedures:

> (1) Ordinal methods have greater power.
> (2) Ordinal data description is based on measures similar to those (e.g., correlations, slopes, means) used in ordinary regression for continuous variables.
> (3) Ordinal analyses can be used in a greater variety of models, most of which have simpler interpretations than the standard models for nominal variables.
> (4) Ordinal models can be applied in settings where the standard nominal models are trivial or else have too many parameters to be tested for goodness of fit [p. 3].

The QUAIL program [Berkman *et al.*, 1979] used by Lau to develop the MLA models also apparently did not generate summary statistics for each variable in the model, nor did the program generate overall statistics for the models (overall test statistics for goodness of fit). Thus, the MLA procedure used by Lau did not enable her to add various funds flow ratios to an established model and then observe the partial statistics to determine the usefulness of particular variables.[16] Lau attempted to overcome these limitations by employing a very unique rank scoring rule and developing

[16]Current nominal logistic statistical packages (SAS, Proc Catmod) provide summary test statistics and are not as limited concerning the testing of the incremental predictive ability of variables. However, nominal logistic techniques still have many limitations when compared to ordinal logistic regression.

four separate models with a separate funds flow variable in each model. However, the rank scoring rule did not allow for statistical tests of significance for each variable. An ordinal logistic procedure is not limited by these problems.

Lau selected the firms with potential loan interest/principal defaults by identifying those firms that had either filed for bankruptcy or had C-rated bonds during 1977 to 1980. She then used the firms' SEC 10-K reports to identify which of the firms had also defaulted loan interest and/or principal payments during 1976 and 1977. This retrospective sampling technique likely understates the percentage of firms which recovered from distress after loan/interest default, causing bias in the sample.[17]

Lau also used data from the 1970s and scaled the funds flow variables by total debt. The increasing gap between income and cash flow during the 1980s [Franz and Thies, 1988] indicates that results may be different if a post-1981 period is used to obtain data to generate the predictive models. Gombola and Ketz [1983] also found that cash flows scaled by total debt had weaker factor loadings than cash flow variables scaled by assets or equity.

Summary of Study

The above limitations of prior financial distress cash flow studies indicate the need for additional financial distress cash flow research. This dissertation addresses this need by correcting for many of the limitations of prior studies through the use of different sample techniques and multi-state prediction models. Similar to Lau, this study is based on multi-state distress models. However, ordinal logistic regression is used to generate the models. Thus, this study differs from prior financial distress studies as follows:

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[17]Eighty percent of the firms in Lau's 1976 sample of loan/interest defaults came from the bankrupt group of firms.

(1) A theoretical representation of the failure process is used to select the cash flow variables to test.

(2) Sample sizes of at least 20(S+1) are obtained for all models tested, thus lowering the amount of sampling bias.

(3) A larger sample of healthy firms is obtained to limit the effects of choice-based sampling bias.

(4) A multi-state financial distress variable is used as the proxy for financial distress; thus, this study is not limited by the weaknesses of using a dichotomous bankrupt/nonbankrupt proxy for the dependent variable, financial distress.

(5) Firms used to generate the predictive models are not pooled across a large time frame but are selected from one year; holdout firms are obtained from a year other than the year used to generate the models in this study.

(6) The data for this study are obtained from the post-1982 period.

(7) Ordinal logistic regression, rather than MDA or MLA (nominal), is used to generate the multi-state models in this study, thus correcting for the limitations of using MDA or MLA. This procedure enables the author to test the incremental predictive ability of cash flow variables using multi-state prediction models. Ordinal logistic regression also takes advantage of the ordinal scale of the financial distress variable and is a more powerful method to test the predictability of cash flow variables than the MLA procedure used by Lau. Thus, the use of ordinal logistic regression represents an extension of prior multi-state financial distress research.

(8) The sampling scheme used to obtain the loan/interest default and debt restructure firms results in the selection of firms which recover from financial distress after loan/interest default and/or debt restructure. Financially distressed firms are also sampled to enable the author to check whether management was under investigation for irregular activities during the period of distress (year the distress is recognized).

CHAPTER 4

RESEARCH METHODOLOGY AND HYPOTHESES

Chapter Four contains a discussion of the methodology used and the hypotheses tested. This chapter is divided into five sections. Section one provides a discussion of the theoretical model of financial distress and is segregated into the following three parts: (1) the unexpected drop in cash flow, (2) the stages leading to financial distress, and (3) the states of financial distress. Section two discusses the development of the independent variables used in this study based on the theoretical model of financial distress. Section three discusses the hypotheses tested in this study. Section four contains a discussion of ordinal logistic regression and the comparisons and statistical tests used to test the hypotheses. The final section contains a discussion of the sampling procedures used to obtain samples of firms for 1988 and 1989.

Theoretical Model of Financial Distress

The theoretical model of financial distress is illustrated in Figure A-2. This theoretical model was used to select the cash flow variables of interest. The theoretical framework is based on Donaldson's [1986] financial mobility concept, Heath's [1978] financial flexibility concept, and the funds flow concept.[18]

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[18]The financial mobility concept of Donaldson and the financial flexibility concept of Heath are basically the same concept except Donaldson's approach is based on a broad definition of funds, while Heath's approach is based on the cash definition of funds. Thus, the author uses the term "financial flexibility" to describe this concept.

Unexpected Drop in Cash Flow

According to Heath [1978], financial flexibility is the capacity of a firm "to control cash receipts and payments to survive a period of financial adversity" [p. 20]. The ultimate aim of financial flexibility is to achieve a state of equilibrium in cash flow so that the available purchasing power will be equal to the needs set by established limits and management decisions [Donaldson, 1986]. The concept of financial flexibility advocated by Heath [1978] was included in the 1980 Discussion Memorandum [FASB]. In this memorandum, the FASB stressed that "financial flexibility is useful in assessing the uncertainty of future cash flows" [p. v], and that "declining funds flows from operations and reduced liquidity may signal an impending cash flow problem" [paragraph 17]. The FASB also stated that the "sources of financial flexibility include the ability to generate additional cash flows by financing, by liquidating assets, and by modifying operations" [paragraph 18].[19]

This framework is similar to Lau's framework, except the funds flow concept (cash basis) discussed in Chapter 2 is incorporated into the theoretical model. As a result, this model is based on a "managerial view" of corporate finance instead of a more traditional view of wealth transfers, or the "maximization of owners' equity" [Donaldson, 1986]. Thus, emphasis is placed on solvency and cash flows instead of profitability and earnings. The activities taken by management in restoring cash flow equilibrium dictates the future cash flows.

Based on this framework, the occurrence of events triggering an unexpected drop in cash flow forces the company to take corrective action to regain cash flow equilibrium.

[19]Heath recommended that the statement of changes in financial position be replaced with three statements: a statement of cash receipts and payments, a statement of financing activities, and a statement of investing activities.

Some of the events occur suddenly, while others can be cyclical in nature. Examples of such events are:

> (1) decline in sales, (2) slowdown in accounts receivable, (3) price or wage increases (contract negotiations), (4) change in general economic condition (recession), increased competition (innovation), and management behavior.

Management has a number of strategies for corrective action to regain cash flow equilibrium to avoid insolvency. Some of these strategies to avoid insolvency would include:

> (1) borrowing money, either directly by borrowing from banks, selling bonds, etc., or indirectly by delaying payments to creditors, and allowing accounts payable to build, etc.; (2) liquidating assets either directly by selling assets, or indirectly by failing to replace inventory as the inventory is sold or failing to replace fixed assets consumed in operations, etc.; (3) reducing costs; (4) reducing dividends; and (5) issuing capital stock [Heath, p. 21].

Stages Leading to Financial Distress

According to Donaldson, management's responses to these events can be modeled using six stages. The six stages represent a chronological process leading to financial distress. Each stage represents an attempt by management to select the appropriate means to bring the company's cash flow back into equilibrium. The success of management dictates whether a firm recovers or progresses towards eventual financial distress. Observing the pattern of decisions made during these stages should offer a viable way of predicting financial distress. Donaldson's stages are summarized below.

> Stage one. Stage one is marked by management trying to maintain the current level of budgeted expenditures and investments. Management attempts to modify cash flows by (1) borrowing basically short-term bank loans to avoid secured borrowing or other forms of high risk debt and (2) planning the timing and amount of discretionary payments.

Stage two. Once the decline in instant reserves (cash and loan reserves) approaches the limits set by the established norm of the company and the bankers, the company is likely to obtain long-term loans. The purpose is to either restore reserves of commercial bank borrowing power or to add new resources while rolling over the existing bank loans.

Stage three. Persistent cash flow deficits have now consumed the company's instant reserves and long-term borrowing power. The company is forced to turn inward to identify cash which can be released without affecting current sales or income. The company will attempt to reduce the investment in inventory, and planned investments will be highly scrutinized, resulting in a decrease in investments.

Stage four. If the deficit continues, the effort to fund financial mobility internally conflicts with the organizational cushions designed to provide operating mobility. Resistance of the organization to the encroachment of its norms of mobility reserves forces a reexamination of the firm's strategic goals and expenditures. New limits of long-term debt will be negotiated, and new lenders will be sought, if old lenders resist.

Stage five. Whether or not cash flow deficits continue, the increased borrowing forces the company to reexamine it's strategic goals and policies. The company is forced to sell some operating assets and/or segments of the business at a substantial sacrifice to induce a quick sale.

Stage six. If the deficit continues, the only alternative left to the company is to curb outflows on operating and capital expenditures, thus leading to reduced current sales and profits. Some residual secured short-term borrowing may occur, but is really a liquidation of the assets offered as security [pp. 233-239].

Companies failing to recover cash equilibrium during these stages will eventually enter financial distress. The severity of this financial distress is directly related to the actions taken by management during the stages leading to distress. However, one would not necessarily expect all companies to go through all the stages in this model. Nor would one expect all companies to follow the exact same order of events.

States of Financial Distress

Since financial distress is a theoretical construct, the researcher must develop proxies for financial distress. Prior predictive financial distress studies primarily used bankrupt/nonbankrupt as the proxy for financial distress. However, as discussed in

Chapter 3, this proxy suffers from a number of limitations. One, the dichotomous classification of bankrupt/nonbankrupt is an overly simple representation of the financial distress construct and may result in the loss of important information. Studies addressing the ability of models to predict marginal levels of distress may be more useful than simple dichotomous bankruptcy prediction studies and should provide better tests of the predictive power of financial information. Two, bankruptcy is a legal event and not an economic event. Only economic events are likely to capture the true financial distress of a firm. Three, bankrupt firms may be a heterogeneous group themselves because some bankrupt firms self-select while other bankrupt firms are forced to declare bankruptcy.

Development of an Ordinal Multi-State Measure of Financial Distress

The severity of the financial distress of a firm can be modeled using ordinal levels of financial distress. The levels of distress used in this study are based on the empirical research of Gioux and Wiggins [1984] and Flagg [1988].

Gioux and Wiggins found that common events of financial distress prior to bankruptcy were subsequent successive losses, dividend reduction/elimination, debt accommodations, and loan/interest default. In fact, all firms in their sample either had a debt accommodation, loan default, or both prior to bankruptcy, with 70 percent of bankrupt firms negotiating debt accommodations and 50 percent defaulting. Seventy-three percent of the debt accommodations involved the renegotiating of loan terms in order to extend cash payment schedules or reduce interest rates. Dividend reduction tended to occur before debt accommodations, and debt accommodations before loan/interest default. However, distinguishing the ordering of the default or accommodations was difficult.. Accommodations may occur to prevent default, or may occur after a company has already defaulted. Flagg subsequently found dividend reductions to be significant predictors of eventual bankruptcy.

Thus, the states (events) of financial distress used in this study are: (1) state zero-financially healthy; (2) state one-dividend reduction/elimination; (3) state two-loan/interest default and/or debt accommodation (extension of cash payment schedules, reduction in principal, or reduced interest rates); and (4) state three-bankruptcy. These states of financial distress represent an ordinal measure of the financial distress of a firm. This measure of financial distress is the dependent variable or response variable used in this study.

Selection of Independent Variables

The theoretical model of financial distress illustrates the primary importance of cash flow information in evaluating solvency and stresses certain points of interest. One, this theoretical framework indicates that cash flow from operating activities (CFFO) alone would not provide sufficient information to develop patterns to predict distress. In fact, the model indicates that although CFFO may be the first to be affected (the initial negative cash flow tends to result from a decrease in CFFO), cash flows from investing activities (CFFI) and financing activities (CFFF) should be just as important in determining whether companies enter a state of financial distress.

Two, the model also indicates that aggregated net flows may not be sufficient to identify trends. This belief is in agreement with Sorter's [1969] events theory, and was the position taken by the FASB in Statement 95. However, current accounting data are not sufficient for researchers to obtain measures of most gross cash flows, especially gross operating cash flows. Still, some gross financing cash flow measures of importance based on the theoretical model of financial distress can be developed from current accounting data. These cash flows are short-term financing and long-term financing flows.

Three, some gross cash flows may not be important in predicting financial distress. Equity financing flow should not provide much information. Donaldson [1986] indicated that companies tended to postpone equity options because there were other options of less cost to the company. However, once these other options were taken, the issue of equity financing was no longer feasible. By the time the company decides to decrease dividends paid to stockholders, the company is entering financial distress. Thus, substantially reducing dividend payments or failing to pay a dividend after a history of dividend payments is considered the first state of financial distress.[20]

Thus, the three net cash flows tested in this study are cash flow from operating activities (CFFO), cash flow from investing activities (CFFI), and cash flow from financing activities (CFFF). However, three of the gross cash flows which make up CFFF, short-term financing flow (SFF), long-term financing flow (LFF), and equity financing flow (EFF) are also tested in this study. The naive operating cash flow (NOF) included in many of the earlier financial distress studies is also tested since researchers found this variable to be one of the most significant predictors of financial distress [Beaver, 1966; Deakin, 1972; Blum, 1974; Norton and Smith, 1979; Mensah, 1983; Holmen, 1988].

The author also compared the predictive power of cash flows to accrual ratios and the incremental predictive power of cash flows when added to accrual ratios. Because of the large number of accrual ratios to choose from, the selection of accrual ratios to test is

[20] A firm is considered in financial distress if the firm takes financial actions which result in a monetary loss to external parties. This criterion is consistent with the financial flexibility concept, and has been used in a number of financial distress studies [Beaver, 1966; Gioux and Wiggins, 1984; Lau, 1982 and 1987; and Flagg, 1988].

somewhat subjective. The following accrual ratios were selected to test because of their acceptance in prior financial distress studies: cash plus marketable securities/total assets (CASHTA), current assets/total assets (CATA), current assets/current liabilities (CACL), sales/current assets (SALESCA), net income/total assets (NITA), and total liabilities/owners' equity (TLOE).

These six ratios were basically the same ones tested by Casey and Bartczak [1984 and 1985] and identified as having high loadings in prior factor analysis studies [Libby, 1975a and Chen and Shimerda, 1981]. The only difference is that cash plus marketable securities/total assets was used instead of cash/total assets. Cash plus marketable securities was used because many firms after changing to a statement of cash flows no longer report (coded as aggregated data on the Compustat tapes) cash but report cash plus marketable securities. Cash plus marketable securities/total assets was found to be useful by Libby [1975b] and Deakin [1972] in two prior financial distress studies.

Hypotheses Tested

The model of financial distress indicates that CFFO, CFFI, and CFFF should have information useful in predicting financial distress. The FASB accepted this belief by requiring that the statement of cash flows show the net cash flows from each of these three activities. Therefore, the following hypotheses, stated in the alternative form, were tested:

H_{1A}: CFFO is a significant predictor of financial distress.

H_{1B}: CFFI is a significant predictor of financial distress.

H_{1C}: CFFF is a significant predictor of financial distress.

However, the model also indicates that, except for equity financing cash flow, the gross cash flows from financing activities may be more useful than CFFF in predicting financial distress.[21] Therefore, the following hypothesis (alternative form) was tested:

> H_2: The gross cash flows of financing activities (exclusive of equity financing) have greater predictive value than the net cash flow, CFFF.

The FASB asserts that accrual information is more useful in predicting financial distress than cash flow information. However, many researchers believe that cash flow information may be more useful than accrual information in predicting insolvency [Carson, 1965; Ijiri, 1978; Lee, 1978; Lawson, 1985]. Thus, the following hypothesis (alternative form) was tested:

> H_3: Cash flows are better predictors of financial distress than accrual ratios.

Even if cash flows are not better predictors of financial distress than accrual ratios, cash flows may still possess incremental predictive power. This opinion is the one stated by the FASB and many researchers [Staubus, 1961 and 1989; Chambers, 1966; Revsine, 1973; Sorter, 1967 and 1982]. Therefore, the following hypothesis (alternative form) was tested:

> H_4: Cash flows, when added to accrual ratios, have incremental predictive usefulness in predicting financial distress.

The naive cash flow, NOF, was found to be a significant predictor of financial distress in prior studies. However, this naive cash flow variable should not be significant in models with more appropriate measures of cash flows also included. Thus, this study hypothesizes that:

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[21]The gross cash flows of investing activities and operating activities were not tested since companies do not report sufficient data to identify these gross flows.

H_5: The naive cash flow, NOF, is not a significant predictor of financial distress when included in models with other more appropriate cash flow variables.

Ordinal Logistic Regression - Comparison and Statistical Tests

Multi-state ordinal models for lag periods from one to three years prior to financial distress were constructed using logistic regression (OLR) to test the hypotheses.[22] Financial data for 1984/85 (year three models), 1985/86 (year two models), and 1986/87 (year one models) were used to predict the financial distress of 1988 firms. The predictive accuracy of these models was validated with a holdout sample of 1989 firms; parameter estimates from the models generated for the original sample of 1988 firms, year one models, year two models, and year three models, were used with data for the 1989 firms lagged one (1988/87), two (1987/86), and three years (1986/85) to predict the financial distress of 1989 firms.

To prevent heteroscedasticity, the cash flows tested were scaled. The three most popular scaling measures used in prior cash flow studies [Beaver, 1966; Deakin, 1972; Blum, 1974; Norton and Smith, 1979; Casey and Bartczak, 1984 and 1985; Gombola *et al.*, 1987; Gilbert *et al.*, 1990] were investigated using univariate models (each cash flow variable tested by itself) and a multivariate model with all three net cash flow variables. The three scaling measures investigated were total assets, current liabilities, and total liabilities. Stockholder's equity was not used as a scaling measure since many distressed firms in the sample had negative equity; thus, scaling the cash flows by equity could produce misleading results.

Prior researchers basically selected the scaling measure which produced the most significant results. Care must be taken when using such a criterion for determining the

[22]The ordinal models developed in this study were proportional odds models. Numerous other ordinal logistic models exist. Interested readers should read Agresti [1984] for a complete discussion of various ordinal logistic models.

most appropriate scaling measure because significance does not necessarily mean that one is getting at the "truth." A model may reject the null hypotheses when it should not. A criterion based on the fit of the model to the data is a more appropriate method for selecting a scaling measure; selection of the scaling (or any transformation) should be based on how well the scaled data fit the model. Thus, the proportional odds test statistic (discussed later in this chapter) was used to determine the scaling measure. In this case, the scaling measure selected was the one that was most compatible with the assumption of proportional odds. A comparison indicated that cash flows scaled by total liabilities resulted in ordinal models which best fit the data. Thus, all cash flows were scaled by total liabilities.

Dependent Variable

Financial distress (with four ordinal levels) was the dependent variable in each ordinal logistic prediction model. The observations were coded based on the following scale depending on the occurrence of certain financial distress events during 1988 or 1989:

DIST =	0	if firm was healthy (no event of distress),
	1	if firm experienced a greater than 40 percent dividend reduction,
	2	if firm experienced a loan/interest default and/or debt accommodation, and
	3	if firm filed, or was forced to file, for Chapter XI protection.

Independent Variables

The independent variables tested are composed of two groups of variables. Cash flow variables were used to develop the cash flows models. Accrual ratios were used to develop the accrual models. Mixed regression models were developed by combining selected accrual ratios and cash flows.

Table C-1 shows the computations of the cash flows tested in this study. These cash flows and the expected signs of the parameter estimates based on the model of financial distress are as follows:

NOF	(-) =	naive operating flow,
CFFO	(-) =	cash flow from operating activities,
CFFI	(+) =	cash flow from investing activities,
CFFF	(-) =	cash flow from financing activities,
LFF	(-) =	long-term financing flow,
SFF	(+) =	short-term financing flow, and
EFF	(+) =	equity financing flow.

The model of financial distress strongly indicates that CFFO should be negatively related to financial distress. Companies with positive cash flow from operating activities are more likely to maintain a stable level of cash flow equilibrium and are more likely to regain cash flow equilibrium when sudden decreases in cash flow occur. Thus, firms generating positive cash flow from operating activities are less likely to enter financial distress. Since NOF is simply an alternative measure of operating flow, NOF should also be negatively related to financial distress.

The model of financial distress also indicates that CFFI should be positively associated with financial distress. Companies investing in long-term assets would tend to be companies maintaining cash flow equilibrium and these companies would have greater financial flexibility to recover cash flow equilibrium during sudden decreases in cash flow. Weak companies are more likely to sell assets to try and regain cash flow equilibrium, thus increasing the likelihood that the company will enter financial distress.

The financial distress model indicates that companies use debt financing to regain cash flow equilibrium. Those companies with the greatest financial flexibility would be those with the greatest capacity to obtain debt and equity financing. Thus, the net financing cash flow, CFFF, should be negatively associated with financial distress.

Companies with the greatest positive inflow of financing flows would be least likely to experience financial distress.

However, the expected relationships between the gross financing flows and financial distress are not as easy to predict. The theoretical model of financial distress indicates that firms entering stages one and two leading to financial distress attempt to obtain both short-term and long-term debt financing. Further, if firms progress to stages five and six, the model indicates that short-term financing and the sale of assets are used to pay off long-term debt. On the other hand, companies not proceeding to stages five and six regain financial health and maintain the ability to obtain long-term financing. This chronological process indicates that LFF should be negatively associated with financial distress while SFF and EFF should be positively associated with financial distress, especially the shorter the period preceding financial distress. However, the financial distress model also indicates that the signs may be different for different periods prior to bankruptcy because management is attempting to regain cash flow equilibrium through a delicate process of identifying the optimal mix of cash flows.

The following accrual ratios represent the accrual variables tested in this study:

NITA	(-)	=	net income/total assets,
SALESCA	(-)	=	sales/current assets,
TLOE	(+)	=	total liabilities/owners' equity,
CACL	(-)	=	current assets/current liabilities,
CATA	(-)	=	current assets/total assets, and
CASHTA	(-)	=	cash plus marketable securities/total assets.

The expected signs of the parameter estimates for the accrual ratios are based on prior financial distress research [Casey and Bartczak, 1984 and 1985; Gentry *et al.*, 1987; Gombola *et al.*, 1987; Aziz *et al.*, 1988; Gilbert *et al.*, 1990].

Ohlson [1980] also found that firm size was a significant negative predictor of bankruptcy; bankrupt firms tend to be smaller than nonbankrupt firms. This result indicates the need to control for firm size in financial distress studies. Many prior studies

[Mensah, 1984; Gentry *et al.*, 1985 and 1987; Lau, 1982 and 1987; Aziz *et al.*, 1988; Aziz and Lawson, 1989] controlled for firm size by matching the nonbankrupt firms with bankrupt firms on size characteristics. However, matching firms creates sampling bias because the sampling scheme results in nonrandom samples. The greater the number of criteria used to match the firms, the lower the number of healthy firms available for selection and the greater the amount of sampling bias. Matching results in distorted sampling proportions of healthy-distressed firms, thus increasing the likelihood of choice-based sampling bias [Zmijewski, 1984].

Controlling for firm size by adding a size variable to all predictive models improves the external validity of the study without increasing the sampling bias. Thus, the author controlled for firm size by adding one of the following control variables to all models tested to determine if firm size was a significant predictor of financial distress:

$$SIZE_1\ (-) \quad = \quad \text{total assets}$$

and,

$$SIZE_2\ (-) \quad = \quad \text{log(total assets).}$$

The use of a log transformation of total assets to control for firm size has been used in numerous prior bankruptcy studies [Altman *et al.*, 1977; Ohlson, 1980; West, 1985; Gentry *et al.*, 1987; Gilbert *et al.*, 1990]. However, a log transformation should be incorporated only if the transformation is needed; the transformation must result in better fitting models and must provide a better control for firm size than the nontransformed variable. Thus, the author also tested the simpler balance sheet item, total assets, to see if this measure controlled for firm size better than the log(total assets). The test statistic for the proportional odds assumption of each model tested was used (one model with total assets and one model with log(total assets)) to determine which measure of firm size resulted in ordinal models which best fit the data. The Wald chi-square statistic for each size variable was used to determine which variable had the greatest predictive value and controlled best for firm size.

Discussion of Statistical Models and Test Statistics

The financial distress prediction models (cash flows, accrual, and mixed models) were constructed using ordinal logistic regression (OLR) through the use of proportional odds models. This procedure fits a parallel lines regression model based on transformed cumulative logits. The Proc Logistic procedure in SAS [1989] was used to fit the model by maximum likelihood estimation.

Ordinal Logistic Regression (Proportional Odds Model)

Suppose the response variable can take on the ordered values 0, ... , k, k+1 where k is an integer ≥ 0. Assuming a four-state financial distress model with 10 predictor variables, and defining CP_i as the cumulative probability that a firm is in state i or lower given the independent variables, the cumulative logit can be estimated as follows:

$$CL_i = \ln\left[CP_i / (1-CP_i)\right] = \alpha_i + b_1X_1 + b_2X_2 + \ldots + b_{10}X_{10}, \quad \text{for each state } i = 0 \text{ to } 2. \tag{1}$$

Then:

$$CP_i = P(Y \leq i|x) = \frac{\exp^{(CL_i)}}{1 + \exp^{(CL_i)}}, \tag{2}$$

where CP_i = the cumulative probabilistic predictor, Y or DIST = financial distress with levels 0 to 3, α_i (i = 0 to 2) are intercept parameters, and the b_w coefficients represent the effect of the wth explanatory variable on a firm's probability of ending up in state i or lower.

With the response variable taking on the ordered values 0 to 3, the conditional probability that the jth observation has response i is given by:

$P(DIST = 0|\mathbf{x}_j) = CP_0$
$P(DIST = 1|\mathbf{x}_j) = CP_1 - CP_0$
$P(DIST = 2|\mathbf{x}_j) = CP_2 - CP_1$
$P(DIST = 3|\mathbf{x}_j) = 1 - CP_2$,

where $\mathbf{x}_j$ is the known vector of predictor variables corresponding to the jth observation.

Proc Logistic uses an iteratively reweighted least squares algorithm to calculate the maximum likelihood estimates of the regression parameters.

Notice that OLR produces three cumulative logits for the four-state financial distress response variable and that each logit has the same slopes for the explanatory variables. Only the intercepts for the three logits differ. Thus, OLR creates three parallel regression lines for a four-state model; the use of the proportional odds assumes that parallel lines fit the data. Because all the cumulative logits have the same slopes, tests similar to those used in ordinary linear regression can be used in the proportional odds OLR model to test the predictive ability of independent variables.

Test of the Proportional Odds Assumption

The cumulative logits generated by OLR and the parallel lines assumption are demonstrated in Figure A-3 for a model with one independent variable (univariate model). This example is for a predictor variable which is positively associated (the larger the predictor variable, the greater the likelihood of financial distress) with financial distress. Using a logistic transformation (equation 1), three cumulative linear logits are generated for a four-state financial distress model. These cumulative logits have identical slopes for the predictor parameter estimates, thus they are parallel. Using these logits, equation 2 produces three cumulative probabilities. The slope generated for a predictor variable **positively** associated with financial distress is negative. This fact would appear to be contrary to reason. However, the three cumulative probabilities represent the P(DIST $\leq i$|x). Thus, the logits generated are based on the lower, healthier, levels of distress. For example, CL_1 (through equation 2) provides the cumulative probability (CP_1) that an observation is either of level one (dividend reduction) distress or healthier. Thus, 1-CP_1 is the probability that the same observation is in groups two or three of distress (more distressed). To obtain the cumulative probabilities that a firm is of a level of distress or higher (distressed), 1-CP_i, take the negative of the cumulative logits. Equation 2 would become:

$$CP_i = P(Y \text{ or DIST} \geq i|x) = \exp^{(-CL_i)} / (1 + \exp^{(-CL_i)}) \tag{3}$$

The slope is now positive and all the logits would be reversed as shown in Figure A-4.

Proportional odds models assume that the cumulative logits are parallel (the relationship between the predictors and a dichotomized Y does not depend on the point at which the dichotomization is made). Thus, a test of the parallel lines assumption, the Score Test for the proportional odds assumption, was used to test the parallel lines assumption and to determine which scaling measure resulted in ordinal models which best fit the data. In a simplified sense, this statistic is basically a comparison of the ordinal model where the slopes are assumed to be constant across the different levels of distress and a model where the slopes are allowed to vary.

Figure A-5 illustrates the relaxation of the proportional odds assumption. In a relaxed model, the cumulative logits are allowed to have different slopes. The degrees of freedom for the proportional odds test equals the difference in the degrees of freedom for the relaxed model and the ordinal model. For the example illustrated in Figures A-3 and A-5 with one independent variable and a four-state prediction model, the proportional odds test statistic is calculated as follows:

$$\chi^2(PO) = \chi^2(R) - \chi^2(OLR), \quad \text{with df} = (3-1), \tag{4}$$

where PO = proportional odds test, R = relaxed slopes model, and OLR = parallel slopes model.

A significant chi-square for this test would indicate that a proportional odds model may not be appropriate for the data and another model, possibly a nominal logistic model, may be more appropriate. An insignificant chi-square would mean that the proportional odds assumption is supported by the data. However, a variable can be a strong predictor of financial distress (all the slopes are steep) and yet the proportional odds assumption can be rejected. In this case, the predictive model is not as strong at all levels of distress, interaction exists along the response scale. As a result, the cumulative logits can even intersect, resulting in decreasing cumulative probabilities (probabilities being lower for a higher level of distress). Thus, models rejecting the parallel lines assumptions may have weaker predictive strength and may understate the usefulness of variables tested.

Goodness of Fit Tests

The -2Log Likelihood chi-square statistic (overall model chi-square) for the covariates and the Akaike Information Criterion (AIC) statistic for the intercept and covariates were used to measure the goodness of fit of the models tested in this study. The -2Log Likelihood chi-square is the difference in the -2Log Likelihood for the intercept only model and the -2Log Likelihood for the current model with intercept and explanatory variables. The -2Log Likelihood chi-square compares the full model (with explanatory variables) to the intercept only model, thus testing the null hypothesis that the contribution of the explanatory variables to the model is null. The -2Log Likelihood statistic is similar to the F test reported in ordinary linear regression.

According to SAS, "the AIC adjusts the -2Log Likelihood statistic for the number of terms in the model and the number of observations used" [p. 1089]. Since a p-value is not reported for the AIC statistic, this statistic is primarily used for comparing different models. A lower value of the AIC statistic indicates a better fitting model.

Tests of Significance of Predictor Variables

The main statistic used to test the predictive value of individual variables was the Wald chi-square statistic. A Wald chi-square statistic for each independent variable in an ordinal logistic model tests the hypothesis that the corresponding parameter is zero and is calculated by dividing the maximum likelihood estimate of each parameter in the model by its estimated standard error. This statistic is comparable to the t test statistic in ordinary least squares regression but has a chi-square distribution.

The change in the -2Log Likelihoods for the reduced and full (with added variable) models was also used to test the incremental predictive ability of a particular variable or group of variables. The difference in the -2Log Likelihood also has a chi-square distribution with degrees of freedom equal to the number of variables added to the reduced model. The Change in -2Log Likelihood is normally preferred over Wald chi-squares for testing the predictive value of variables. However, because of the computation difficulties of calculating the Change in -2Log Likelihood chi-squares for numerous predictor variables, the Wald chi-square was the primary statistic used in this study. The two statistics should produce virtually identical results provided collinearity is not a problem; collinearity can result in misleading Wald chi-squares.

Testing the Predictive Ability of Models Generated

After selecting the best fitting model for each hypothesis, the "ranked probability score rule" (hereafter RPS) proposed by Epstein [1969] and used by Lau [1982 and 1987] in her earlier studies and classification accuracy were used to assess the predictive strength of each of the final models generated from the original sample (1988 sample).[23] The RPS and classification accuracy were also used to determine the predictive ability of the models generated from the 1988 sample on the holdout sample for 1989, thus testing the validity of the models generated.

RPS is a better measure of the predictive ability of an ordinal logistic regression model's predictive power than classification accuracy because RPS considers the continuous nature of the predicted cumulative probabilities. Evaluating the predictive ability of OLR models using classification accuracy would not be as appropriate as using RPS.

For example, the researcher may classify an observation among the levels of distress based on the highest predicted probability received for each level. This classification scheme assumes equal prior probabilities for each level of response (probability of 25 percent for each of the four levels). However, population proportions are much different for the four groups of distress. More than twenty-five percent of all firms do not declare bankruptcy. Also, classification tables do not adjust for the continuous nature of the cumulative probabilities generated. For example, two models can have identical classification accuracy rates for the four levels of distress. However, one model may misclassify with probabilities slightly lower than each arbitrary cutoff point while the other model misclassifies with probabilities substantially below each cutoff point. Clearly model one would be the better model. However, classification tables would not distinguish the two models.

The RPS is a ranked scoring method which takes into consideration the rank of the ordinal response scale and the continuous probabilities generated by the ordinal logistic models. Thus, this particular scoring rule is ideal in situations where OLR is

[23]The Somers' D index reported by SAS was reported during the model building process as a measure of the predictive ability of models tested.

used. Assume that two competing models from the same data generated the following predicted conditional probabilities that observation one has response i (where i = the ordered response levels coded 0 to 3, with 3 being bankrupt):

$$P_1 = [.4, .3, .1, .2] \text{ and } P_2 = [.1, .3, .4, .2].$$

Assuming that the actual outcome is state three or bankrupt, unranked scoring rules would weigh P_1 and P_2 equally. However, P_2 obviously provides a better prediction of the financial distress outcome than P_1. The RPS would rank the prediction from each model accordingly.

For example, assume a probabilistic prediction:

$$(p_1, p_2, p_3, p_4),$$

According to Epstein [1969], the RPS for this prediction is:

$$S = (3/2) - [1 / (2(n-1))] \sum_{i=1}^{n-1} [(\sum_{j=1}^{i} p_j)^2 + (\sum_{j=i+1}^{n} p_j)^2] - (1/(d-1)) \sum_{i=1}^{n} | i-k | p_i. \tag{5}$$

where p_i is the predicted probability of response i, k is the actual state observed, and d = number of states of distress.

To compute S for $P_1 = [.4, .3, .1, .2]$ for an observed response of 3 (bankrupt), the term

$\sum_{i=1}^{n-1} [(\sum_{j=1}^{i} p_j)^2 + (\sum_{j=i+1}^{n} p_j)^2]$ in equation (5) is

$$\begin{aligned} [(.4)^2 + (.3 + .1 + .2)^2] &= .52 \\ [(.4 + .3)^2 + (.1 + .2)^2] &= .58 \\ [(.4 + .3 + .1)^2 + (.2)^2] &= \underline{.68} \\ &= 1.78, \end{aligned} \tag{6}$$

and the term $\sum | i-k | p_i$ in equation (5) is

$$[|0 - 3| \times .4] + [|1 - 3| \times .3] + [|2 - 3| \times .1] = 1.9. \tag{7}$$

Substituting (6) and (7) into equation (5) produces the following rank score for P_1 for an observed response of state 3 (bankrupt):

$$
\begin{aligned}
S(P_1) &= 3/2 - [1 / (2(n - 1))]\,(1.78) - (1/(n-1))\,(1.9) \\
&= 3/2 - [1 / (2(4 - 1))]\,(1.78) - (1/3)\,(1.9) \\
&= .57 \qquad (8)
\end{aligned}
$$

Equation (5) would give P_2 a rank score of $S(P_2) = .73$, thus indicating that P_2 provides a better prediction of that observation than P_1 does. The total RPS for a particular model, SS, is simply the sum of the scores for each observation in the model.

Classification accuracy was also used to determine the predictive ability of the best fitting models tested. This technique was used for comparative purposes only. Classification accuracy is a deterministic method for evaluating the predictive ability of models and is, by itself, an inappropriate method for testing probabilistic models such as those generated using OLR. As was mentioned before, classification tables fail to consider the ranking of the ordinal response variable and the continuous predicted probabilities for these ordered levels of distress.

Nominal Polytomous Logistic Regression

For comparative purposes, nominal models were also fitted in those cases where the parallel lines assumption was violated. Comparing OLR results with nominal logistic results in those cases where the proportional odds assumption is violated would indicate where the problem is occurring. Even though the parallel lines assumption is violated, OLR may generate the best predictor models since it takes into consideration the ordinal nature of the response variable and uses fewer degrees of freedom. Because of the similarities between OLR and ordinary regression and the ease of testing hypotheses, OLR would be preferred over nominal logistic procedures provided nominal logistic procedures are not significantly superior to OLR in predicting financial distress.

However, since nominal logistic regression does not take into consideration the ordinal scale of distress, much of the output for nominal logistic models is not relevant. Reaching conclusions using nominal logistic regression are extremely difficult since this procedure produces three parameter estimates and three p-values for each variable tested using a four state distress model. Thus, the author used nominal logistic regression to obtain event probabilities for classification purposes only.

Proc Catmod (SAS) was used to generate the nominal logistic models. This procedure produces three logits (rather than cumulative logits) for a four-state response variable. The slopes of each logit function vary (unlike OLR) for each parameter estimate. A four-state nominal model generates three logits with three predicted slopes and three predicted test statistics for each variable. If **X** is a vector of independent variables and Y is the dependent variable (DIST with levels 0 to 3), the three logit functions are calculated as follows:

$$L_0 = \ln[P(Y = 0|\mathbf{x}) / P(Y = 3|\mathbf{x})] = a_0 + b_{01}X_1 + b_{02}X_2 + \ldots + b_{0p}X_p, \quad (9)$$

$$L_1 = \ln[P(Y = 1|\mathbf{x}) / P(Y = 3|\mathbf{x})] = a_1 + b_{11}X_1 + b_{12}X_2 + \ldots + b_{1p}X_p, \quad (10)$$

$$L_2 = \ln[P(Y = 2|\mathbf{x}) / P(Y = 3|\mathbf{x})] = a_2 + b_{21}X_1 + b_{22}X_2 + \ldots + b_{2p}X_p, \quad (11)$$

where b_{iw} = the parameter estimate for the *w*th explanatory variable on the *i*th logit.

Thus, the three logits are the natural log of the conditional probability that Y or DIST = 0, 1, or 2 given **x** divided by the probability of the reference group Y or DIST = 3 (bankrupt) given **x**. From the above logits, conditional probabilities that an observation has response *i* given **x** are calculated as follows:

$$P(DIST = 0|\mathbf{x}_j) = \frac{\exp^{(L0)}}{1 + \exp^{(L0)} + \exp^{(L1)} + \exp^{(L2)}} \quad (12)$$

$$P(DIST = 1|\mathbf{x}_j) = \frac{\exp^{(L1)}}{1 + \exp^{(L0)} + \exp^{(L1)} + \exp^{(L2)}} \quad (13)$$

$$P(DIST = 2|\mathbf{x}_j) = \frac{\exp^{(L2)}}{1 + \exp^{(L0)} + \exp^{(L1)} + \exp^{(L2)}} \quad (14)$$

$$P(DIST = 3|x_j) = \frac{1}{1 + \exp^{(L0)} + \exp^{(L1)} + \exp^{(L2)}} \quad (15)$$

Sample Selection

An original sample of firms falling into the four states of financial distress during 1988 was used to construct the ordinal prediction models. A holdout sample of firms from 1989 was then used to test the predictive power of the models.[24] The two samples of firms were basically obtained through a four-step process. The first step involved the identification of probable financially distressed firms and the selection of a group of probable healthy firms matched by industry. Multiple sources were used to identify these firms. Second, Compustat tapes were used to determine whether firms had sufficient data to calculate the cash flows and accrual ratios of interest. Firms not included in the Compustat tapes and firms with incomplete data were dropped. Third, firms' SEC 10-Ks and annual reports were used to validate the occurrence or nonoccurrence and timing of the events of distress. These reports were also used to identify other important information; companies not meeting specific criteria were eliminated from the samples. Finally, firms poorly matched by industry codes among the levels of distress were also dropped from the samples. The accrual ratios and cash flows were then calculated from Compustat data for the firms in the final samples.

Since firms in finance, banking, and utility industries operate under different economic conditions, these firms were excluded from the samples. A complete discussion of the sampling process is discussed in the following parts of this section. The sampling process is summarized in Tables C-2 (original sample) and C-3 (holdout sample).

[24]Companies experiencing more than one event of financial distress in the same year were assigned to the highest level of distress recognized to maintain the ordinal scale of distress.

Step One - Initial Identification of Firms

Distressed firms were first identified using one or more of the following sources: Compustat Industrial/Primary/Supplementary/Tertiary, Research, and Full tapes (Compustat tapes); Compact Disc Disclosure; and the Wall Street Journal Index. Next, a random sample of healthy firms with four digit industry codes similar to the distressed firms identified was selected. The author matched the firms by industry to control for possible industry effects. The large number of industry groups prevented the author from controlling for industry effects by adding control variables to the models. Although controlling for industry effects by matching firms lowers the external validity of this study, matching firms by industry increases the internal validity of this study and was deemed necessary by the author.

Selection of State 1 Firms: Dividend Reductions

The Compustat tapes were used to identify firms which reduced their annual dividend per share by more than 40 percent from the previous year for 1988 and 1989 after three years of consistent dividends per share.[25] A firm was identified as having three consistent years of dividends if the firm did not decrease dividend per share by more than 40 percent during any of the three years prior to 1988 for the original sample and 1989 for the holdout sample or experience an unusually high dividend per share in the year preceding 1988 or 1989. A dividend was considered unusually large if it exceeded 500 percent of the previous three years' average dividend per share. This

[25] The Compustat tapes include approximately 12,600 Over-the-Counter, New York Stock Exchange, and American Stock Exchange firms. Excluding firms in finance, banking, and utilities industries still resulted in over 10,000 firms remaining in the population.

requirement was implemented because an unusually large dividend in the preceding year normally resulted in a greater than 40 percent dividend reduction for 1988 or 1989.

The author identified 94 firms which reduced their annual dividend per share by more than 40 percent in 1988 and 81 firms which reduced their annual dividend per share by more than 40 percent in 1989. The author then randomly sampled 40 percent of these firms resulting in an initial 1988 sample of 37 dividend reduction firms and an initial 1989 sample of 32 dividend reduction firms.

Selection of State 2 Firms: Default and/or Debt Accommodation

Compact Disc Disclosure was used to identify firms which defaulted on loan/interest payments and/or renegotiated loan terms in order to extend cash payment schedules or reduce interest rates or principal payments during 1988 or 1989. Compact Disc Disclosure was used to identify State 2 firms because the data base includes selected 10-K information for over 12,000 Over-the-Counter, New York Stock Exchange, and American Stock Exchange firms. Using this source to identify State 2 firms resulted in a much broader group of distressed firms (more smaller and younger firms), thus increasing the external validity of this study. The author identified 54 probable firms that experienced loan/interest defaults and/or debt accommodations in 1988 and 62 probable firms that experienced loan/interest defaults and/or debt accommodations in 1989.

Selection of State 3 Firms: Bankruptcy

The Wall Street Journal Index and Compact Disc Disclosure were used to identify firms which voluntarily filed, or were forced to file, for Chapter XI protection during 1988 and 1989. Again, Compact Disc Disclosure was used to identify bankrupt firms because this source resulted in the initial identification of a much larger and broader sample of firms. Identifying a large number of firms for one year enabled the author to control for a greater number of confounding items. These sources identified 59 firms that filed for Chapter XI bankruptcy in 1988 and 84 firms that filed for Chapter XI bankruptcy in 1989 bankrupt firms.

Selection of State 0 Firms: Financially Healthy

Random samples of 243 healthy firms for 1988 and 183 healthy firms for 1989 were selected from the Standard and Poor's Compustat tapes. These firms were selected if they had not been identified as financially distressed during 1988 and 1989 and they were in the same four-digit industry code as one of the financially distressed firms.

Step Two - Elimination of Firms With Insufficient Compustat Data

Compustat tapes were reviewed to determine whether identified firms were listed on the tapes, and if they were listed, whether sufficient data were available to develop the variables of interest in this study. This review resulted in the elimination of 10 dividend reduction, 18 loan default and/or accommodation, 33 bankrupt, and 50 healthy firms from the 1988 sample. For the 1989 sample, 7 dividend reduction, 31 loan default and/or accommodation, 47 bankrupt, and 38 healthy firms were eliminated from the sample.

Step Three - Verification of Events and Other Important Information

Firms' SEC 10-Ks and annual reports were reviewed to validate the occurrence or nonoccurrence of events of financial distress and other important information. Firms were deleted from the samples for the following reasons:

(1) Dividend reduction firms experiencing mergers during 1988 or 1989, the year of distress, were eliminated from the samples. This step was taken to eliminate those companies which reduced or eliminated dividends because of merger activity rather than financial distress.

(2) Identified default/accommodation firms and bankrupt firms were eliminated if the date of distress could not be verified or if the author could not verify that an event of distress had definitely occurred. Firms experiencing an event of distress of greater severity or bankruptcy during the three years preceding 1988 for the original sample and 1989 for the holdout sample were also dropped from the samples.

(3) A firm was also eliminated from the samples if the management of the firm was under investigation for fraudulent activities related to the misstatement of financial statement information.

(4) Firms with insufficient 10-Ks or annual reports to verify the event or nonevent of distress were dropped from the samples (no recent 10-Ks or annual reports or incomplete 10-Ks or annual reports).

(5) Firms were also deleted because of unreliable data. Firms considered to have unreliable data were: those with unaudited financial statements; those incorporated outside the United States which failed to follow U. S. GAAP procedures in developing financial statements; and those created by mergers, thus resulting in noncomparable statements for part of the estimation period (1984-87 for 1988 firms and 1985-88 for 1989 firms).

The above criteria resulted in the elimination of 4 dividend reduction, 12 loan default and/or accommodation, 7 bankrupt, and 27 healthy firms from the 1988 sample and 6 dividend reduction, 14 loan default and/or accommodation, 15 bankrupt, and 35 healthy firms from the 1989 sample.

Step Four - Matching Among the Distressed Groups

When incorporating a multi-state model, matching healthy firms and distressed firms by industry may not be sufficient to control for industry effects. Firms should also be matched among the various levels of distress (states 1 through 3). If the various levels of distress are composed of firms in industries not present in other levels of distress, the ordinal logistic regressions models may produce misleading results. To control for this confounding, the author also matched the firms in the different distress groups by two-digit industry codes. Firms in a distressed group (states 1, 2, or 3) with two-digit industry codes not represented in one of the other distress groups (states 1, 2, or 3) were eliminated from the sample. This procedure resulted in the elimination of 1 dividend firm, 1 loan default/accommodation firm, and 1 bankrupt firm from the 1988 sample and 2 dividend firms, 3 loan default/accommodation firms, and 6 bankrupt firms from the 1989 sample.

Summary of Sample

The four-step sampling process resulted in the selection of a final sample size of 229 firms for the original sample of 1988 firms and 158 firms for the holdout sample. The break-down of the 1988 sample is as follows:

State 0 - Healthy	166
State 1 - Dividend Reduction	22
State 2 - Default and/or Debt Accommodation	23
State 3 - Bankrupt	18
Total 1988 Sample Size	229 firms

The break-down of the 1989 sample is as follows:

State 0 - Healthy	111
State 1 - Dividend Reduction	17
State 2 - Default and/or Debt Accommodation	14
State 3 - Bankrupt	16
Total 1989 Sample Size	158 firms

Firms included in the 1988 sample were excluded from the 1989 sample. Inclusion of firms used to generate the 1988 models in the holdout group would violate the fundamental assumption of using a holdout group to validate the results of generated models. Since several firms that experienced lower levels of distress during 1988 also experienced a higher level of distress in 1989, excluding these firms from the holdout sample lessens the ability of models generated in this study to predict the financial distress of the holdout firms.

The Problem of Back-casting

Ohlson [1980] showed that, for some firms, the financial reports for the preceding year are issued after the announcement of bankruptcy. Thus, the financial reports include information about a firm's bankruptcy. For example, the financial information for the model lagged one year, 1987, would include information about the 1988 bankruptcy if the 1987 financial report was issued in 1988 after the firm's announcement of bankruptcy. This problem would also occur for firms experiencing a loan/interest default or debt accommodation. Including these firms in the sample would bias the results toward overstating the usefulness of models tested.

To account for this bias, the author used the firms' SEC 10-Ks and annual reports to identify the date a firm filed for bankruptcy and the date of the loan/interest default and/or debt accommodation. The author identified 2 loan default/accommodation and 4 bankrupt 1988 firms and 5 loan default/accommodation and 5 bankrupt 1989 firms that released financial statements after the event of distress. For these firms, the reports from the previous fiscal year were substituted for the most current year of interest. For example, the reports for 1984, 1985, and 1986 replaced the 1985, 1986, and 1987 reports for the 6 firms in the 1988 sample. This procedure increases the lead time between the date of the last relevant report and the event of distress. Thus, this procedure eliminates the problem of "back-casting" [Ohlson, p. 110], resulting in less biased models. However, this procedure would also result in model predictions weaker than those reported in previous studies which failed to correct for this problem.

CHAPTER 5

ANALYSIS OF THE RESULTS

Chapter 5 contains the empirical results for this study. The chapter is divided into seven main sections. Section one discusses the selection of a scaling measure for the cash flows. Section two contains a discussion of the means and standard deviations for the variables used in this study. Section three discusses the testing of the hypotheses using various ordinal logistic regression (OLR) models. This section of the chapter is divided into five parts. Each part contains a description of the models used to test one of the five main hypotheses and the results of the tests. Section four contains an analysis of the tendency of accrual and mixed models to reject the parallel lines assumption. Section five discusses the predictive power of OLR models tested using RPS scores. Section six discusses the classification accuracy of the models tested. Finally, section seven discusses the results for the two-state logistic models with only loan default/accommodation firms and bankrupt firms included and illustrates the primary reason why the proportional odds assumption is rejected for the accrual and mixed models.

Selection of a Scaling Measure

Since larger (smaller) firms tend to generate larger (smaller) cash flows, cash flows must be scaled by some measure to prevent heteroscedasticity. Prior studies [Beaver, 1966; Deakin, 1972; Blum, 1974; Norton and Smith, 1979; Casey and Bartczak, 1984 and 1985; Gombola *et al.*, 1987; Gilbert *et al.*, 1990] predominantly used one, or all, of the following three (or forms of these three) scaling measures: total assets, total liabilities, and current liabilities. These researchers basically selected the scaling measure which resulted in the most significant results for the predictor variables of interest. An alternative method is to select the measure which results in models which best fit the data. This approach was the one taken by the author to select an appropriate scaling measure.

Seven univariate OLR cash flow models (one cash flow included as the predictor variable) and one multivariate OLR cash flows model (three gross cash flows, CFFO, CFFI, and CFFF) were run for each year using each of the three scaling measures. The Score Test for the proportional odds assumption was then observed to determine which scaling measure resulted in OLR cash flow(s) model(s) that best fit the data (those failing to reject the proportional odds assumption).

Rejection (significant p-value) of the proportional odds test indicates that the assumption of parallel lines is violated; the relationship between the predictor(s) and ordinal response variable is not constant across the various levels of the ordinal response variable. In this case, OLR models would tend to distort the importance of a predictor variable and may result in weaker predictive power. In cases where the proportional odds assumption is violated, other models such as nominal logistic models may be more appropriate for the data.

Table D-1 shows the results of the proportional odds tests for the OLR cash flow(s) model(s). This table includes the chi-square statistic of the proportional odds test for each cash flow(s) model and indicates whether the parallel lines assumption was violated. The results show that, overall, the OLR cash flow(s) model(s) fit the proportional odds assumption very well. Thus, the use of OLR cash flow(s) model(s) would appear to be appropriate with these data. This fact is especially true for the multivariate model incorporating the three net cash flows. The results also indicate that rejection of the parallel lines assumption is a problem primarily for the NOF model only. In every year, and for all three scaling measures (except for current liabilities in Year - 1 and total liabilities in Year - 3), the proportional odds assumption was violated for the NOF model.

Cash flows scaled by total liabilities resulted in OLR models which rejected the proportional odds assumption (parallel lines assumption) the least number of times, once at p-value = .05 and twice at p-value = .01. Scaling by total liabilities generated better OLR models primarily for periods two and three years before financial distress.

Based on the above results, total liabilities was selected as the scaling measure for the cash flows. Thus, results presented throughout the remainder of this chapter are for cash flows scaled by total liabilities. However, overall, the three scaling measures differ very little concerning the proportional odds assumption. As a result, one would not expect substantial differences using different scaling measures.

Means and Standard Deviations

This section includes a discussion of the means and standard deviations for the variables tested. Tables D-2 through D-4 show the means and standard deviations for the original 1988 sample and Tables D-5 through D-7 show the means and standard deviations for the holdout sample. Although OLR does not test the differences in means as in ANOVA, the means should still tend to be increasing or decreasing across the levels of distress if the levels do represent an ordinal measure of financial distress in relationship to the predictor variables.

A review of Tables D-2 through D-7 indicates that the means of the variables for the 1988 and 1989 samples do basically differ as expected across the levels of distress, especially one year and two years prior to distress. The major exception for the 1988 sample concerns the gross cash flow variable CFFF. This cash flow was expected to be negatively associated with financial distress. However, the means for CFFF fail to form any specific pattern for either year. The variables SFF and EFF (years 2 and 3) also exhibit a weak linear pattern across the levels of distress.

The results for the two samples tend to be similar. The major exceptions are: (1) SFF does not exhibit a strong linear pattern in Year - 1 for the 1989 sample, while it does for the 1988 sample, (2) SALESCA is weak in all three years for the 1989 sample and weak only in Year - 1 for the 1988 sample, and (3) CATA exhibits a weak linear pattern in Year - 2 and Year - 3 for the 1989 sample and only in Year - 3 for the 1988 sample. As one would expect, the linear patterns of the means are weaker the longer the period preceding financial distress.

The means and standard deviations also point out four additional points of interest. First, the means of many variables for the bankrupt group tend to reverse their linear trend when compared to the previous level of distress. Otherwise, the means for the bankrupt group indicate that the bankrupt group of firms, as a whole, may not be as distressed as the loan default/accommodation group but are still more distressed than the dividend reduction group (based on these predictor variables).

For example, CFFO was expected to be negatively associated with financial distress. A review of the means for Year - 1 indicates that this trend is observed for states 0 through 2 (means are .281, .082, and -.141). However, the mean of the bankrupt group is not smaller than the mean of the preceding distress group, default/accommodation group; the mean (CFFO) of the bankrupt group is -.080. This result was true for Year - 1 and Year - 3 for the 1988 sample and for all three years for the 1989 sample. Another example concerns the two size variables. Based on prior research, firm size should be a negative predictor of financial distress. The means of the size variables for Year - 1 indicate this expectation is true for the first three states of distress but is not true for the bankrupt group. The size variables' means decrease as expected for states 0 through 2; however, the bankrupt group's means are larger than the means for the default/accommodation group. This tendency was observed for many of the variables for both samples, mostly for Year - 1 and Year - 3.

Overall, the patterns of the means do indicate that the assumed ordinal relationship between the response variable and the predictor variables is appropriate, although the means for the bankrupt group often are not consistent with expectations. The bankrupt group means, however, do appear to be in the direction expected when compared to state 0 and state 1. This result provides some indirect evidence that bankrupt firms, as a group, may not be as *economically* distressed as default/accommodations firms. This result also indicates that bankruptcy alone may not be the best proxy for financial distress and indicates the need to investigate events of financial distress other than bankruptcy.

Second, Casey and Bartczak [1984 and 1985] and Gentry *et al.* [1985] found that bankrupt firms' cash flows exhibit greater variability than healthy firms' cash flows, thus making it difficult to obtain statistical significance. The standard deviations of the cash flows tested in this study do not appear to validate this result. In fact, the opposite result was observed. For both samples, the standard deviations of the cash flows for the healthy group tend to be larger than the standard deviations of the cash flows for the bankrupt group. This result was also observed for most (particularly Year - 1) of the accrual ratios, especially for the size variables. The standard deviations of the size variables for the healthy group of firms were greater than the standard deviations for the bankrupt group. The major exception to this tendency was for the accrual ratio, TLOE.

Third, the standard deviations indicate heteroscedasticity should not be a problem for the cash flows when scaled by total liabilities. The standard deviations, overall, are moderate and fairly stable.

Fourth, the means and standard deviations for the accrual variable TLOE indicate a problem. One would expect TLOE to be positively associated with financial distress. However, the mean of TLOE for the bankrupt group is smaller than the mean for the loan default/accommodation group in Year - 1. This occurrence was also observed for many other variables. However, the mean of TLOE for the bankrupt group in Year - 1 was not only lower than the mean for the loan default/accommodation group but the mean was also negative (-10.188 for the 1988 sample and -1.152 for the 1989 sample), indicating a possible scaling problem. The standard deviations for TLOE also indicate a possible scaling problem. The standard deviations of TLOE for the last two states of financial distress (default/accommodations and bankruptcy) are very unstable, especially for Year - 1 and Year - 2 (both 1988 and 1989 samples).

The unusual results for TLOE are most likely caused by the use of owners' equity as the denominator part of the ratio. A review of the data indicated that many higher distressed firms (state 2 and state 3) had negative owners' equity. For firms with negative owners' equity, TLOE would also be negative. Since TLOE is hypothesized to be positively associated with financial distress, a negative TLOE would indicate, incorrectly, that a firm is very healthy. This problem produces a statistical modeling inconsistency and questions the use of ratios with owners' equity as the denominator in financial distress studies.

Reversing the numerator and denominator of TLOE would change the expected relationship with financial distress to a negative relationship. Thus, replacing TLOE with owners' equity/total liabilities (OETL) should correct for the above scaling problem (maintaining a consistent scaling measure) and still capture the same information. Distressed firms should exhibit lower owners' equity and higher total liabilities than healthy firms. A negative OETL caused by a negative owners' equity would maintain the negative association and indicate correctly that the firm is severely distressed. Forms of OETL have been found useful in previous bankruptcy studies [Tamari, 1966; Blum, 1974; and Elam, 1975].

Tables D-8 and D-9 compare the means and standard deviations for both variables, TLOE and OETL. The tables indicate that converting the ratio to OETL eliminates much of the scaling problem. The standard deviations of OETL are much more stable than the standard deviations of TLOE. The pattern of the means for OETL are also consistent with expectations for all three years for the 1988 sample and are not as severely distorted as the means of TLOE for the 1989 sample.

As a result of the improvement in the means, all subsequent analyses are reported using the variable OETL instead of TLOE. However, all models were run a second time using TLOE to validate whether the reverse scaling lessened the scaling problem. For all analyses reported later in this chapter, OETL was always more significant than TLOE. In fact, TLOE was never a significant predictor of financial distress.

Testing of the Hypotheses

Testing of Hypotheses H_{1A}, H_{1B}, and H_{1C}

This part of Chapter 5 discusses the testing of hypotheses H_{1A}, H_{1B}, and H_{1C}. These three hypotheses address whether the three net cash flows, CFFO, CFFI, and

CFFF, are significant predictors of financial distress. These hypotheses were stated previously in the alternative form as follows:

H_{1A}: CFFO is a significant predictor of financial distress.

H_{1B}: CFFI is a significant predictor of financial distress.

H_{1C}: CFFF is a significant predictor of financial distress.

The following four-state OLR net cash flows model was used to test the above hypotheses:

$SIZE_1$ + CFFO + CFFI + CFFF.

This model was labeled the net cash flows model and was lagged one year (Year - 1 model), two years (Year - 2 model), and three years (Year -3 model) prior to financial distress. The size variable was included to control for the confounding impact of firm size on financial distress. The author only reports the results for models incorporating $SIZE_1$ (total assets). However, all analyses were done a second time using $SIZE_2$, log(total assets), instead of $SIZE_1$. However, $SIZE_2$ was never a more significant predictor of financial distress than $SIZE_1$ and models with $SIZE_2$ included as the control variable always rejected the proportional odds assumption, indicating that ordinal models incorporating $SIZE_2$ tended to not fit the data very well. This finding indicates that, at least for the ordinal financial distress models used in this study, the simpler item, total assets, controls for firm size better and provides a better fit to the data than the more complex variable, log(total assets).

Results of the Net Cash Flows Model

Table D-10 includes the results for the net cash flows models. This table shows the Wald chi-square statistic for each variable, the Score Test chi-square which tests the proportional odds assumption, the -2Log Likelihood (overall model test chi-square) chi-square, AIC Criterion of goodness of fit, and the Somers' D index of predictive ability.

The results show that the parameter estimates have signs consistent with expectations and that the standard deviations appear to be reasonable. The Score Test chi-square indicates that the model fits the proportional odds assumption (failed to reject the assumption) and the -2Log Likelihood chi-square indicates that the net cash flows, as a group, are significant predictors of financial distress.

The Wald chi-squares for each parameter estimate indicate, however, that the results are not consistent across the three years. Only the CFFO is a significant predictor of financial distress all three years prior to financial distress. However, CFFF is significant in Year - 1 and CFFI is significant in Year - 2. The AIC Criterion indicates that the longer the period prior to financial distress, the poorer the fit of the model. Somers' D also indicates that the cash flows are weaker as predictors the longer the period prior to financial distress.

These results are consistent with the theoretical model of financial distress discussed in Chapter 4. This theoretical model indicated that CFFO should be the earliest predictor of financial distress but that CFFI and CFFF should also provide predictive information leading to financial distress.

The correlation matrix for the parameter estimates of the four-state net cash flows model for each year were reviewed to determine if multicollinearity was a problem. These matrices are shown in Table D-11. The presence of high correlations could produce unstable parameter estimates and standard deviations. This problem greatly affects the Wald chi-square statistic since this statistic is calculated by dividing the parameter estimate by the estimated standard deviation. If collinearity is severe, the researcher must place more emphasis on the Change in -2Log Likelihood chi-square (from adding a variable to a reduced model) to determine the significance of a predictor variable rather than rely on the Wald chi-square.

In a simulation study of logistic regression, Stone and Rasp [1991] found that logistic parameter estimates were very stable in cases where collinearity was moderate; the authors used $\rho = .50$ as the cutoff point for moderate. The matrix for the net cash flows model for each year indicates that the only correlation above .50 is between CFFO and CFFF for Year - 1 and Year - 2 models (.6109 and .6784, respectively). To determine if collinearity was affecting the results reported in Table D-10, the following two reduced models were run:

$SIZE_1$ + CFFO + CFFI
$SIZE_1$ + CFFO + CFFF

These reduced models were run to see if the results changed when only CFFI, which was not highly correlated with CFFO, was run with CFFO and when only CFFF, which was highly correlated with CFFO, was run with CFFO. Major changes in the parameter estimates and standard deviations from those reported for the full model in Table D-10 would indicate a problem of collinearity. However, the results for the reduced models were basically the same as the results for the full net cash flows model; the parameter estimates and standard deviations for the parameter estimates were very similar.

Thus, the results indicate that hypotheses H_{1A}, H_{1B}, and H_{1C} are accepted. The three net cash flows are significant predictors of financial distress. However, the importance of each cash flow depends on the period prior to financial distress. CFFO is a significant predictor in each year prior to distress while CFFI is only significant two years prior to distress and CFFF is only significant one year prior to distress.

Testing of Hypothesis H2

This part of Chapter 5 addresses whether the gross financing cash flows, LFF, SFF, and EFF, possess greater predictive power than the net cash flow CFFF. The FASB took the position with Statement No. 95 that gross cash flows were more useful than net cash flows. This position is consistent with the model of financial distress. This model indicates that the gross cash flows of financing, exclusive of EFF, should be more important in predicting financial distress than the net cash flow, CFFF. This hypothesis was stated previously in the alternative form as follows:

> H_2: The gross cash flows of financing activities (exclusive of equity financing) have greater predictive value than the net cash flow, CFFF.

Predictive Ability of Gross Cash Flows

This hypothesis was tested by testing both the predictive ability of the gross cash flows and the incremental predictive ability of the gross cash flows. First, the author tested the predictive ability of the gross cash flows by running the following four-state gross cash flows model for each year:

$SIZE_1$ + CFFO + CFFI + LFF + SFF + EFF.

The results of this model were compared with the results for the net cash flows model incorporating CFFF shown in Table D-10. The only difference in the two models is that the gross cash flows model includes the gross cash flows, LFF, SFF, and EFF, instead of CFFF.

The results for the gross cash flows model lagged one, two, and three years are shown in Tables D-12 through D-14. An additional test statistic is reported in addition to the ones reported in the previous tables. The Change in -2Log Likelihood chi-square was also reported. This chi-square was calculated by taking the difference in the base model's

($SIZE_1$ + CFFO + CFFI) -2Log Likelihood chi-square and the -2Log Likelihood chi-square for the gross cash flows model. This statistic tests the predictive ability of cash flows added to the base model.

For Year - 1 (Table D-12), the results show that the signs of the cash flows parameter estimates were as expected except for SFF and EFF. However, the Wald chi-squares for SFF and EFF were very low; both are very insignificant predictors of financial distress when they have opposite signs than expected. The Change in -2Log Likelihood chi-square of 12.122 indicates that the three cash flows, as a group, are significant predictors of financial distress. To prevent overparameterization, the author dropped the cash flows with a Wald chi-square less than 1.30 and reran the model. This decision resulted in dropping variables with p-values greater than .25. It is unlikely that variables with p-values greater than .25 provide much predictive power; the gain in degrees of freedom and the simplification of the model by limiting the number of variables more than offset any loss in predictive power.

For Year - 1, SFF and EFF were dropped and the model was run again (reduced model). The AIC Criterion decreased, indicating that dropping the two variables increased the fit of the model. Dropping the two insignificant variables also improved the Score Test chi-square for the parallel lines assumption. The assumption was not violated for the reduced model but was violated for the full gross cash flows model (chi-square of 13.1316 with 8 degrees of freedom versus 22.5441 with 12 degrees of freedom). The Somers' D indicates that dropping the two variables resulted in very little loss of predictive power. This result is also indicated by looking at the -2Log Likelihood chi-squares for both models. The overall chi-square decreased from 89.1886 to 88.1590, a decrease of only 1.0296 with a gain of 2 degrees of freedom. The Change in -2Log Likelihood chi-square, comparing the model $SIZE_1$ + CFFO + CFFI and the new model

$SIZE_1$ + CFFO + CFFI + LFF, of 11.093 indicates that, for Year - 1, the gross cash flow LFF is a very significant predictor of financial distress.

The above model building process was repeated for Year - 2 and Year - 3. The results are reported in Tables D-13 and D-14. Again, the signs of the parameter estimates were as expected except for EFF in both years and SFF in Year - 3. However, SFF was never close to significant when the sign was opposite from expected and possessed an appropriate sign in Year - 2 when it was significant. The results indicate that SFF is a significant positive predictor of financial distress two years prior to financial distress while neither of the gross cash flows possess much predictive power three years prior to distress.

The results in Tables D-12, D-13, and D14, indicate that LFF is a significant negative predictor of financial distress one year prior to financial distress and SFF is a significant positive predictor two years prior to financial distress. The positive significance of SFF in Year - 2 and the negative significance of LFF in Year -1 indicates that financially distressed firms are more likely to obtain larger inflows of SFF two years prior to financial distress to pay off huge long-term debt requirements. One year prior to financial distress, those firms most distressed pay off the greatest amount of long-term debt, possibly as a last attempt to prevent distress. As expected, EFF was never a significant predictor of financial distress in either year, while the signs of the parameter estimates were opposite from expected. These results are consistent with the model of financial distress.

The correlation matrices of the parameter estimates for the full gross cash flows model are shown in Table D-15. The correlations indicate little problem with high correlations except for a moderately high correlation of -.5921 between the parameter estimates of CFFO and EFF in Year - 2. The correlations do indicate that incorporating the gross cash flows in the models instead of just including CFFF decreases the problem of collinearity. The parameter estimates of CFFO and CFFF for the net cash flows model (Table D-11) were more highly correlated than CFFO and LFF, SFF, or EFF for the gross cash flows model (Table D-15).

Incremental Predictive Ability of the Gross Cash Flows

To test the incremental predictive power of the gross cash flows, the author added each gross cash flow separately to the net cash flows model (CFFF included), resulting in the following models:

$SIZE_1$ + CFFO + CFFI + CFFF + LFF,
$SIZE_1$ + CFFO + CFFI + CFFF + SFF, and
$SIZE_1$ + CFFO + CFFI + CFFF + EFF.

One cannot run a model with all three gross cash flows combined with CFFF since CFFF is simply the sum of the three gross cash flows (when combined with cash dividends paid). Thus, collinearity would be a major problem and no test statistics would be available for most of the financing flows because of redundancy. Adding each gross cash flow separately to the net cash flows model, and observing the Change in -2Log Likelihood chi-square, provides a test of the incremental predictive power of the gross cash flows without incurring the statistical problems.

The results of adding each gross cash flow separately are shown in Table D-16. The change in the -2Log Likelihood (overall) chi-squares for the reduced model (net cash flows model) and added models (each cash flow added separately to the net cash flows model) show that LFF has significant incremental predictive power (at p-value < .001) even with CFFF in the model for Year - 1 and SFF has significant incremental predictive power even with CFFF in the model for Year - 2. Even the gross cash flow EFF has incremental predictive power above CFFF in Year - 3, although the gross cash flows model with SFF and LFF also included (Table D-14) indicated that EFF was not significant when the other gross cash flows were also included.

Thus, not only are LFF and SFF significant predictors of financial distress but they also possess incremental predictive power above CFFF. Comparing the results for the gross cash flows in Tables D-12 through D-14 with the results for CFFF in Table D-10 indicate that the gross cash flows are the dominant financing flows. Table D-10 indicates that the net flow CFFF is only significant in the Year - 1 model (overall chi-square of 81.018). However, breaking up CFFF into it's gross cash flow components results in significance for particular gross financing cash flows in two of the three years. LFF is significant in Year - 1 and SFF is significant in Year - 2 (Tables D-12 and D-13). Notice that the overall model chi-square for the reduced model with only LFF added to $SIZE_1$ + CFFO + CFFI is 88.159 (Table D-12) compared to the overall model chi-square of 81.018 reported with only CFFF added to $SIZE_1$ + CFFO + CFFI in Table D-10. The fact that LFF is the dominant variable is better illustrated by showing the model with both LFF and CFFF included. This model is reported in Table D-17. Notice that CFFF is no longer significant for Year - 1 when LFF is included in the model (Wald chi-square of .2053). In fact, CFFF is highly insignificant while LFF is still significant at a p-value $< .01$.

To summarize, the results support H_2. The gross cash flows of financing, except for EFF, do provide more predictive power than the net cash flow CFFF. The gross cash flows are important predictors by themselves and also important incremental predictors when combined with CFFF. However, the gross cash flows are not significant for all years. LFF is significant one year prior to financial distress and SFF is significant two years prior to financial distress. These results are consistent with the model of financial distress and also consistent with the position taken by the FASB in Statement

No. 95. Reporting only CFFF would result in the loss of important information; the gross financing cash flows provide more information than the net financing flow CFFF.

Testing of Hypothesis H3

This section tests whether cash flows are better predictors of financial distress than traditional accrual ratios. The FASB asserts that accrual ratios are more useful than cash flow information. However, as discussed in Chapter 4, many researchers believe that cash flow information may be more useful than accrual information. Thus, the following alternative hypothesis was tested:

> H_3: Cash flows are better predictors of financial distress than accrual ratios.

This hypothesis was tested by running an accrual model with six accrual ratios and comparing the results for the accrual model with the results for the final gross cash flows models. The accrual model used was as follows:

$$DIST = SIZE_1 + NITA + SALESCA + CACL + OETL + CATA + CASHTA.$$

Results for Accrual Model

The results for this model are shown in Tables D-18, D-19, and D-20. Similar to the cash flows models, the author eliminated the variables with Wald chi-squares < 1.30. The results indicate that only NITA is a significant predictor of financial distress for all three years. However, OETL is significant for Year - 1 and Year - 2, while SALESCA is significant for Year - 1 and CASHTA is significant for Year - 2 and Year - 3. Also, the parameter estimates are as expected.

The correlation matrices of the full accrual model for each year are shown in Table D-21. None of the correlations among the parameter estimates exceed .50 except for the correlation between CACL and OETL for Year - 3 (-.5438). Table D-20 (Year -

3) shows that the Wald chi-squares for both OETA and CATA were less than 1.30, resulting in both variables being dropped from the full accrual model. The Change in -2Log Likelihood chi-square of 4.193 (34.429 - 30.236) is not significant at a p-value of .05, with 2 degrees of freedom. However, high correlations between OETL and CACL may cause the two variables to be insignificant when combined but either variable may be significant when included in a model by itself. To determine if this was the case, the author ran full and reduced models for Year - 3. First, OETL was added to the reduced model $SIZE_1$ + NITA + SALESCA + CASHTA. Next, the author added CACL to the reduced model $SIZE_1$ + NITA + SALESCA + CASHTA. However, neither variable was significant when included in an accrual model by itself.

One disturbing result for the accrual models was that the Score Test chi-square was always significant for the accrual models (although at different critical values), indicating that the parallel lines assumption was violated. This assumption was never violated for any of the final cash flows models tested. This finding indicates that the results concerning the predictive ability of accrual ratios may be understated and another model, such as a nominal logistic regression model, may be more appropriate. This occurrence was a consistent and interesting element of this study and is discussed more thoroughly later this chapter.

Comparison of the Results for the Accrual and Gross Cash Flows Models

Comparing the results for the final accrual models shown in Tables D-18, D-19, and D-20 with the results for the final gross cash flows models shown in Tables D-12, D-13, and D-14 provides evidence concerning whether cash flows are better predictors of financial distress than accrual ratios. The author used the gross cash flows models for the basis of comparison rather than the net cash flows model because of the previous results which indicated that the gross cash financing flows were more dominant predictors of financial distress than the net financing flow CFFF.

Comparing the gross cash flow models and the accrual models indicates that cash flows are not stronger predictors of financial distress than accrual ratios, although cash flows, by themselves, are significant predictors of financial distress. The Somers' D and -2Log Likelihood chi-square are always higher (every year) for the accrual model than the cash flow model, and the AIC Criterion is lower each year for the accrual model, indicating that the accrual models are better fitting models. The one difference in favor of the cash flow model is that the parallel lines assumption is never violated by the final cash flows models but is always violated by the accrual models.

Based on the results discussed above, H_3 was not accepted. Cash flows are not better predictors of financial distress than accrual ratios.

Tests of Hypothesis H4

Even if cash flows are not better predictors of financial distress than accrual ratios, cash flows may still possess incremental predictive power when added to accrual ratios. This opinion was stated by the FASB in Statement No. 95 and is the opinion expressed by many researchers. This opinion was hypothesized in the alternative form as:

> H_4: Cash flows, when added to accrual ratios, have incremental predictive usefulness in predicting financial distress.

To test this hypothesis, the author developed mixed four-state OLR models. The mixed models incorporated the cash flows shown to be important predictors of financial distress in Tables D-12, D-13, and D-14 (final gross cash flows models) and the accrual ratios of importance in Tables D-18, D-19, and D-20 (final accrual models). This combination of accrual ratios and cash flows resulted in the development of the following four-state mixed OLR models:

Year - 1 model: $SIZE_1$ + NITA + SALESCA + CACL + OETL + CFFO + CFFI + LFF,

Year - 2 model: $SIZE_1$ + NITA + SALESCA + CACL + OETL + CASHTA + CFFO + CFFI + SFF + EFF, and

Year - 3 model: $SIZE_1$ + NITA + SALESCA + CASHTA + CFFO + CFFI.

The results of the above mixed models are shown in Tables D-22, D-23, and D-24. The Wald chi-square statistics indicate that CFFO and LFF are also significant incremental predictors of financial distress one year prior to financial distress. CFFI and SFF are also significant incremental predictors of financial distress two years prior to financial distress. However, neither cash flow is incrementally significant in predicting financial distress three years prior to financial distress. Also, CFFO is only significant for Year - 1 and NITA is only significant for Year - 2 and Year - 3 when the cash flows are combined with the accrual ratios.

The Change in -2Log Likelihood chi-square also validates the Wald chi-squares results. This statistic represents the difference in the overall model chi-square of the base accrual model and the overall model chi-square of the mixed model with the cash flows added. For example, the Change in -2Log Likelihood chi-square for the final Year - 1 mixed model in Table D-22 is 22.577 with three degrees of freedom. This index indicates that the three cash flows (CFFO, CFFI, and SFF), as a group, are significant incremental predictors of financial distress (p-value < .001). The Change in -2Log Likelihood chi-square for this model was obtained by taking the chi-square for the mixed model of 130.759 and subtracting the final accrual model chi-square of 108.182 (Table D-18). Except for Year - 3, the Change in -2Log Likelihood chi-squares indicate that the added cash flows have incremental predictive value when added to the accrual ratios.

The Somers' D index and AIC Criterion also indicate that one loses little predictive power while gaining better fitting models by dropping CFFI in Year - 1, EFF in Year - 2, and CFFO in Year - 3. A review of the correlations of the parameter estimates for the mixed models indicated no correlations above .50 existed; thus collinearity should not present a problem with the mixed models.

Again, a troubling result is that the Score Test statistic chi-square is significant, indicating a violation of the parallel lines assumption. The fact that this statistic was never violated for the final gross cash flows models and was always violated by the accrual and mixed models indicates that some of the accrual ratios are not linearly related to the ordinal response variable as scaled in this study. This result was also evident in that the Score Test chi-squares (Tables D-22, D-23, and D-24) were not as significant for the mixed models as they were for the accrual models in Tables D-18, D-19, and D-20 (rejected at .05 in Year - 1 and Year - 2 for the mixed models and at .01 for the accrual models).

In summary, H_4 is accepted. Cash flows are significant incremental predictors of financial distress. However, the relevant cash flows are not significant in all years. The period of time prior to financial distress is important. CFFO and LFF are incrementally significant predictors one year prior to financial distress and CFFI and SFF are incrementally significant two years prior to financial distress. Neither cash flow has incremental predictive power three years prior to financial distress. These results are consistent with the opinion expressed by the FASB and various researchers [Sorter, 1982; Staubus, 1989] that cash flows are not better predictors of financial distress than accrual ratios but when combined with accrual ratios, are important incremental predictors. However, the OLR mixed models may be understating the importance of combining accrual ratios and cash flows since the parallel lines assumption is violated.

Testing of Hypothesis H_5

The naive cash flow, NOF, was found to be a significant predictor of financial distress in many early dichotomous distress studies [Beaver, 1966; Deakin, 1972; Blum, 1974; Norton and Smith, 1979; Mensah, 1983]. The reason for the strong predictive strength of this variable was normally attributed to the belief that adjusting net income for depreciation and amortization created a naive measure of operating cash flow. This naive cash flow was considered an important predictor of bankruptcy because researchers believed that the variable was closer to a "true" operating cash flow.

However, more recent cash flow studies used better measures of operating cash flow than NOF. For example, the CFFO variable reported in this study is much closer to the true operating cash flow construct than NOF. As a result, if NOF is simply a naive measure of operating cash flow, NOF should no longer be a significant predictor of financial distress when incorporated in models with the cash flows used in this study. Thus, the following hypothesis was offered:

> H_5: The naive cash flow, NOF, is not a significant predictor of financial distress when included in models with other more appropriate cash flow variables.

This hypothesis was tested by adding the variable NOF to the final gross cash flows models shown in Tables D-12, D-13, and D-14. The models tested were as follows:

Year - 1 model: $SIZE_1$ + CFFO + CFFI + LFF + NOF,

Year - 2 model: $SIZE_1$ + CFFO + CFFI + SFF + EFF + NOF, and

Year - 3 model: DIST = $SIZE_1$ + CFFO + CFFI + NOF.

The change in the -2Log Likelihood chi-squares for the full model with NOF added and the base model without NOF (Change in -2Log Likelihood chi-square) was used to test the above hypothesis. The results are shown in Table D-25. The results indicate that adding NOF to the cash flows models results in a significant increase in the predictive power of the model for Year - 1 and Year - 2; NOF is a significant incremental predictor of financial distress. Thus, H_5 is not accepted.

The results of testing H_5 are consistent with earlier research studies. The variable, NOF, has continuously been shown to be a significant predictor of bankruptcy. In fact, in a recent bankruptcy study, Holmen [1988] found that the single naive cash flow variable reported by Beaver [1966], net income plus depreciation and amortization (NOF), predicted bankruptcy better than the five variable Z-score model developed by Altman [1968].

However, recent cash flow bankruptcy studies have basically ignored NOF and concentrated their tests on better measures of operating cash flow. Undoubtedly, the failure to test NOF with other cash flows was based on the belief that NOF is a very naive measure of operating cash flows and should no longer be an important predictor of bankruptcy when combined with a better measure of operating cash flow.

If NOF is a significant predictor of financial distress because it is another measure of operating cash flow, then the parameter estimates for NOF and CFFO should be highly correlated. Section 1 of Table D-26 shows the correlations of the parameter estimates for CFFO and NOF. Notice that the correlations are moderate; for all three years, the correlations are less than .50. The correlations question the reason assumed in prior studies for the usefulness of NOF; the reason NOF is a significant predictor of financial distress is not because it is a naive cash flow measure.

Another reason must exist for why NOF is such a significant predictor of financial distress. To investigate whether another reason would explain this result, the author added the variable NOF to the final accrual models shown in Tables D-18, D-19, and D-20. The results are reported in Table D-27. NITA was significant every year in the accrual models without NOF. The results of the models with both NOF and NITA included indicate that NOF dominates NITA; NITA is no longer a significant predictor of financial distress when NOF is included in the model while NOF is still significant in Year - 2. The Wald chi-square for NOF is always larger than the Wald chi-square for NITA (every year).

The correlations of the parameter estimates between NITA and NOF are shown in Section 2 of Table D-26 and illustrate an interesting result. The parameter estimates for NOF are much more highly correlated with the parameter estimates of NITA than they are with the parameter estimates of CFFO. These results indicate that NOF is more likely a significant predictor of financial distress because NOF is simply another measure of income, not because NOF is a measure of operating cash flow. This result is not surprising considering NOF is simply net income adjusted for one of the largest allocations. This reason has been basically ignored in prior studies; however, the result is consistent with the allocation fallacy paradigm espoused by Thomas [1975] that allocations such as depreciation and amortization are useless and do not represent economic reality.

To obtain additional evidence addressing this issue, the author ran a reduced accrual model without NOF or NITA and two models with NOF and NITA added separately. The Change in -2Log Likelihood chi-square was used to determine the importance of adding NOF or NITA to the base model. This chi-square represents the difference in the -2Log Likelihood chi-square of the base model without NOF and NITA and the -2Log Likelihood chi-square of the model with NITA or NOF added. For all three years, adding NOF to the base model resulted in a larger and more significant Change in -2Log Likelihood chi-square than adding NITA.

Combining this evidence with the fact that NITA was no longer a significant predictor of financial distress when incorporated in models with NOF (Table D-27) indicates that NOF may simply be an alternative measure of income that predicts financial distress better than traditional net income. This may explain why NOF has tended to be a very strong predictor of financial distress in earlier dichotomous financial distress studies and why NOF is still a significant predictor of financial distress when incorporated with more appropriate cash flow variables.

In summary, H_5 was not accepted. NOF is still a significant predictor of financial distress when added to the gross cash flows models. However, additional analyses indicate that the reason NOF is still a significant predictor of financial distress may be because NOF is an alternative measure of income (and better measure of income for predicting financial distress) and not because NOF is a naive measure of operating cash flow as believed in earlier studies.

Analysis of the Tendency of Accrual and Mixed Models to Reject the Parallel Lines Assumption

The results of adding NOF and NITA separately to the base accrual model pointed out another interesting fact. As stated previously in this chapter, accrual and mixed models tend to reject the proportional odds assumption. Since this was not a problem with the cash flows models, the problem must lie among the accrual ratios. The results of adding NOF and NITA separately to the base accrual model seemed to indicate that the problem may lie in the variables based on forms of net income. For example, the base model without NITA or NOF included did not violate the proportional odds assumption for Year - 2 or Year - 3.

To determine if the income variables were the main variables causing the rejection of the parallel lines assumption for the accrual and mixed models, the author ran seven four-state univariate (one predictor variable) OLR models with a different accrual ratio or NOF in each model. The results are shown in Table D-28. The results indicate that the income variables, NITA and NOF, are the primary variables causing the rejection of the proportional odds assumption for the OLR models tested. However, the effect for NOF is not as severe as the effect for NITA; the Score Test chi-square statistic is not as large and is insignificant in Year - 3.

The univariate models indicate that the variables NITA and NOF may not be linearly related to the ordinal response variable as scaled in this study and that the problem is more severe for NITA. Table D-1, which included the Score Test chi-squares for the cash flows scaled by different scaling measures, also indicated that this problem occurred for CFFO (scaled by total liabilities). These three variables may not be linearly related to the ordinal response, as ordered in this study. If this fact is true, nominal logistic regression models may be more appropriate for accrual and mixed models.

Predictive Power of OLR Models Tested

The final OLR models were validated by testing the predictive power of each model. The primary method used to determine the predictive power of the models was the rank scoring rule (RPS) explained in Chapter 4. This method takes into consideration the ordinal nature of the response scale and penalizes model prediction probabilities not close to the actual observed state of distress. As a result, this method is preferred over classification accuracy for testing the predictive power of models developed [Lau, 1982 and 1987].

The RPS provides a score for each observation by comparing the conditional probabilities generated by the model for each of the levels of distress with the actual observed state of distress. A perfect rank score for one observation would be a score of one. For example, assume that a model generated the following vector of probabilities for a particular observation:

(1.00, 0.00, 0.00, 0.00).

The predicted probabilities are the conditional probabilities that the observation is in state i given the predictor variables in the model. If the observed firm is actually in state 0, then RPS would assign a score of 1 to this observation. The total score for a model is simply the sum of the rank scores for each observation, SS. Thus, the highest possible score for a model using the original 1988 sample is 229 and the total possible score for a model applied to the 1989 holdout sample is 158 (total possible SS = n, where n = total sample size).

The usefulness of any prediction model depends on the ability of the model to outperform a naive or chance model. The problem with using classification accuracy to validate the strength of a model is that the overall accuracy rate depends upon the arbitrary cutoff used by the researcher and the sampling proportions of the firms. For example, most bankruptcy researchers use an equal prior probability criterion for classifying bankrupt and nonbankrupt firms. That is, firms are classified based on the highest probability received (> .50).

As explained in Chapter 4, the RPS takes into account the rank of the ordinal response scale and the continuous probabilities generated by the ordinal logistic model.

Thus, RPS is ideal in situations where ordinal OLR is used. Also, the RPS does not involve arbitrary cutoffs to test the usefulness of a model and a score can be obtained for the naive model. Thus, one can compare various studies. Assuming the sample proportions are known in advance, a naive model applied to the 1988 and 1989 samples would give probability predictions for every observation equal to the sample proportions. For the 1988 sample, the vector of probabilities for each firm would be

(.725, .096, .100, .079).

The vector of probabilities for each firm in the holdout sample of 1989 would be

(.702, .108, .089, .101).

Using the above predicted probabilities for each observation, one can calculate a RPS score for a naive model.

Predictive Results Using the RPS

The RPS scores for the models are shown in Table D-29. The scores indicate that all of the models have fairly strong predictive power. The scores are very high, and all of the models outpredict the naive model except for the NOF model applied to the holdout sample in Year - 3. Generally, the gross cash flows models outperform the net cash flows models and the accrual models outperform the gross cash flows models. The mixed models also outperform the accrual models for the 1988 sample, although the difference is small. The models also perform very well when applied to the holdout sample. For example, the accrual model received a score of 140.193 for Year - 1 out of a possible score of 158 when applied to the holdout sample of 1989. However, the mixed OLR models fail to outpredict the accrual models for Year - 1 and Year - 2 when applied to the holdout samples.

Comparison To Lau's Model

Table D-30 includes the RPS scores for the two best models tested in this study, the accrual and mixed models, and the RPS scores for the best model tested by Lau [1987]. A direct comparison of the total RPS scores is not possible since the scores depend on the total number of observations. Since Lau sampled a larger number of firms for her study than sampled in this study, the RPS scores she reported will be larger.[26] However, one can compare the models for the two studies by determining whether the models outpredict a naive model (RPS scores exceeding the RPS scores produced by a naive model). Since the naive model's RPS scores incorporate the sampling proportions used in a study, RPS is the most appropriate method for comparing the results from this study with the results from Lau's studies.

As stated earlier, the results in Table D-30 show that the accrual and mixed models developed in this study outpredict the naive model every year for both samples. However, the best nominal model generated by Lau, working capital model with ten predictors, failed to outpredict the naive model when applied to the holdout sample. This failure to outpredict the naive model was true for all three years tested.

Thus, the OLR models developed in this study compare very favorably to the nominal models generated by Lau. This result provides some evidence that OLR models may be more stable across time than nominal logistic models.

Investigation of the Proportional Odds Problem Using RPS Scores

RPS scores were used to investigate further the reasons for why the proportional assumption was violated for the accrual and mixed models. The RPS scores

[26]Lau's original and holdout samples both included 400 firms. However, because of the numerous sampling criteria used by the author, this study sample sizes totaled 229 and 158 for the original and holdout groups, respectively.

for the accrual and mixed OLR models were broken down by state of distress. The highest possible score for each state of distress equals the number of firms in each group. For example, the highest possible RPS score for the bankrupt group (state 3) is 18 for the original sample and 16 for the holdout sample.

Nominal logistic accrual and mixed models were also developed using Proc Catmod [SAS, 1989]. Nominal models should outpredict OLR models for those states of distress which do not follow the ordinal scale as established in this study. The nominal models should outperform OLR models for these states because nominal models relax the parallel (ordinal) lines or constant slopes assumption. The relaxed slopes approach is what the Score Test of the proportional odds assumption uses to test the parallel lines assumption. Thus, if some of the states of distress fail to actually follow the ordinal response as established (in relationship to the predictor variables tested in this study), the nominal model can adjust for such departures from the ordinal response assumption while the OLR model cannot.

The results of breaking down the RPS scores for each state of distress are shown in Table D-31. The results for the OLR models are shown in the top part of Table D-31 while the results for the nominal models are shown in the bottom part of the table. The results show that the OLR models do a very good job of predicting the healthy and dividend reduction firms (for Year - 1, an accrual RPS score of 161.25 and 17.60 out of a possible score of 166 and 22 for the original sample and 107.47 and 13.61 out of a possible score of 111 and 17 for the holdout sample). However, the OLR models do a poorer job of predicting the last two states of distress. The OLR models were especially weak in predicting the bankrupt firms (state 3). For example, in Year - 1, the OLR mixed model's RPS scores for the bankrupt group were 13.15 and 7.45 (out of a possible score of 18 and 16) for the original and holdout samples.

The results for the OLR and nominal models indicate that the OLR models better predict the healthy and dividend reduction firms (overall) than the nominal models; the RPS scores for state 0 and state 1 are generally higher for the OLR models than for the nominal models. However, the nominal models outperform the OLR models when only the last two groups of distress are considered. The RPS scores for state 2 and state 3 are generally higher for the nominal models, especially for state 3.

Apparently, the nominal models better predict loan default/accommodation and bankrupt firms. The results seem to indicate that interaction occurs between state 2 and state 3. The predictors for the models may not be linearly related to these two states of distress as ordered, at least not in the direction expected.[27] Also, although the nominal logistic accrual and mixed models better predict financial distress than the accrual and mixed OLR models for the 1988 sample, the OLR models better predict financial distress when the models are applied to the holdout sample. This finding again indicates that OLR models are more stable across time than nominal logistic models.

Classification Accuracy of Models

The prediction accuracies of the final models were also validated using classification accuracy as the criterion. However, another important reason for using classification accuracy was to provide additional evidence concerning the reasons for the rejection of the proportional odds assumption by the accrual and mixed OLR models.

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[27]The author also broke down the RPS scores for the cash flows models and compared these OLR models to nominal cash flows models. However, since the parallel lines assumption was not violated for the cash flows models, one would not expect major differences between the OLR and nominal cash flows models. As expected, the differences between the nominal and OLR cash flows models were much smaller than the differences for the accrual and mixed models (especially for the overall RPS scores). However, the nominal models still tend to outpredict the OLR models for the 1988 sample and the OLR models always outpredict the nominal models when applied to the holdout sample; the cash flows models also slightly outpredict the nominal models in state 0 and state 1 and the nominal models slightly outpredict the OLR models in state 2 and state 3.

Classification accuracy is not the most appropriate method for validating the predictive strength of a logistic model because it does not take into consideration the ordinal scale of the response variable; nor does classification accuracy take into consideration the continuous probabilities generated by OLR.

The researcher should consider the prior probabilities when selecting a cutoff point for classification. Prior researchers have primarily used an equal priors assumption concerning the classification of observations. Researchers using logistic regression classified observations based on the highest probability received by the two groups, bankrupt and nonbankrupt. Otherwise, the firms were classified as bankrupt or nonbankrupt based on receiving a probability of bankrupt greater than 50 percent. This criterion was used by Lau in classifying firms into one of her five states of distress, except the cutoff point was 20 percent.

However, assuming equal prior probabilities (higher Type II costs) can result in misleading results. If one samples a much larger percentage of healthy firms in relation to the distressed firms, total classification accuracy will be very high because the model weighs the results based on the observations in both groups. Thus, virtually all of the healthy firms will be classified correctly and a few distressed (bankrupt) firms will be classified correctly. Thus, the researcher can increase the predictive accuracy of a model by simply sampling a very large percentage of healthy firms.

When using classification accuracy to validate models, the researcher should adjust the cutoff rates to account for the cost of errors and the prior probabilities. For example, according to Jones [1987], "if the cost of a Type I error (classification of a bankrupt firm as a nonbankrupt firm) were five times that of a Type II error, classification costs would be minimized by using a cutoff of .167, such that a firm with a probability of bankruptcy greater than .167 would be presumed bankrupt" [p. 154]. This cutoff of .167 is much lower than the normal cutoff of 50 percent used in prior bankruptcy studies and will result in a greater percentage of the bankrupt firms being classified correctly and a smaller percentage of the healthy firms being classified correctly.

The author classified firms based on the sample proportions rather than on the highest state probability received. This method adjusts for the prior probabilities and places more weight on the cost of misclassifying a distressed firm as healthy (Type I error). For example, assume an OLR model generates a vector of probabilities for an observation in the 1988 sample as follows:

(.60, .30, .08, .02).

The sample proportions for the 1988 sample were:

(.725, .096, .100, .079).

Classifying an observation into one of the four states of distress based on the highest probabilities received would result in the classification of this firm as a state 0, or healthy firm. However, chance would dictate that the firm stood a 72.5 percent chance of being a healthy firm. The model generated a conditional probability that the firm was healthy much lower than chance, 60 percent.

The author used a criterion whereby a firm was classified to the state of distress which received a conditional probability exceeding the sample proportion by the greatest amount. Classifying firms by this criterion means that a firm must receive a probability greater than chance for the firm to be classified in a particular state of financial distress. Using this criterion, the above firm is classified as a state 1, dividend reduction firm.

The use of this criterion will result in a greater percentage of the distressed firms being classified correctly and a lower percentage of the healthy firms being classified correctly. Since 72.5 percent of the 1988 sample consists of healthy firms and 70.25 percent of the 1989 holdout sample consists of healthy firms, the overall classification rates will be lower than using the highest probability rule.

Classification of firms by the criterion used in this study is also more likely to determine the true cause of the proportional odds assumption rejection since this cutoff criterion will result in a greater percentage of the distressed firms being classified correctly.

Classification Rates for the OLR Models

Table D-32 includes the classification rates for the final OLR models used to test the hypotheses. The rates are based on the number of firms correctly classified by state of distress. The classification rates are consistent with the statistical results discussed earlier, and indicate that:

> (1) the gross cash flows models correctly classified a greater percentage of firms than the net cash flows model (except in Year - 3 for the holdout group),
> (2) the accrual models tended to outclassify the gross cash flows models (especially for the holdout group),
> (3) the mixed models tended to outclassify the accrual models, and
> (4) the NOF models outclassified the gross cash flows model (except in Year - 1 for the holdout sample).

The classification rates also point out other interesting results. First, the models lose little power when applied to the holdout sample. The rates are almost the same, especially for the accrual and mixed OLR models. In fact, a greater percentage of the holdout firms are classified correctly in Year - 1. This indicates that the OLR models are fairly stable across 1988 and 1989. This stability was also illustrated by the RPS scores discussed earlier; the OLR models outperformed the naive model in every year, and the results differed little for the holdout sample.

Second, none of the models predict financial distress very well three years prior to bankruptcy, especially for the holdout group. However, this tendency is more apparent for the cash flows models. This finding is consistent with the belief that cash flows are predominantly useful in the short-run, while accrual information is more useful in predicting long-run solvency [FASB, 1987; Sorter, 1982; and Staubus, 1989]. This fact is also illustrated by comparing the mixed OLR models with the accrual OLR models. The mixed models outpredicted the accrual models every year (original sample and holdout sample) except for Year - 3 (both samples). Adding cash flows to the accrual ratios resulted in a decrease in the classification accuracies in Year - 3 (for both samples).

Third, the models tend to have trouble predicting the bankrupt group of firms correctly, especially for the holdout group. This result indicates that the reason for the rejection of the proportional odds assumption for the OLR accrual and mixed models is probably caused, as indicated by the RPS scores, by a break-down in the ordinal scale for the loan default/accommodation and bankrupt groups of firms.

Comparison of OLR Accrual and Mixed Classification Rates With Nominal Models' Classification Rates

In order to better understand the reason for the rejection of the proportional odds assumption, the author generated nominal logistic models for those cases where the proportional odds assumption was violated (accrual and mixed models). Table D-33 shows the classification rates for the OLR and nominal accrual and mixed models. These rates indicate that the nominal models outpredicted the OLR models, based on overall accuracy, in every year except Year - 3 for the holdout sample. Also, the nominal models, overall, tend to correctly classify a larger percentage of state 2 and state 3 firms than the OLR models. Otherwise, the nominal models can better distinguish loan default/accommodation firms from bankrupt firms. This result was anticipated and indicates that a break-down of the ordinal scale between the loan default/accommodation and bankrupt groups is causing the rejection of the proportional odds assumption.

Unexpectedly, the nominal model also predicted a larger percentage of the healthy firms correctly (state 0) than the OLR models. This result was unexpected since the RPS scores indicated that the OLR models tended to outpredict the nominal models for the first two states of distress. A thorough investigation of the misclassifications, however, indicated that the OLR models tended to misclassify firms less severely than the nominal models. The OLR models normally misclassified healthy firms as dividend reduction firms and misclassified dividend reduction firms as healthy firms. In other words, when an OLR model misclassifed a healthy or dividend reduction firm, the firm was seldom misclassified as a firm in one of the extreme states of distress. However, the nominal models often misclassified a firm more severely, especially firms in the first two states of financial distress.

This difference between the RPS score results and classification accuracy rates illustrates the problem of using misclassification rates alone to evaluate the predictive performance of logistic models. Overall classification rates fail to take into consideration the degree of error in a misclassification. The RPS scoring rule discussed earlier does take this fact into consideration.

Classification Rates After Collapsing the Four States Into Two Groups

To determine if the results for RPS scores and classification rates would agree if the degree of misclassification was considered, the author collapsed the four states into a dichotomous grouping for classifications. The same four-state probabilities and same classification criterion (exceeding the sampling proportion by the greatest amount) as discussed before were used. The only difference was that the four states of distress were collapsed into a two by two classification table (group 0+1 by group 2+3). State 0 and state 1 were grouped together and state 2 and state 3 were grouped together. Healthy or dividend reduction firms were considered correctly classified if the model classified the firms as either healthy or dividend reduction firms. Loan default/accommodation and bankrupt firms were considered correctly classified if the model classified the firms as either loan default/accommodation or bankrupt firms. The results of the classification rates using a dichotomous grouping scheme are shown in Table D-34.

The results show that the overall classification rates are higher (less overall likelihood of misclassification). The rates for the OLR mixed and accrual models are now generally higher than those of the nominal mixed and accrual models for the original sample. The improvement in the misclassification rates means that the OLR models tend to misclassify firms with less severity than the nominal models. However, the nominal models still outpredicts the OLR models for the most distressed group (last two states combined) when using the original sample. For example, the mixed nominal model predicted 92.7 percent of the most distressed firms correctly, while the OLR mixed model only predicted 85.4 percent of the most distressed firms correctly. This result was evident for both accrual and mixed models, mostly for the original sample. This result again suggests the reason that the accrual and mixed models reject the proportional odds assumption is because of the last two states of distress.

Two-State Logistic Prediction Models: Further Evidence Concerning the Rejection of the Proportional Odds Assumption by the Accrual and Mixed Models

In order to further investigate the possible scaling problem, the author ran univariate two-state distress models (one predictor variable). A univariate two-state model was run with only the loan default/accommodation and bankrupt firms. The default/accommodation firms were coded as DIST = 2 and the bankrupt firms were coded as DIST = 3. All the other firms (healthy and dividend reduction firms) were dropped from the original sample to develop the two-state models. The loan default/accommodation and bankrupt firms were coded in the same order as coded in the four-state models to maintain the ordinal scale as hypothesized (bankrupt firms are more distressed than loan default/accommodation firms). The author investigated the signs of the parameter estimates for the two-state models to determine if they were in the direction hypothesized. Signs directly opposite from expected would indicate that the bankrupt group of firms is less financially distressed than the loan default/accommodation group (for the predictor variables tested). The author ran only one predictor variable at a time because of the small sample size (n = 23 loan default/accommodation firms + 18 bankrupt firms, or 41 firms). Running one variable resulted in the sample size meeting the ratio of 20(S+1) [Noreen, 1988; Stone and Rasp, 1991] needed to limit the likelihood of biased parameter estimates (where S = the number of predictor variables).

The results of the two-state (loan default/accommodation and bankrupt groups) univariate logistic models are shown in Table D-35. The results vividly point out why the proportional odds assumption was violated for the OLR accrual and mixed models. The signs for the accrual variables are generally opposite from expected, especially for those variables which were most significant in the four-state OLR models discussed earlier. For example, the parameter estimate for NITA is positive for all three years. A positive NITA parameter estimate indicates that NITA is higher for bankrupt firms than loan default/accommodation firms. In fact, NITA is a significant predictor of distress in Year - 3 (when compared to loan default/accommodation), but is significant in the opposite direction than expected. The tendency of the accrual ratios to have signs opposite from expected also held true for the size variable, $SIZE_1$.

The results also indicate additional points of interest. One, the accrual, CATA, is a significant variable in predicting bankrupt and loan default/accommodation firms in Year - 1 and Year - 2, but in the opposite direction than expected. Higher values of CATA are associated with the bankrupt firms. CATA was never a significant predictor of financial distress in the four-state models; the reverse association explains the reason why.

Two, the reversed pattern is still apparent for the cash flows; however, the problem is not as severe, especially for Year - 2. For example, the parameter estimate for CFFO was as expected for Year - 2 but was opposite than expected for Year - 1 and Year - 3. This result was observed for most of the cash flow variables. This result explains why the proportional odds assumption was not violated for the final OLR cash flows models; the reversing of states two and three was not severe enough to overcome the strong linear relationship between the cash flows and the other levels of distress.

For comparative purposes, the author also ran two-state univariate logistic models for the healthy versus dividend reduction firms. The healthy firms were coded DIST = 0 and the dividend reduction firms were coded DIST = 1 (n = 188). However, this analysis failed to identify a problem in the ordinal response scale for state 0 and state 1. Virtually all of the parameter estimates of the variables were in the direction hypothesized, especially the parameter estimates for the variables most dominant in the four-state prediction models.

In summary, the rejection of the proportional odds assumption is apparently caused by the bankrupt group of firms. The models indicate that, for the predictor variables tested in this study, the bankrupt firms tend be less financially distressed than the loan default/accommodation firms. Bankrupt firms tend to have higher net income as a percentage of total assets, higher cash flow from operations as a percentage of total liabilities, higher cash (plus marketable securities) as a percentage of total assets, and higher current assets as a percentage of total assets than loan default/accommodation firms.

This finding questions the use of a simple dichotomous bankrupt/nonbankrupt response as a proxy for financial distress to evaluate the usefulness of financial accounting ratios, and also questions the use of bankruptcy in prior bankrupt/nonbankrupt studies. If a dichotomous response is used to evaluate accounting information, this study indicates that a more appropriate dichotomous response would be loan default/accommodation and healthy (or not loan default/accommodation). The use of loan default/accommodation as the criterion variable for evaluating the usefulness of accounting information also makes more sense from an applied perspective. Lenders are primarily interested in whether a firm defaults on a loan. Developing models which predict loan default/accommodation would probably provide greater benefit to lenders than predicting bankruptcy. Most firms which default on loans do not become bankrupt. Even for those default/accommodation firms which do become bankrupt, predicting the default/accommodation would be of more interest to the lender because default normally occurs prior to bankruptcy; predicting loan default/accommodation would provide lenders more time to react.

CHAPTER 6

CONCLUSION

As stated earlier, the 1970s and 1980s saw an increased interest in cash flows as a result of three main occurrences. First, a renewed interest in the importance of the solvency of a firm emerged during this period. Second, this renewed interest in solvency also resulted in a renewed interest in the "funds flow" approach for determining the survivability of a company. Coupled with the renewed interest in solvency analysis and the "funds flow" concept, the creation of future cash flows as a criterion for evaluating the usefulness of accounting information by the FASB led accounting information users, accountants, and researchers to investigate the importance of current cash flow information.

The above occurrences led to substantial research on the usefulness of cash flow information. The primary stream of research testing the importance of cash flow information has concerned the ability of accounting information to predict financial distress, where financial distress surrogates for future cash flows. Most of these studies have primarily used a dichotomous bankrupt/nonbankrupt response for financial distress. As discussed in Chapter 1 and Chapter 3, these dichotomous financial distress studies suffered from many limitations. Lau [1982 and 1987] attempted to control for many of these limitations by investigating the feasibility of using multi-state prediction models. However, Lau's published work [1987] was primarily a methodology study stressing the feasibility of multi-state models. Her study had several limitations, primarily because of the statistical limitations of the nominal statistical package she used, a 1979 package called the Quail program [Berkman *et al.*].

This study better evaluates the ability of cash flows to predict financial distress by: incorporating different sampling techniques, using a different sampling period, developing a theoretical framework of financial distress to select the cash flow variables to test, and developing ordinal multi-state predictive models of financial distress. This study also investigates the feasibility of using OLR models to predict financial distress and the appropriateness of the multi-state ordinal response as stated in this study. A more thorough discussion of how this study differs from prior financial distress studies appears in chapters 1 and 4.

Findings and Contributions of Study

For many firms, substantial time and cost is involved in maintaining the records to prepare a statement of cash flows. Yet, prior financial distress research studies have found little evidence that cash flows have incremental usefulness in predicting financial distress. However, the results of this study indicate that cash flows (by activities) do have both predictive and incremental predictive power in predicting financial distress. However, cash flows are not better predictors of financial distress than traditional accrual ratios. Also, cash flows apparently have little long-run incremental usefulness. Adding cash flows to accruals resulted in a decrease in classification accuracy three years prior to financial distress. An important result of this study is that the gross financing cash flows, LFF and SFF, have greater predictive power than the net financing cash flow CFFF.

These findings lend support to the FASB's decision to require a statement of cash flows, especially for the requirement that companies disclose gross cash flows from investing and financing activities. These findings are consistent with the opinion expressed by the FASB in Statement No. 95 that cash flows have predictive usefulness in predicting financial distress when combined with accrual information but that this usefulness is limited primarily to the short-run.

This study extends the financial distress methodology by using multi-state OLR models. The results indicate that the multi-state models offer a viable way of using financial distress to test accounting information because of the ease of testing accounting predictor variables. Using OLR (proportional odds) models enables the researcher to use basically the same tests, and draw similar statistical inferences, as in ordinary least squares regression. This study also provides evidence that, in addition to the ease of testing, OLR models may be more stable across time than nominal logistic models, especially if the proportional odds test is not rejected.

This study also provides evidence questioning the validity of using legal events such as bankruptcy as proxies for financial distress. The proportional odds test (parallel lines assumption test) was used to test the validity of the OLR multi-state models. In all cases, the proportional odds test was rejected for the accrual and mixed models, indicating that the ordinal scale (as stated) may not fit the data very well for the variables tested in these models. Further analyses using descriptive statistics nominal models, RPS, classification accuracy, and two-state OLR models (only loan default/accommodation firms and bankrupt firms) indicated that the scaling problem occurred because the bankrupt firms, overall, were not as financially distressed as the loan default/accommodation firms, based on the financial variables tested in this study. This scaling problem was more severe for the accrual ratios. However, this scaling problem was also apparent in the cash flows models, although the problem was not severe enough to cause the rejection of the parallel lines assumption for the cash flows models.

The finding that the bankrupt firms tended to be less distressed than the loan default/accommodation firms questions the use of a simple dichotomous bankrupt/nonbankrupt response as a proxy for financial distress and validates the use of multi-state prediction models. If a dichotomous response is used, this study indicates that one should use loan default/accommodation as the dichotomous response for financial distress. In fact, developing predictive models with loan default/accommodation as the financial distress proxy should be more useful to financial statement users than bankruptcy prediction models such as the Z-score model developed by Altman [1968] and the ZETA model developed by Altman *et al.* [1977]. Predicting bankruptcy one or two years prior to bankruptcy may be of little usefulness to lenders since many, if not most, of these firms have probably already defaulted on their loans. Also, since most firms recover from distress after loan default/accommodation, using loan default/accommodation would result in prediction models with greater external validity. These models would include a much larger number of firms and a greater variety of firms.

This study also provides insight into why early financial distress studies found net income adjusted for depreciation and amortization (NOF) to be such a strong predictor of financial distress. Early researchers basically attributed the predictive power of NOF to the fact that this measure was considered a naive measure of the true operating cash flow. However, the author found that a more likely reason that NOF is such a strong predictor of financial distress is that NOF is an alternative measure (and better measure for predicting financial distress than net income) of income. When incorporated in models with NITA, NOF tended to swamp the NITA variable.

Limitations

Since the distressed firms in this study were sampled in proportions larger than found in the population, some choice-based sampling bias probably exists. However, the use of multiple response levels together with a larger percentage of healthy firms should minimize the effect of choice-based sampling bias on the results. The author is unaware of prior studies addressing the existence of choice-based sampling bias in multi-state distress models.

The author used various criteria for insuring that the firms sampled were labeled correctly along the distress scale. However, it is unlikely that all of the firms were identified correctly. To the extent that some firms were incorrectly labeled, confounding exists.

The cash flows used in this study are estimates of the actual cash flows of a company. Although an attempt was made to obtain as close a proxy as possible, it is unlikely that these proxies are the same as the companies' actual cash flows. Thus, the results may be different if actual cash flows are used.

The proportional odds tests for the accrual and mixed OLR models indicated that the parallel lines assumption was violated for these models. The rejection of the parallel lines assumption casts doubts about the validity of the ordinal scale and suggests that other models, possibly nominal models, may fit the data better. This finding indicates that the OLR models may distort the predictive usefulness of these variables. However, a comparison of the OLR models and nominal logistic models indicated that although the nominal accrual and mixed models outpredicted the OLR accrual and mixed models for the original sample, the OLR accrual and mixed models still tended to outpredict the nominal accrual and mixed models when applied to the holdout sample, indicating that OLR models may still be more stable across time.

The decision to match firms by industry limits the external validity of this study. However, the author considers the decision to match by industry to be acceptable in order to control for possible confounding, thus strengthening the internal validity of this study.

Recommendations for Future Research

The results of this study indicate a number of recommendations for future research in the area of financial distress. First, additional research is needed to determine if gross investing and operating cash flows also provide greater predictive value than the net cash flows, CFFO and CFFI. Although the author was unable to obtain gross operating and investing cash flows from the data available during the time frame of this study, subsequent studies based on data from the statement of cash flows may be able to test these gross cash flows, especially the gross investing cash flows.

Second, additional research is needed concerning the predictive usefulness of NOF. The results of this study seem to indicate that NOF may be an alternative measure of net income and not a measure of operating cash flow. The results also indicate that NOF is a stronger predictor of financial distress than net income. However, the results of this study may be affected by the use of the scaling measure for net income and net income plus depreciation. The predictive dominance of NOF over NITA may result from the fact that net income was scaled by total assets (NITA) while net income plus depreciation and amortization (NOF) was scaled by total liabilities. Also, one may obtain different results if operating income is used instead of net income in the calculation of the two predictive variables.

Third, this study provides evidence that bankrupt firms tend to be less distressed than loan interest/accommodation firms, thus questioning the use of a bankrupt/nonbankrupt response for financial distress. Another dichotomous response such as loan default/accommodation and healthy may produce results different from those using a bankrupt/nonbankrupt response. Additional research is needed to determine whether results using loan default/accommodation as the response variable differ from the results of prior studies using bankruptcy as the response variable. This research is needed to determine the validity of using a legal event such as bankruptcy to test the economic usefulness of accounting information.

Also, research is needed to determine the best ordinal multi-state models possible for predicting financial distress. This research needs to address whether other events such as merger and executive firing (or hiring) also represent states of financial distress. And, if other states of distress are identified, this research must attempt to identify the ordering of such events.

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APPENDICES

APPENDIX A

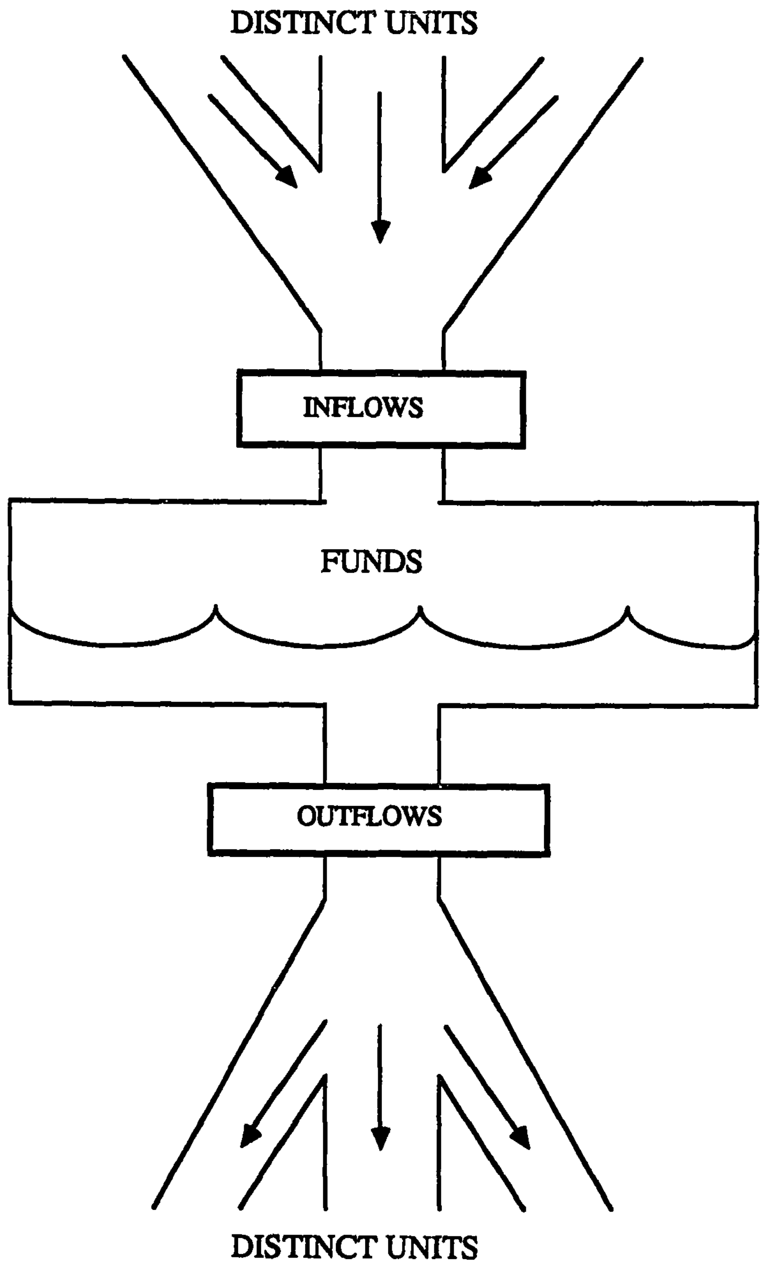

Figure A-1. **Illustration of the Funds Flow Concept**

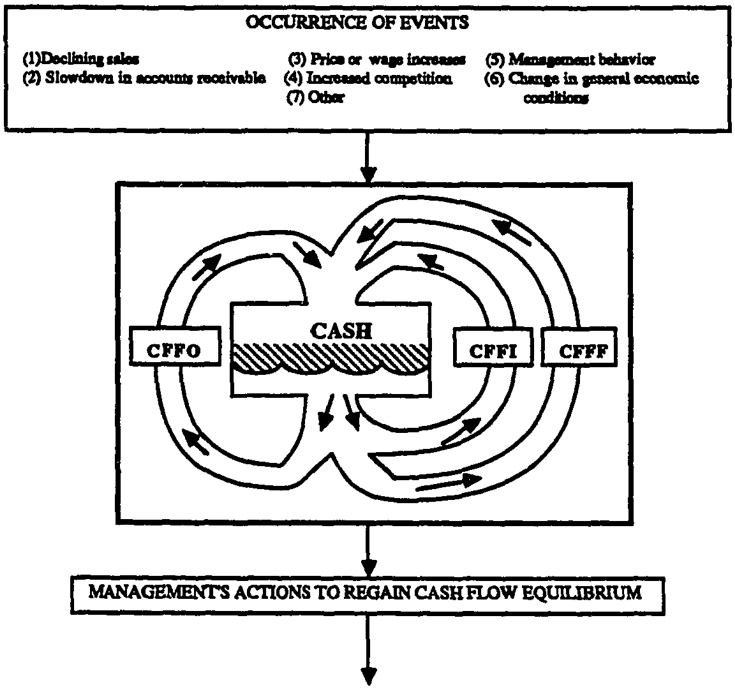

Figure A-2. Theoretical Model of Financial Distress

Adapted from:

Donaldson, G., Strategy for Financial Mobility (Harvard Business School Press, 1986).

Heath, L. C., Financial Reporting and the Evaluation of Solvency (AICPA, 1978).

Lau, A. Hing-Ling, "On the Prediction of Firms In Financial Distress, With An Evaluation of Alternative Funds-Flow Concepts," Ph.D. dissertation, Washington University, 1982.

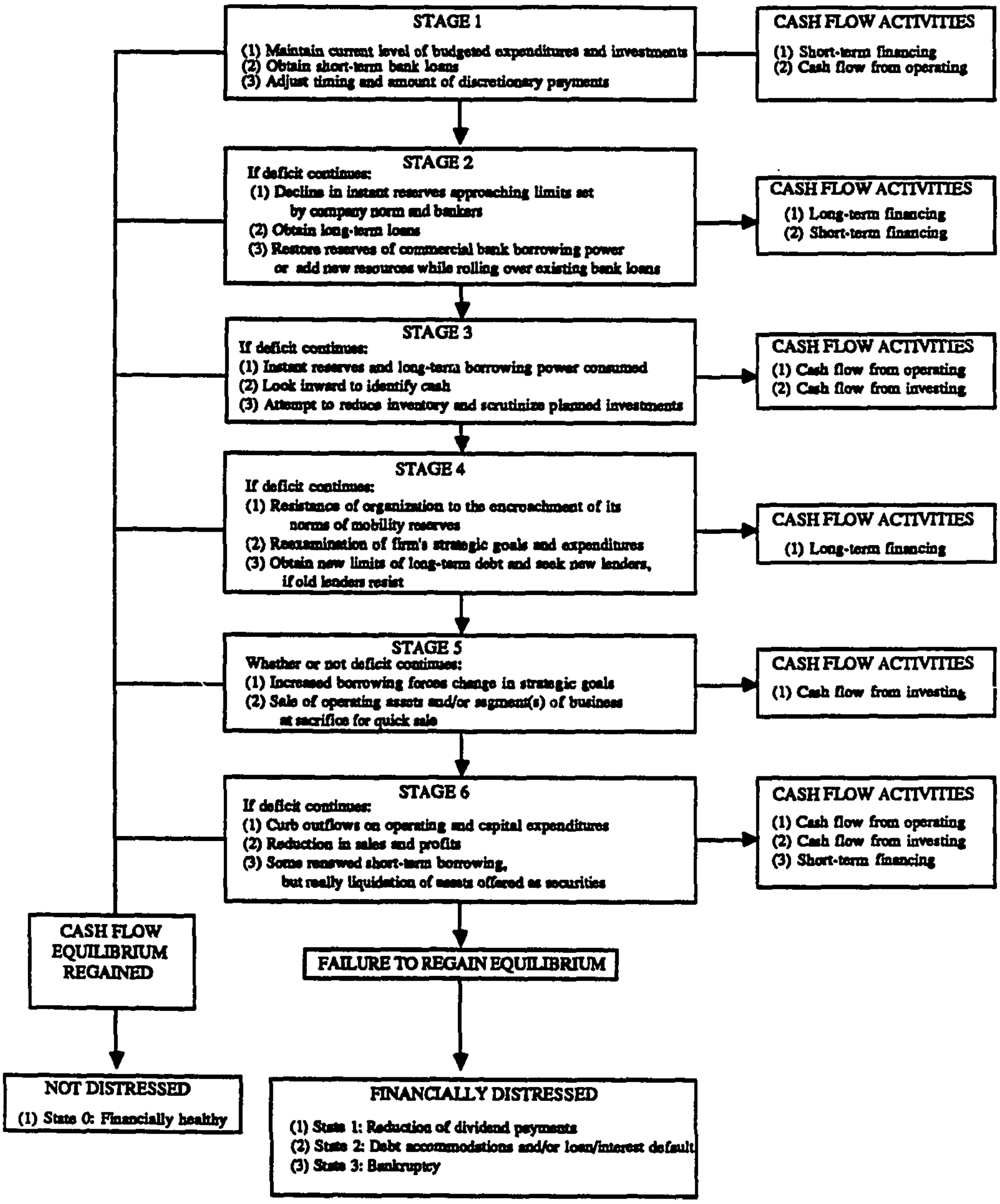

Figure A-2. (continued)

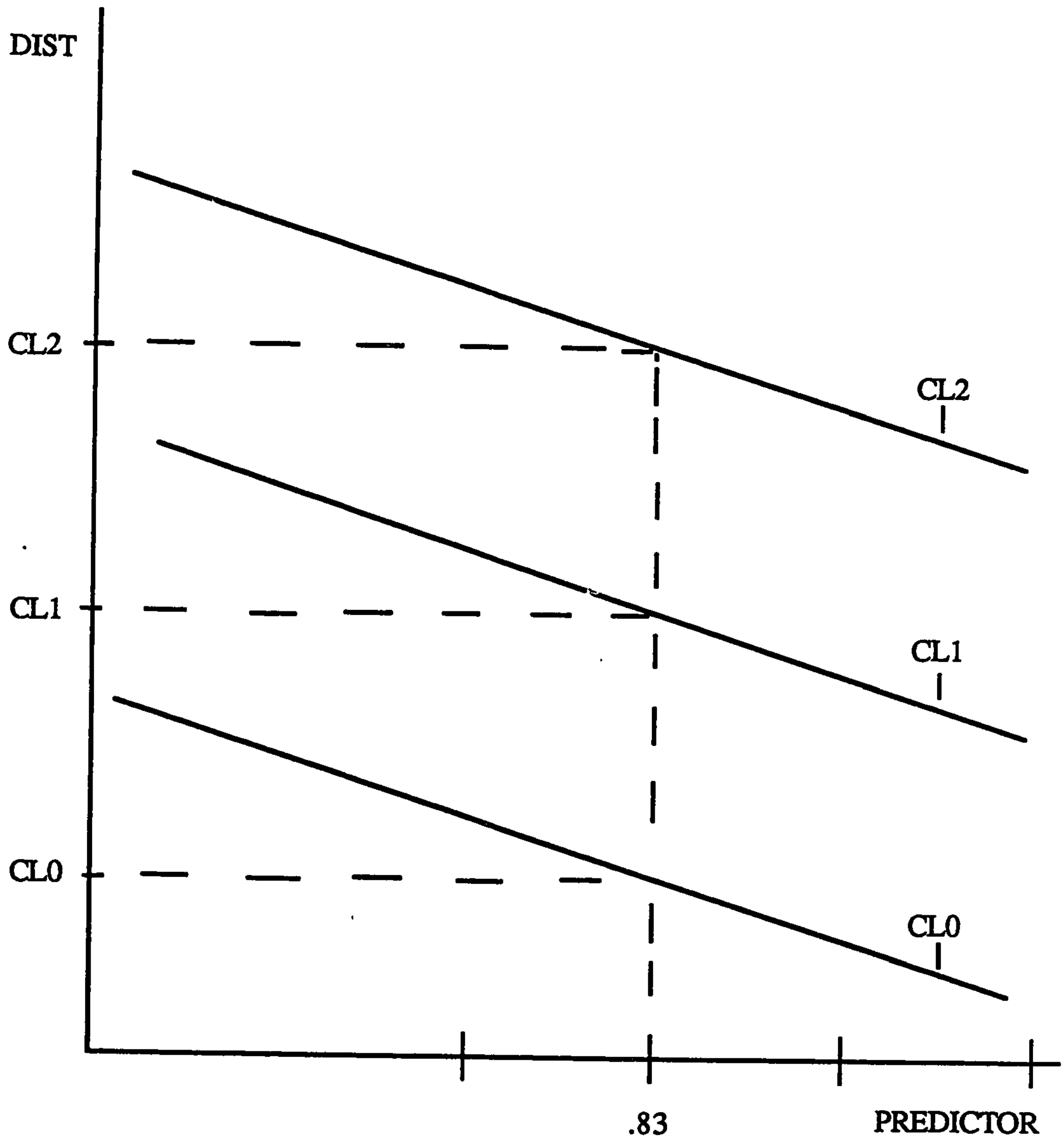

Figure A-3. Illustration of OLR and the Parallel Lines Assumption - $P(Y \leq i \mid x)$

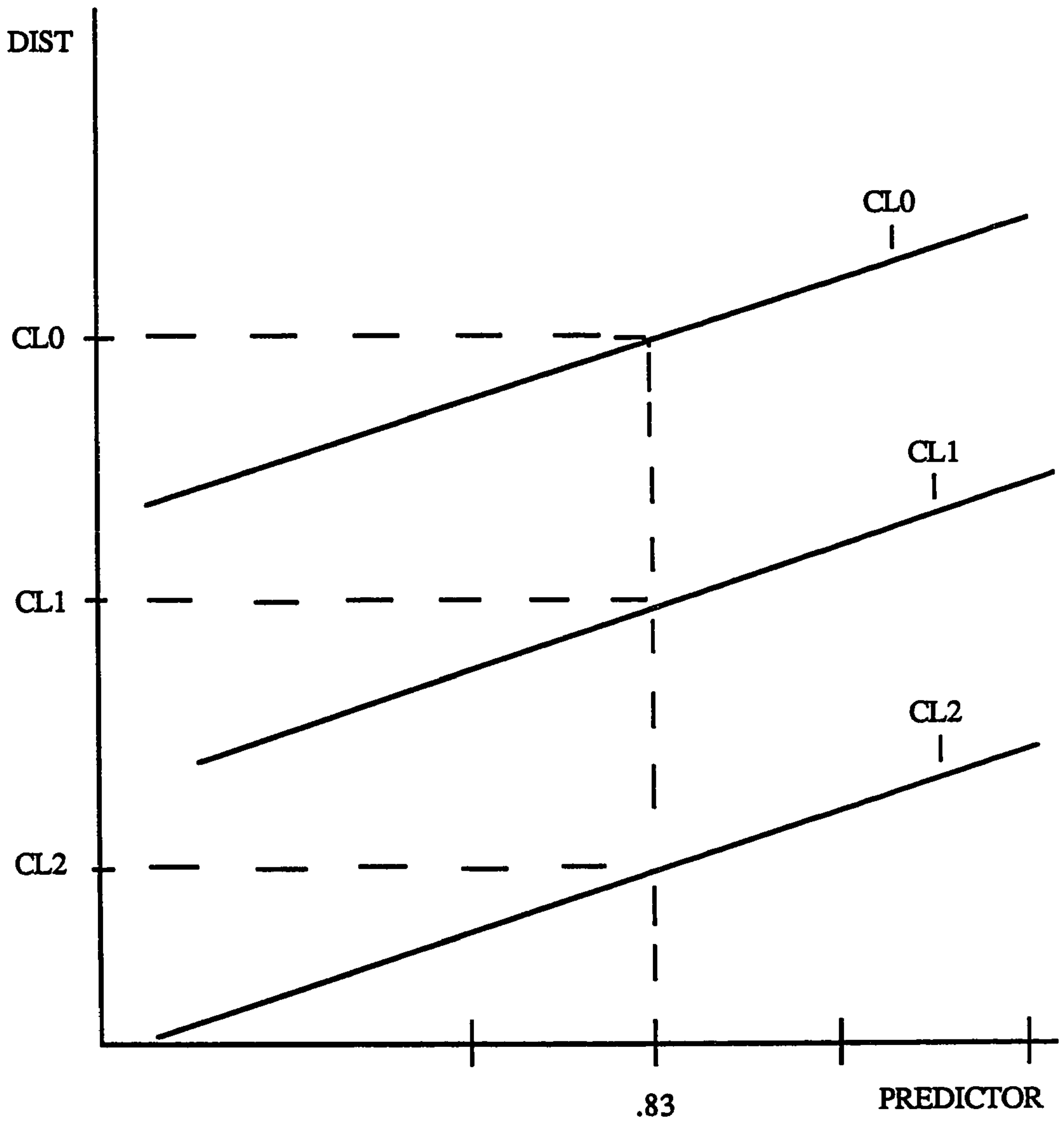

Figure A-4. Illustration of OLR and the Parallel Lines Assumption - $P(Y \geq i \mid x)$

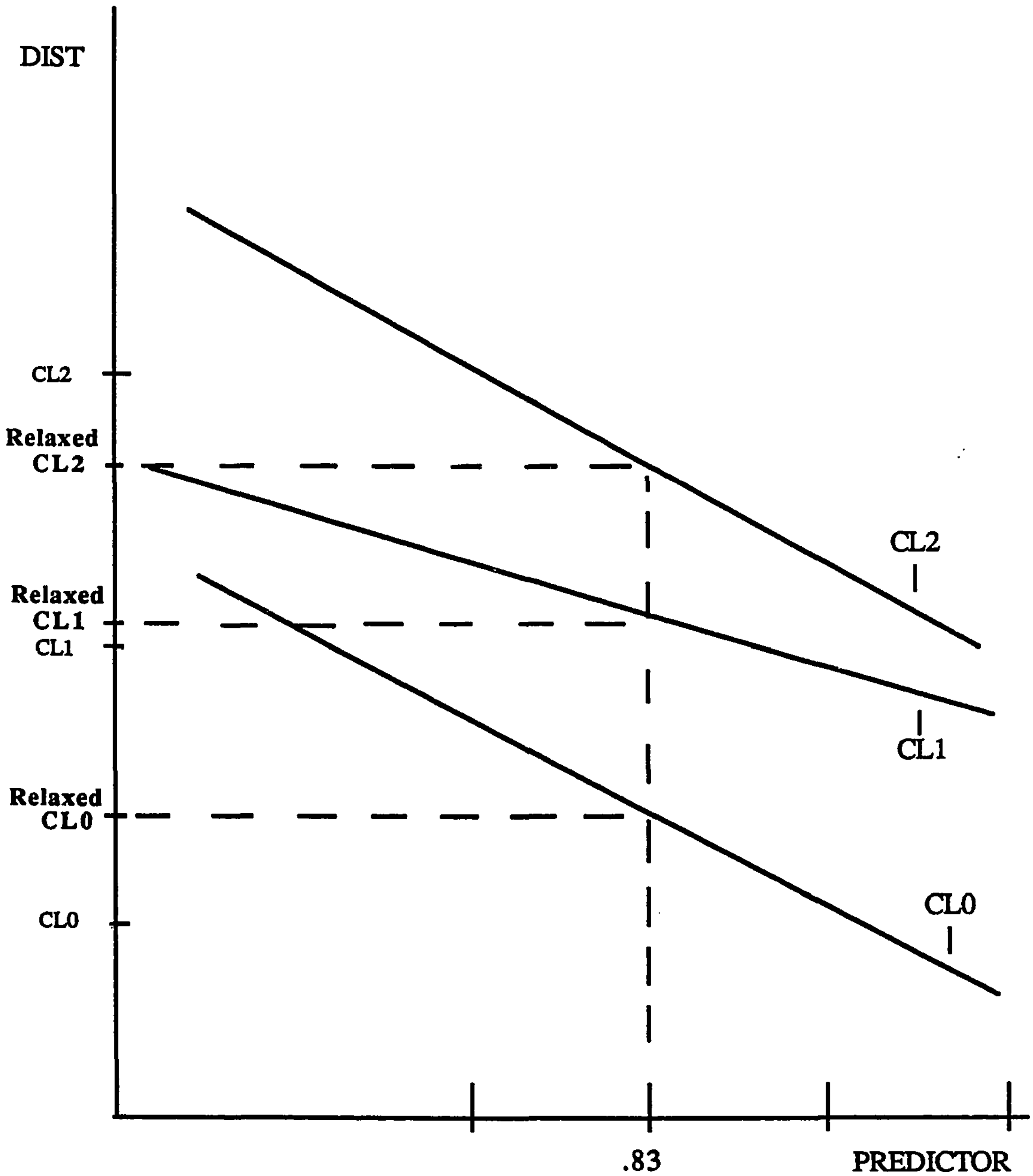

Figure A-5. Illustration of the Relaxation of the Parallel Lines Assumption

APPENDIX B

Table B-1

Financial Distress Studies Which Defined Cash Flow as Income Plus Depreciation

Study	Number and Types of Firms	Time Period of Data	Cash Flow Variables	Methods	Findings
Beaver [1966]	79 failed and 79 nonfailed firms from Moody's & D&B (failed = bankruptcy, bond default, overdrawn bank account, or nonpayment of preferred dividends)	1949-1963	CF/S CF/TA CF/NW CF/TD	Dichotomous classification where sample was divided and the firms were classified using cut-off points for each ratio derived from the other subsample	CF/TD best single predictor
Deakin [1972]	32 failed and nonfailed firms used for dichotomous classification test A second sample of 32 nonfailed firms used in discriminant analysis	1959-1969 1957-1965	CF/TD	Dichotomous classification test and single-year and multiple-years discriminant analysis: all for 1 to 5 years prior to failure	CF/TD most significant in all models
Blum [1974]	115 failed industrial firms from D&B and Beaver with minimum of $1M in liabilities at time of failure 115 nonfailed firms randomly chosen from the January 1969 index to *Compustat*	1951-1967	CF/TD	Multivariate discriminant analysis with 21 models, 1 to 6 years prior to failure with various ranges of data preceding the failure data	CF/TD variable generally received high rankings
Altman, Haldeman, and Narayanan [1977]	53 bankrupt and 58 nonbankrupt firms from manufacturing and retailing	1964-1974	CF/Fixed charges CF/TD	Performed six tests to identify most useful variables to include in the final ZETA discriminant model (forwards and backwards stepwise discriminant analysis and various other tests)	Out of 27 variables, the CF variables were not found to be a part of the best model

Table B-1 (continued)

Study	Number and Types of Firms	Time Period of Data	Cash Flow Variables	Methods	Findings
Norton and Smith [1979]	30 bankrupt (per 8-Ks or 10-Ks) and 30 nonbankrupt publicly traded firms	1967-1974	CF/S CF/TA CF/NW CF/TD	Linear multiple stepwise discriminant analysis models prepared for 1, 2, 3, and 4 years prior to bankruptcy using a potential of 32 variables Stepwise, linear multiple regression was also used	CF/TA and CF/TD were part of best discriminant model 3 years prior to bankruptcy (83.3% classification accuracy) CF/TD was identified by regression for inclusion in second discriminant
Mensah [1983]	For *ex ante* prediction purposes, 35 nonbankrupt firms were randomly selected and 11 bankrupt firms were used	1974-1978	CF/CL CF/S CF/TA CF/NW CF/TD	Used the means and standard deviations of the ratios instead of the ratios Stepwise multiple discriminant	CF/NW was most important ratio in discriminant (historical cost) model

Source: Gombola, M. J., M. E. Haskins, J. E. Ketz, and D. D. Williams, "Cash Flow in Bankruptcy Prediction," Financial Management (Winter 1987), p. 56.

Table B-2

Studies Which Tested Cash Flow Variables as Predictors of Financial Distress

Study	Sample / Time Period of Data	Variables Tested / Methodology	Findings
Largay and Stickney [1980]	One firm 1966-1974 No holdout sample & no matched pairs	WCFO, CFO, and various accrual ratios Selected variables based on subjective judgment Tested by levels and trends	CFO provided a more accurate & timely signal of W. T. Grant eventual failure
Casey and Bartczak [1984 & 85]	60B/230NB 1966-1981 Matched (industry) Holdout (same period as models)	CFO/CL, CFO/TL, CFO, and 6 accrual ratios Adjusted WCFO to obtain CFO Variables selected based on results of prior factor analysis studies Linear MDA and conditional stepwise logit analysis 1, 2, 3, 4, & 5 year models	Cash flow ratios are sig. during certain years. However, neither cash flow variable had higher classification than the combined 6 accrual ratios Addition of various cash flow variables did not increase classification accuracy
Gentry, Newbold, and Whitford [1985]	33B&L/33NB 1967-1980 Matched (size, industry, & sales) No holdout, but 2nd sample of weak/nonweak	7 cash-based funds flows (each divided by total net flow) Never tested CFO, but tested components of CFO MDA, probit, & logit techniques 1, 2, & 3 year models Funds flow ratios based on Helfert's cash-based funds flow model	Funds flow components have predictive content, but the cash flow components of CFO do not improve classification accuracy
Gentry, Newbold, and Whitford [1987]	Same as before	11 funds flow variables, and 6 accrual ratios MDA & probit techniques Never tested CFO, but tested components of CFO Rest is same as before	Investment, dividend, and receivable funds flow variables are sig. Funds flow components have incremental predictive power
Aziz, Emanuel, and Lawson [1988]	49B/49NB 1966-1981 Matched by asset size & industry No holdout, jackknife tech.	6 cash flow variables, each scaled by BV of firm CFO variable is C&B's + taxes paid + interest paid MDA & logistic regression 1, 2, 3, 4, & 5 year models Selected cash flows based on Lawson's cash flow identity Compared to Altman's Z-score model and ZETA model of Altman *et al.* [1977]	Logit models superior to discriminant models Taxes paid, operating cash flow, & lender cash flow most sig. CFO & taxes paid sig. as early as the 5th year

Table B-2 (continued)

Study	Sample / Time Period of Data	Variables Tested / Methodology	Findings
Aziz and Lawson [1989]	Same as before, except also used a holdout sample of 26B/67NB firms	5 cash flow variables, each scaled by BV of firm, & the 5 ratios in Altman's Z-score model Same definition of CFO as above Same methodology as above, except tested incremental predictive power of cash flow variables	Cash flow variables do not improve on existing models' overall accuracy However, cash flow based models and mixed models exhibited superior prediction accuracy
Rujoub [1989] unpublished	33B/33NB 1970-1981 Matched by asset size and industry	8 cash flow ratios, 6 accrual ratios used by Beaver [1966], and 8 ratios from the statement of changes in financial position MDA & multivariate logit analysis	Cash flow variables are better predictors of financial distress than accrual ratios and also have incremental predictive content

Table B-3

Relevant Methodology Studies

Study	Sample	Variables Tested	Methodology	Findings
Mensah [1984]	11, 30, 37 & 32 pairs of B/NB firms 1970-1978 Matched (industry & assets) Holdout	10 factor scores, of which one was a cash flow factor	Logistic on analysis of factors, and MDA on original ratios 2 year model	Models not stationary across time
Gombola, Haskins, Ketz, and Williams [1987]	77B/77NB Two separate models: early (1967-1972) & late (1973-1981)	CFFO/assets, WCFO/assets, INCDEP/assets & 6 other ratios loading highest on factors	Primarily linear discriminant analysis, but also used quadratic discriminant and probit analysis 1, 2, 3, & 4 year models	CFFO variables not sig. CFFO variables not more useful in late-year models
Lau [1987]	350, 20, 15, 10 & 5 firms in 5 states: healthy, omitting or reducing dividends, default of loan interest &/or principal payments, protection under Chapter X or XI, and bankruptcy and liquidation for 1976 Holdout (separate period-1977) Matched by size	10 variables, of which working capital flow was the funds flow variable tested	MLA and MDA 1, 2, & 3 year models	Models fairly strong
Lau [1982] unpublished	Same as 1987 study	Attempted to test 3 other funds flow variables, of which one was CFO	Same as 1987 study	Results mixed

Table B-3 (continued)

Study	Sample/ Time Period of Data	Variables Tested	Methodology	Findings
Noreen [1988]	Sample sizes of 50 and 100	Three ratios and one dummy variable	Simulations: Monte Carlo trials Probit and OLS	For sample size of 50, probit rejected null hypothesis twice the normal level & greater than OLS regression Results basically reversed for sample size of 100
Gilbert, Menon and Schwartz [1990]	Two main samples: (1) sample of 76 bank. & 304 randomly selected firms and (2) sample of 76 bank. & 304 distressed Distressed firms where those which had neg. cumulative earnings over a consecutive three year period Holdout (above samples split into two groups)	Replicated Casey and Bartczak's study [1985] and Altman's study [1968]	Logistic regression	CFO has incremental predictive power, especially for bankrupt/distressed models Bankruptcy models performed poorly in distinguishing bankrupt from distressed firms for the holdout sample
Stone and Rasp [1991]	Sample sizes of 50 and 100 Effects of sample size, number, correlation, & distribution of predictor variables on logit error rates	Three ratios and one dummy variable	Simulations & actual data Logistic & OLS regression	Biased estimators for sample sizes of 50: overall logit models incorrectly rejected the null while individual test statistics were conservatively biased Skewed data increases the bias Even for small samples, logit models resulted in lower Type I errors Sample sizes of greater than 10(S+1) are needed Logistic regression should be used (over OLS regression) for studies with categorical response variables

Table B-4

Limitations of Prior Financial Distress Cash Flow Studies

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1. Lack of a Theoretical Framework for Selection of Variables

2. Violations of Statistical Assumptions

   -MDA assumes:

   (1) normality of independent variables
   (2) equal variance/covariance matrices for linear MDA

   -Logistic (probit) assumes:

   (1) response variables are randomly drawn
       a. violation leads to choice-based sample based bias
   (2) sufficient sample size of 10(S + 1)
       a. violation leads to biased estimators

3. Pooling of Firms Across Time

   -Assumes stationarity

4. Selection of holdout group from the same period used to develop the models

   -Assumes stationarity

5. Use of Bankruptcy/Nonbankrupty to Operationalize Financial Distress

   -Overly simple representation of distress construct (results in the loss of information)

   -Legal event and not an economic event

   (1) only economic events are likely to capture the true financial distress of a firm

   -Bankrupt group may be a heterogeneous group because some firms self-select, while others are forced to declare bankruptcy

   -Confounding of bankrupt firms

6. Period Used to Select the Data

APPENDIX C

Table C-1

Cash Flow Variables Tested

(1) Naive Operating Flow (NOF)	= net income + depreciation and amortization
(2) Cash Flow from Operating Activities (CFFO)	= Income before extraordinary items + depreciation and amortization + deferred taxes + equity in net loss (earnings) + loss (gain) from sale of property, plant, and equipment and investments + funds from operations-others + accounts receivable-decrease (increase) + inventory-decrease (increase) + other current assets-decrease (increase) + current liabilities other than current debt-increase (decrease)
(3) Cash Flow from Investing Activities (CFFI)	= sale of property, plant and equipment - capital expenditures - acquisitions - increase in investments + sale of investments + short-term investments-change
(4) Short-term Financing Flow (SFF)	= change in current debt
(5) Long-term Financing Flow (LFF)	= change in long-term debt
(6) Equity Financing Flow (EFF)	= sale of common and preferred stock - purchase of common and preferred stock
(7) Cash Flow from Financing Activities (CFFF)	= (4) + (5) + (6) - cash dividends

Table C-2

Selection of 1988 Sample

	State 1- Dividend Reduction	State 2- Loan/Int. Default &/or Debt Accommodation	State 3- Bankrupt	State 0- Healthy	Total
I. Initial Identification of Firms:					
A. From Compustat tapes, of which 40% were randomly selected	37				
B. From WSJ Index and Compact Disc Disclosure		54	59		
C. Healthy firms randomly selected from group of healthy firms with four-digit industry codes similar to the distressed firms				243	
II. Insufficient Compustat Data	(10)	(18)	(33)	(50)	
III. Verification Using SEC 10-Ks and Annual Reports:					
A. Merger in year of dividend reduction	(4)				
B. Failure to verify event or prior/current distress of equal or greater severity	(0)	(9)	(4)	(7)	
C. Fraudulent activities	(0)	(1)	(1)	(0)	
D. Insufficient information to verify or unreliable financial information	(0)	(2)	(2)	(20)	
IV. Poor match with other distressed firms	(1)	(1)	(1)	N/A	
Totals	22	23	18	166	229
Percentage of Sample	9.61%	10.04%	7.86%	72.49%	100.00%
Ratio of Healthy to Distressed Firms	7.55 to 1	7.54 to 1	9.22 to 1		

Table C-3

Selection of 1989 Sample

	State 1- Dividend Reduction	State 2- Loan/Int. Default &/or Debt Accommodation	State 3- Bankrupt	State 0- Healthy	Total
I. Initial Identification of Firms:					
A. From Compustat tapes, of which 40% were randomly selected	32				
B. From WSJ Index and Compact Disc Disclosure		62	84		
C. Healthy firms randomly selected from group of healthy firms with four-digit industry codes similar to the distressed firms				184	
II. Insufficient Compustat Data	(7)	(31)	(47)	(38)	
III. Verification Using SEC 10-Ks and Annual Reports:					
A. Merger in year of dividend reduction	(1)				
B. Failure to verify event or prior/current distress of equal or greater severity	(3)	(9)	(4)	(6)	
C. Fraudulent activities	(0)	(3)	(4)	(0)	
D. Insufficient information to verify or unreliable financial information	(2)	(2)	(7)	(29)	
IV. Poor match with other distressed firms	(2)	(3)	(6)	N/A	
Totals	17	14	16	111	158
Percentage of Sample	10.76%	8.86%	10.13%	70.25%	100.00%
Ratio of Healthy to Distressed Firms	6.53 to 1	7.93 to 1	6.94 to 1		

APPENDIX D

Table D-1

Selection of Scaling Measure Using the Score Test for the Proportional Odds Assumption

	Chi-Square Reported for Each Proportional Odds Test		
	Scaling Measures		
	Total Assets	Total Liabilities	Current Liabilities
I. Year-1 Cash Flow(s) Models:			
NOF	6.38*	8.28*	5.56
CFFO	9.51**	10.58**	7.54*
CFFI	1.82	3.58	5.76
CFFF	5.25	3.67	6.13*
LFF	.55	3.18	1.25
SFF	4.36	3.30	5.03
EFF	2.02	2.78	.41
CFFO + CFFI + CFFF	10.40	12.25	10.38
II. Year-2 Cash Flow(s) Models:			
NOF	12.26**	12.94**	12.03**
CFFO	1.19	1.51	2.60
CFFI	6.19	2.31	1.58
CFFF	.92	1.23	1.63
LFF	7.79*	5.93	1.74
SFF	1.00	1.79	2.90
EFF	3.82	3.54	4.60
CFFO + CFFI + CFFF	11.09	4.79	4.62
III. Year-3 Cash Flow(s) Models:			
NOF	6.77*	4.42	8.55*
CFFO	3.68	3.21	2.29
CFFI	.25	1.69	.78
CFFF	.21	.36	.89
LFF	3.90	1.17	2.85
SFF	1.42	.92	.01
EFF	1.82	.95	.23
CFFO + CFFI + CFFF	4.42	4.74	5.27

[1]Each univariate test has 2 df while each multivariate test has 6 df - chi-square distribution.
**Significant (rejected) at p-value = .01
*Significant (rejected) at p-value = .05

Table D-2

Means (Standard Deviations) for Year - 1, 1988 Sample

Variable	Expected Sign	State 0-Healthy (n = 166)	State 1-Dividend Reduction (n = 22)	State 2-Loan Int. Default &/or Debt Accommodations (n = 23)	State 3-Bankrupt (n = 18)
		States of Financial Distress			
NOF	(-)	.292	.084	-.175	-.323
		(.448)	(.203)	(.251)	(.407)
CFFO	(-)	.281	.082	-.141	-.080
		(.326)	(.197)	(.206)	(.231)
CFFI	(+)	-.234	-.147	-.028	-.068
		(.266)	(.150)	(.196)	(.250)
*CFFF	(-)	-.015	.036	.157	.039
		(.374)	(.227)	(.264)	(.552)
LFF	(-)	.018	.010	-.060	-.124
		(.202)	(.149)	(.289)	(.262)
SFF	(+)	.003	.042	.161	.078
		(.107)	(.090)	(.277)	(.244)
EFF	(+)	.024	.012	.055	.087
		(.263)	(.118)	(.136)	(.262)
NITA	(-)	.043	-.011	-.367	-.350
		(.135)	(.125)	(.476)	(.407)
TLOE	(+)	1.340	1.619	14.937	-10.188
		(1.465)	(.915)	(64.544)	(24.089)
*SALESCA	(-)	3.414	3.861	2.313	3.304
		(3.291)	(4.509)	(1.529)	(2.839)
CACL	(-)	2.567	1.975	.932	.844
		(1.826)	(1.056)	(.929)	(.404)
CATA	(-)	.531	.456	.374	.525
		(.237)	(.224)	(.227)	(.260)
CASHTA	(-)	.137	.051	.045	.052
		(.150)	(.049)	(.032)	(.047)
$SIZE_1$	(-)	1129.630	736.526	164.417	174.172
		(3657.430)	(905.932)	(449.512)	(253.739)
$SIZE_2$	(-)	5.118	5.817	3.081	4.154
		(1.995)	(1.572)	(1.913)	(1.500)

*Pattern is weak or not consistent with expectations

Table D-3

Means (Standard Deviations) for Year - 2, 1988 Sample

		States of Financial Distress			
Variable	Expected Sign	State 0-Healthy (n = 166)	State 1-Dividend Reduction (n = 22)	State 2-Loan Int. Default &/or Debt Accommodations (n = 23)	State 3-Bankrupt (n = 18)
NOF	(-)	.298	.137	-.321	-.288
		(.409)	(.112)	(.526)	(.684)
CFFO	(-)	.336	.124	-.123	-.280
		(.447)	(.205)	(.611)	(.576)
CFFI	(+)	-.272	-.189	-.091	-.019
		(.411)	(.151)	(.238)	(.441)
*CFFF	(-)	.017	.039	.121	.120
		(.486)	(.204)	(.524)	(.347)
*LFF	(-)	.010	.057	-.074	-.017
		(.161)	(.144)	(.256)	(.291)
SFF	(+)	-.008	.006	.077	.109
		(.132)	(.099)	(.183)	(.343)
*EFF	(+)	.068	.014	.119	.034
		(.435)	(.085)	(.547)	(.065)
NITA	(-)	.037	.029	-.306	-.183
		(.116)	(.044)	(.344)	(.223)
TLOE	(+)	1.345	1.468	1.542	1.822
		(2.062)	(.906)	(4.863)	(24.185)
SALESCA	(-)	3.184	3.303	2.793	2.639
		(2.684)	(1.616)	(2.149)	(1.984)
CACL	(-)	2.969	2.131	1.417	1.171
		(4.064)	(.892)	(1.315)	(.520)
CATA	(-)	.789	.485	.371	.534
		(3.100)	(.200)	(.272)	(.269)
CASHTA	(-)	.149	.078	.055	.056
		(.152)	(.064)	(.053)	(.055)
$SIZE_1$	(-)	1043.650	710.500	175.350	217.912
		(3470.270	(854.340)	(481.132)	(358.429)
$SIZE_2$	(-)	4.995	5.793	3.208	4.295
		(2.002)	(1.558)	(1.851)	(1.560)

*Pattern is weak or not consistent with expectations

Table D-4

Means (Standard Deviations) for Year - 3, 1988 Sample

		States of Financial Distress			
Variable	Expected Sign	State 0-Healthy (n = 166)	State 1-Dividend Reduction (n = 22)	State 2-Loan Int. Default &/or Debt Accommodations (n = 23)	State 3-Bankrupt (n = 18)
NOF	(-)	.333	.160	-.178	.105
		(.675)	(.125)	(.756)	(.386)
CFFO	(-)	.356	.251	-.183	.090
		(.672)	(.555)	(.926)	(.373)
*CFFI	(+)	-.282	-.157	-.283	-.158
		(.383)	(.322)	(.518)	(.262)
*CFFF	(-)	.008	-.045	-.020	.094
		(.684)	(.832)	(.765)	(.397)
*LFF	(-)	-.001	.028	-.089	.010
		(.256)	(.368)	(.455)	(.109)
*SFF	(+)	-.005	-.016	-.014	-.011
		(.167)	(.094)	(.300)	(.202)
*EFF	(+)	.083	.007	.091	.085
		(.544)	(.327)	(.234)	(.333)
NITA	(-)	.039	.039	-.210	-.006
		(.138)	(.054)	(.381)	(.159)
TLOE	(+)	1.320	1.218	2.776	3.791
		(2.214)	(.588)	(5.424)	(4.578)
SALESCA	(-)	3.496	3.371	2.475	3.165
		(3.959)	(1.662)	(1.911)	(1.934)
CACL	(-)	2.625	2.329	1.872	1.580
		(1.879)	(1.328)	(1.551)	(.985)
*CATA	(-)	.532	.492	.692	.520
		(.239)	(.190)	(1.355)	(.260)
CASHTA	(-)	.131	.086	.056	.075
		(.137)	(.088)	(.047)	(.076)
$SIZE_1$	(-)	1043.95	700.315	189.089	229.634
		(3639.42)	(1019.57)	(458.763)	(420.346)
$SIZE_2$	(-)	4.941	5.681	3.393	4.272
		(1.988)	(1.593)	(1.869)	(1.571)

*Pattern is weak or not consistent with expectations

Table D-5

Means (Standard Deviations) for Year - 1, 1989 Sample

		States of Financial Distress			
Variable	Expected Sign	State 0-Healthy (n = 111)	State 1-Dividend Reduction (n = 17)	State 2-Loan Int. Default &/or Debt Accommodations (n = 14)	State 3-Bankrupt (n = 16)
NOF	(-)	.338	.130	-.236	-.133
		(.424)	(.256)	(.584)	(.293)
CFFO	(-)	.309	.061	-.043	-.023
		(.542)	(.234)	(.230)	(.217)
CFFI	(+)	-.237	-.163	-.054	-.124
		(.729)	(.182)	(.149)	(.194)
*CFFF	(-)	.018	.031	.016	.148
		(.445)	(.176)	(.318)	(.282)
*LFF	(-)	.013	.020	-.056	.112
		(.171)	(.150)	(.209)	(.195)
*SFF	(+)	.005	.040	.028	-.025
		(.235)	(.103)	(.393)	(.131)
EFF	(+)	.019	-.001	.047	.064
		(.431)	(.010)	(.123)	(.130)
NITA	(-)	.036	-.025	-.248	-.302
		(.138)	(.207)	(.540)	(.550)
TLOE	(+)	1.126	2.054	3.628	-1.152
		(1.163)	(2.870)	(18.434)	(6.112)
*SALESCA	(-)	2.700	2.809	2.706	4.680
		(2.489)	(1.832)	(1.778)	(3.254)
CACL	(-)	2.964	2.782	1.229	1.240
		(2.287)	(3.313)	(.732)	(.715)
CATA	(-)	.538	.580	.519	.501
		(.202)	(.403)	(.135)	(.236)
CASHTA	(-)	.170	.056	.087	.051
		(.301)	(.050)	(.105)	(.043)
$SIZE_1$	(-)	870.228	361.168	48.371	41.287
		(2762.650)	(531.213)	(63.351)	(47.257)
$SIZE_2$	(-)	4.427	4.859	2.912	3.030
		(2.120)	(1.566)	(1.621)	(1.314)

*Pattern is weak or not consistent with expectations

Table D-6

Means (Standard Deviations) for Year - 2, 1989 Sample

		States of Financial Distress			
Variable	Expected Sign	State 0-Healthy (n = 111)	State 1-Dividend Reduction (n = 17)	State 2-Loan Int. Default &/or Debt Accommodations (n = 14)	State 3-Bankrupt (n = 16)
NOF	(-)	.271	.172	-.149	-.461
		(.658)	(.189)	(.531)	(.738)
CFFO	(-)	.181	.115	-.146	-.034
		(.560)	(.285)	(.355)	(.194)
CFFI	(+)	-.386	-.294	-.193	-.158
		(.956)	(.251)	(.196)	(.276)
*CFFF	(-)	.155	.157	.145	.184
		(1.169)	(.295)	(.344)	(.263)
*LFF	(-)	.017	.101	.061	.068
		(.158)	(.286)	(.312)	(.228)
SFF	(+)	-.002	.021	.066	-.058
		(.138)	(.135)	(.115)	(.315)
*EFF	(+)	.176	.050	.020	.177
		(1.162)	(.179)	(.140)	(.311)
NITA	(-)	.031	.029	-.141	-.390
		(.154)	(.038)	(.320)	(.539)
TLOE	(+)	1.053	2.116	3.691	10.222
		(.909)	(2.455)	(4.209)	(43.358)
*SALESCA	(-)	2.662	2.677	2.381	4.030
		(2.612)	(1.441)	(1.300)	(2.785)
CACL	(-)	2.984	2.597	1.720	1.414
		(2.285)	(1.782)	(1.030)	(.918)
*CATA	(-)	.537	.495	.554	.541
		(.215)	(.143)	(.223)	(.274)
CASHTA	(-)	.142	.091	.096	.090
		(.134)	(.083)	(.116)	(.097)
$SIZE_1$	(-)	798.237	321.969	46.126	41.991
		(2404.260)	(446.642)	(60.990)	(54.879)
$SIZE_2$	(-)	4.330	4.767	2.939	2.901
		(2.132)	(1.569)	(1.574)	(1.477)

*Pattern is weak or not consistent with expectations

Table D-7

Means (Standard Deviations) for Year - 3, 1989 Sample

		States of Financial Distress			
Variable	Expected Sign	State 0-Healthy (n = 111)	State 1-Dividend Reduction (n = 17)	State 2-Loan Int. Default &/or Debt Accommodations (n = 14)	State 3-Bankrupt (n = 16)
*NOF	(-)	.097	.244	-.026	.134
		(1.422)	(.193)	(.594)	(.350)
CFFO	(-)	.156	.232	-.207	-.039
		(.690)	(.214)	(.418)	(.233)
CFFI	(+)	-.492	-.217	-.209	-.189
		(1.325)	(.339)	(.360)	(.299)
CFFF	(-)	.696	.092	.377	.216
		(3.446)	(.257)	(.880)	(.422)
LFF	(-)	.031	.122	.052	.037
		(.189)	(.216)	(.427)	(.301)
SFF	(+)	-.025	.016	.051	.049
		(.307)	(.067)	(.109)	(.246)
*EFF	(+)	.735	.005	.275	.132
		(3.428)	(.083)	(.693)	(.367)
NITA	(-)	.008	.054	-.041	-.043
		(.203)	(.040)	(.403)	(.136)
TLOE	(+)	1.085	1.391	2.488	1.721
		(1.013	(.820)	(4.117)	(2.885)
*SALESCA	(-)	2.580	2.795	2.603	3.662
		(2.380)	(1.339)	(1.500)	(3.415)
CACL	(-)	3.305	2.994	1.862	3.847
		(3.767)	(1.824)	(.866)	(6.313)
*CATA	(-)	.550	.531	.557	.716
		(.219)	(.161)	(.226)	(.647)
CASHTA	(-)	.161	.135	.087	.107
		(.171)	(.160)	(.096)	(.136)
$SIZE_1$	(-)	738.719	209.281	37.723	42.683
		(2309.44)	(290.030)	(51.713)	(57.636)
$SIZE_2$	(-)	4.215	4.498	2.740	2.970
		(2.135)	(1.404)	(1.518)	(1.352)

*Pattern is weak or not consistent with expectations

Table D-8

Means (Standard Deviations) for TLOE and OETL, 1988 Sample

		States of Financial Distress			
Variable	Expected Sign	State 0-Healthy (n = 166)	State 1-Dividend Reduction (n = 22)	State 2-Loan Int. Default &/or Debt Accommodations (n = 23)	State 3-Bankrupt (n = 18)
Year - 1 Data:					
TLOE	(+)	1.340	1.619	14.937	-10.188
		(1.465)	(.915)	(64.544)	(24.089)
OETL	(-)	1.661	.861	.232	.121
		(1.614)	(.534)	(.647)	(.297)
Year - 2 Data:					
TLOE	(+)	1.345	1.468	1.542	1.822
		(2.062)	(.907)	(4.863)	(24.185)
OETL	(-)	1.857	.934	.748	.577
		(1.849	(.569)	(1.008)	(.987)
Year - 3 Data:					
TLOE	(+)	1.320	1.218	2.766	3.791
		(2.214)	(.588)	(5.424)	(4.578)
OETL	(-)	1.859	1.203	1.198	.896
		(1.970)	(1.247)	(1.551)	(1.036)

Table D-9

Means (Standard Deviations) for TLOE and OETL, 1989 Sample

		States of Financial Distress			
Variable	Expected Sign	State 0-Healthy (n = 111)	State 1-Dividend Reduction (n = 17)	State 2-Loan Int. Default &/or Debt Accommodations (n = 14)	State 3-Bankrupt (n = 16)
Year - 1 Data:					
TLOE	(+)	1.126	2.054	3.628	-1.152
		(1.163)	(2.870)	(18.434)	(6.112)
OETL	(-)	2.325	.746	.363	.388
		(2.960)	(.717)	(.640)	(.710)
Year - 2 Data:					
TLOE	(+)	1.053	2.116	3.691	10.222
		(.909)	(2.455)	(4.209)	(43.358)
OETL	(-)	1.857	.893	.401	.593
		(1.849	(.721)	(.387)	(.744)
Year - 3 Data:					
TLOE	(+)	1.085	1.391	2.488	1.721
		(1.013)	(.820)	(4.117)	(2.885)
OETL	(-)	2.755	1.141	.585	2.104
		(2.380)	(.9587)	(.551)	(4.80)

Table D-10

Four-State Net Cash Flows Model - $SIZE_1$ + CFFO + CFFI + CFFF

		Year - 1 Model		Year - 2 Model		Year - 3 Model	
		Parameter[1] Estimates (sd)	Wald χ^2 Statistic	Parameter Estimates (sd)	Wald χ^2 Statistic	Parameter Estimates (sd)	Wald χ^2 Statistic
Variable	Expected Sign						
Intercept1		.0730	.1093	-.0341	.0242	-.5060	6.6439**
		(.2210)		(.2192)		(.1961)	
Intercept2		-.7354	10.1224**	-.7335	10.1972**	-1.1074	27.2840***
		(.2312)		(.2297)		(.2120)	
Intercept3		-1.9685	43.9288***	-1.8955	40.3707***	-2.1056	58.5903***
		(.2970)		(.2965)		(.2751)	
$SIZE_1$	(-)	-.000177	1.2931	-.000273	2.5779	-.000286	3.0709
		(.000156)		(.000170)		(.000163)	
CFFO	(-)	-6.1226	33.2056***	-2.1340	12.8679***	-.8563	7.6464**
		(1.0625)		(.5949)		(.3097)	
CFFI	(+)	1.5573	2.2373	2.4178	5.5492*	.4742	1.2064
		(1.0411)		(1.0264)		(.4317)	
CFFF	(-)	-1.2681	4.4635*	-.4345	.5317	-.2735	.7339
		(.6002)		(.5317)		(.3193)	
Score Test[2]			14.4431		8.4713		7.7188
-2Log Likelihood[3]			81.018***		55.389***		19.229***
AIC Criterion[4]			340.155		365.783		401.944
Somers' D[5]			.680		.572		.338

[1]Estimated ordinal parameters and standard deviations for the net cash flows model. $SIZE_1$ = total assets, CFFO = cash flow from operating activities, CFFI = cash flow from investing activities, and CFFF = cash flow from financing activities.

[2]Score Test for the proportional odds assumption - distributed as a chi-square distribution with eight degrees of freedom. This test compares the ordinal model with parallel slopes to a relaxed model with slopes allowed to vary. A significant chi-square indicates the parallel lines assumption is violated.

[3]-2Log Likelihood for the covariates - distributed as a chi-square distribution with four degrees of freedom. This test compares the full model with the four covariates to the intercept only model and is an overall test of the null hypothesis that all four explanatory variables in the model are zero.

[4]Akaike Information Criterion - the AIC adjusts the -2Log Likelihood statistic for the number of terms in the model and the number of observations used. A lower value of the AIC statistic indicates a better fitting model.

[5]The Somers' D index is a measure of the rank correlation between the observed responses and predicted probabilities.

***Significant at p-value = .001

**Significant at p-value = .01

*Significant at p-value = .05

Table D-11

Correlation Matrices for the Parameter Estimates of the Four-State Net Cash Flows Model - $SIZE_1$ + CFFO + CFFI + CFFF

Year - 1 Estimated Correlation Matrix for Model - $SIZE_1$ + CFFO + CFFF + CFFI

Variable	INTERCEPT1	INTERCEPT2	INTERCEPT3	$SIZE_1$	CFFO	CFFI	CFFF
INTERCEPT1	1.0000	.7574	.4426	-.2802	-.1193	.4662	-.0048
INTERCEPT2		1.0000	.5962	-.2519	.0080	.4228	.0415
INTERCEPT3			1.0000	-.1908	.1479	.3050	.0801
$SIZE_1$				1.0000	-.1654	.0206	-.0165
CFFO					1.0000	.2476	.6109
CFFI						1.0000	.4382
CFFF							1.0000

Year - 2 Estimated Correlation Matrix for Model - $SIZE_1$ + CFFO + CFFF + CFFI

Variable	INTERCEPT1	INTERCEPT2	INTERCEPT3	$SIZE_1$	CFFO	CFFI	CFFF
INTERCEPT1	1.0000	.8094	.5173	-.3031	-.0843	.4955	-.0294
INTERCEPT2		1.0000	.6381	-.2703	-.0273	.4383	-.0198
INTERCEPT3			1.0000	-.1951	.0642	.3172	-.0015
$SIZE_1$				1.0000	-.0446	.0494	.0374
CFFO					1.0000	.3591	.6784
CFFI						1.0000	.4164
CFFF							1.0000

Year - 3 Estimated Correlation Matrix for Model - $SIZE_1$ + CFFO + CFFF + CFFI

Variable	INTERCEPT1	INTERCEPT2	INTERCEPT3	$SIZE_1$	CFFO	CFFI	CFFF
INTERCEPT1	1.0000	.8348	.5620	-.3443	-.2197	.4549	-.0174
INTERCEPT2		1.0000	.6781	-.3027	-.1679	.4083	-.0036
INTERCEPT3			1.0000	-.2213	0.0778	.3049	.0168
$SIZE_1$				1.0000	-.0474	-.0270	-.0108
CFFO					1.0000	.0932	.3356
CFFI						1.0000	.2071
CFFF							1.0000

Table D-12

Year-1, Four-State Gross Cash Flows Models

		$SIZE_1$+CFFO+CFFI+LFF+SFF+EFF		$SIZE_1$+CFFO+CFFI+LFF	
		Parameter[1] Estimates (sd)	Wald χ^2 Statistic	Parameter Estimates (sd)	Wald χ^2 Statistic
Variable	Expected Sign				
Intercept1		.0153	.00455	-.0058	.0007
		(.2273)		(.2233)	
Intercept2		-.8413	12.3706***	-.8545	13.1459***
		(.2392)		(.2357)	
Intercept3		-2.1359	46.6413***	-2.1438	47.8779***
		(.3128)		(.3098)	
$SIZE_1$	(-)	-.000174	1.1892	-.000164	1.1039
		(.000159)		(.000156)	
CFFO	(-)	-6.0340	31.7342***	-5.6278	39.6677***
		(1.0711)		(.8935)	
CFFI	(+)	1.4598	1.8161	1.8914	3.7664*
		(1.0833)		(.9746)	
LFF	(-)	-2.6465	11.4337***	-2.4812	11.9646***
		(.7827)		(.7173)	
SFF	(+)	-.1429	.0169		
		(1.0999)			
EFF	(+)	-.8108	.9415		
		(.8357)			
Score Test[2]			22.5441* (12 df)		13.1316 (8 df)
-2Log Likelihood[3]			89.1886*** (6 df)		88.1590*** (4 df)
Change in -2Log Likelihood[4]			12.1220** (3 df)		11.0930*** (1 df)
AIC Criterion			335.985		333.013
Somers' D			.699		.689

[1]Estimated ordinal parameters and standard deviations for the gross cash flows models. $SIZE_1$ = total assets, CFFO = cash flow from operating activities, CFFI = cash flow from investing activities, LFF = long-term financing flow, SFF = short-term financing flow, and EFF = equity financing flow.

[2]Score Test for the proportional odds assumption - distributed as a chi-square distribution with degrees of freedom in parentheses.

[3]-2Log Likelihood for the covariates - distributed as a chi-square distribution.

[4]Change in -2Log Likelihood for the covariates - distributed as a chi-square distribution. This test compares the reduced model $SIZE_1$ + CFFO + CFFI to each full model, $SIZE_1$ + CFFO + CFFI + LFF + SFF + EFF and $SIZE_1$ + CFFO + CFFI + LFF, and is calculated by taking the difference in the overall model chi-squares for the reduced and full models. A significant Change in -2Log Likelihood for the covariates indicates that the added variable(s) has(ve) incremental predictive power.

***Significant at p-value = .001

**Significant at p-value = .01

*Significant at p-value = .05

Table D-13

Year-2, Four-State Gross Cash Flows Models

		$SIZE_1$+CFFO+CFFI+LFF+SFF+EFF		$SIZE_1$+CFFO+CFFI+SFF+EFF	
		Parameter[1] Estimates (sd)	Wald χ^2 Statistic	Parameter Estimates (sd)	Wald χ^2 Statistic
Variable	Expected Sign				
Intercept1		-.1075	.2219	-.1024	.2020
		(.2283)		(.2278)	
Intercept2		-.8567	12.5760***	-.8493	12.4225***
		(.2416)		(.2410)	
Intercept3		-2.1346	46.0818***	-2.1232	46.0717***
		(.3145)		(.3128)	
$SIZE_1$	(-)	-.000307	2.9792	-.000308	2.9782
		(.000178)		(.000179)	
CFFO	(-)	-1.8483	10.7125***	-1.7693	11.8641***
		(.5647)		(.5137)	
CFFI	(+)	2.6107	5.9836*	2.7765	8.3904**
		(1.0673)		(.9585)	
LFF	(-)	-.3799	.1287		
		(1.059)			
SFF	(+)	3.6015	8.0144**	3.8112	11.1257***
		(1.2722)		(1.1426)	
EFF	(+)	-.5736	1.3028	-.5053	1.1034
		(.5026)		(.4810)	
Score Test[2]			16.0340 (12 df)		11.8155 (10 df)
-2Log Likelihood[3]			69.5200*** (6 df)		69.3980*** (5 df)
Change in -2Log Likelihood[4]			14.7560** (3 df)		14.6340*** (2 df)
AIC Criterion			355.652		353.774
Somers' D			.572		.571

[1]Estimated ordinal parameters and standard deviations for the gross cash flows models. $SIZE_1$ = total assets, CFFO = cash flow from operating activities, CFFI = cash flow from investing activities, LFF = long-term financing flow, SFF = short-term financing flow, and EFF = equity financing flow.

[2]Score Test for the proportional odds assumption - distributed as a chi-square distribution with degrees of freedom in parentheses.

[3]-2Log Likelihood for the covariates - distributed as a chi-square distribution.

[4]Change in -2Log Likelihood for the covariates - distributed as a chi-square distribution. This test compares the reduced model $SIZE_1$ + CFFO + CFFI to each full model, $SIZE_1$ + CFFO + CFFI + LFF + SFF + EFF and $SIZE_1$ + CFFO + CFFI + SFF + EFF, and is calculated by taking the difference in the overall model chi-squares for the reduced and full models. A significant Change in -2Log Likelihood for the covariates indicates that the added variable(s) has(ve) incremental predictive power.

***Significant at p-value = .001
**Significant at p-value = .01
*Significant at p-value = .05

Table D-14

Year-3, Four-State Gross Cash Flows Models

		$SIZE_1$+CFFO+CFFI+LFF+SFF+EFF		$SIZE_1$+CFFO+CFFI	
		Parameter[1] Estimates (sd)	Wald χ^2 Statistic	Parameter Estimates (sd)	Wald χ^2 Statistic
Variable	Expected Sign				
Intercept1		-.5009 (.1968)	6.4777*	-.5077 (.1959)	6.7144**
Intercept2		-1.1059 (.2127)	27.0276***	-1.1046 (.2115)	27.2747***
Intercept3		-2.1089 (.2761)	58.3456***	-2.0980 (.2737)	58.7476***
$SIZE_1$	(-)	-.000277 (.000163)	2.8951	-.000288 (.000164)	3.1092
CFFO	(-)	-.8537 (.2996)	8.1209**	-.7836 (.2947)	7.0721**
CFFI	(+)	.4951 (.4351)	1.2946	.5487 (.4262)	1.6580
LFF	(-)	-.5380 (.5631)	.9129		
SFF	(+)	-.3751 (.9090)	.1703		
EFF	(+)	-.1782 (.3801)	.2198		
Score Test[2]			12.3300 (12 df)		7.0065 (6 df)
-2Log Likelihood[3]			19.9610** (6 df)		18.3330*** (3 df)
Change in -2Log Likelihood[4]			1.6280 (3 df)		N/A
AIC Criterion			405.212		400.839
Somers' D			.349		.337

[1]Estimated ordinal parameters and standard deviations for the gross cash flows models. $SIZE_1$ = total assets, CFFO = cash flow from operating activities, CFFI = cash flow from investing activities, LFF = long-term financing flow, SFF = short-term financing flow, and EFF = equity financing flow.
[2]Score Test for the proportional odds assumption - distributed as a chi-square distribution with degrees of freedom in parentheses.
[3]-2Log Likelihood for the covariates - distributed as a chi-square distribution.
[4]Change in -2Log Likelihood for the covariates - distributed as a chi-square distribution. This test compares the reduced model $SIZE_1$ + CFFO + CFFI to each full model, $SIZE_1$ + CFFO + CFFI + LFF + SFF + EFF and $SIZE_1$ + CFFO + CFFI, and is calculated by taking the difference in the overall model chi-squares for the reduced and full models. A significant Change in -2Log Likelihood for the covariates indicates that the added variable(s) has(ve) incremental predictive power.
***Significant at p-value = .001
**Significant at p-value = .01
*Significant at p-value = .05

Table D-15

Correlation Matrices for the Parameter Estimates of the Four-State Gross Cash Flows Model - $SIZE_1$ + CFFO + CFFI + LFF + SFF + EFF

Year - 1 Estimated Correlation Matrix

Variable	INT1	INT2	INT3	$SIZE_1$	CFFO	CFFI	LFF	SFF	EFF
INT1	1.0000	.7478	.4430	-.2787	-.1620	.4022	.0305	-.1354	-.0963
INT2		1.0000	.5999	-.2499	-.0299	.3555	.1013	-.1302	-.0699
INT3			1.0000	-.1871	.1165	.2645	.1825	-.1075	-.0294
$SIZE_1$				1.0000	-.1635	.0203	-.0432	-.0445	.0360
CFFO					1.0000	.2649	.4398	.4342	.4424
CFFI						1.0000	.2801	.2741	.4188
LFF							1.0000	.3491	.1992
SFF								1.0000	.2841
EFF									1.0000

Year - 2 Estimated Correlation Matrix

Variable	INT1	INT2	INT3	$SIZE_1$	CFFO	CFFI	LFF	SFF	EFF
INT1	1.0000	.8001	.5019	-.3180	-.0342	.4753	.0778	-.0988	-.0523
INT2		1.0000	.6283	-.2765	.0195	.4121	.0807	-.1540	-.0379
INT3			1.0000	-.1914	.0897	.2774	.0876	-.2033	-.0125
$SIZE_1$				1.0000	-.0883	.0047	-.0085	-.0403	.0122
CFFO					1.0000	.4187	.3970	.3522	-.5921
CFFI						1.0000	.4439	.3182	.3468
LFF							1.0000	.4384	.3377
SFF								1.0000	.2940
EFF									1.0000

Year - 3 Estimated Correlation Matrix

Variable	INT1	INT2	INT3	$SIZE_1$	CFFO	CFFI	LFF	SFF	EFF
INT1	1.0000	.8242	.5604	-.3441	-.2330	.4408	-.0062	-.0021	-.0724
INT2		1.0000	.6769	-.3032	-.1779	.3929	.0009	.0072	-.0618
INT3			1.0000	-.2228	-.0809	.2948	.0298	.0228	-.0390
$SIZE_1$				1.0000	-.0542	-.0205	-.0653	-.0091	.0305
CFFO					1.0000	.0563	.1954	.0899	.1360
CFFI						1.0000	.0738	.0394	.2102
LFF							1.0000	-.1527	.2249
SFF								1.0000	-.0620
EFF									1.0000

Table D-16

Incremental Predictive Power of the Gross Financing Cash Flows, the Addition of Each Gross Financing Cash Flow to the Four-State Net Cash Flows Model $SIZE_1$ + CFFO + CFFI + CFFF

Gross Cash Flow Added	-2Log L[1] (Reduced)	-2Log L[2] (Added)	Δ -2Log L[3]	Degrees of Freedom	P -Value
LFF:					
Year - 1	81.018	88.343	7.325**	1	.0068
Year - 2	55.389	56.727	1.338	1	.2474
Year - 3	19.229	19.720	.491	1	.4835
SFF:					
Year - 1	81.018	84.022	3.004	1	.0831
Year - 2	55.389	69.008	13.619***	1	.00022
Year - 3	19.229	19.302	.073	1	.7870
EFF:					
Year - 1	81.018	81.444	.426	1	.5140
Year - 2	55.389	60.341	4.952*	1	.0261
Year - 3	19.229	19.400	.171	1	.679

[1]-2Log Likelihood for the covariates for the net cash flows model $SIZE_1$ + CFFO + CFFI + CFFF - distributed as a chi-square distribution with four degrees of freedom.
[2]-2Log Likelihood for the covariates for each full model (one of the gross cash flows added to the net cash flows model) - distributed as a chi-square distribution with five degrees of freedom.
[3]The change in the -2Log Likelihood statistic for the net cash flows model and the -2Log Likelihood for the full cash flows model.
***Significant at p-value = .001
**Significant at p-value = .01
*Significant at p-value = .05

Table D-17

Four-State Gross Cash Flows Model $SIZE_1$ + CFFO + CFFI + CFFF + LFF

		Year - 1 Model		Year - 2 Model		Year - 3 Model	
		Parameter[1] Estimates (sd)	Wald χ^2 Statistic	Parameter Estimates (sd)	Wald χ^2 Statistic	Parameter Estimates (sd)	Wald χ^2 Statistic
Variable	Expected Sign						
Intercept1		-.0043 (.2293)	.0004	-.0667 (.2220)	.0904	-.5076 (.1964)	6.6808**
Intercept2		-.8456 (.2369)	12.7418***	-.7775 (.2333)	11.1051***	-1.1119 (.2124)	27.4142***
Intercept3		-2.1361 (.3103)	47.3747***	-1.9594 (.3026)	41.9224***	-2.1146 (.2759)	58.7421***
$SIZE_1$	(-)	-.000166 (.000157)	1.1276	-.000271 (.000168)	2.6099	-.000277 (.000163)	2.9028
CFFO	(-)	-5.9052 (1.0695)	30.4880***	-2.1790 (.5924)	13.5302***	-.8596 (.3047)	7.9611**
CFFI	(+)	1.6790 (1.0704)	2.4603	2.1619 (1.0479)	4.2564*	.4958 (.4340	1.3054
CFFF	(-)	-.3143 (.69355)	.2053	-.3965 (.5269)	.5663	-.1446 (.3153)	.2102
LFF	(-)	-2.3296 (.8593)	7.3492**	-1.0692 (.8867)	1.4542	-.4147 (.5861)	.5006
Score Test[2]			16.1869		13.5754		13.1882
-2Log Likelihood[3]			88.343***		56.7271***		19.720**
Change in -2Log Likelihood[4]			7.325**		1.338		.491
AIC Criterion			334.829		366.415		403.453
Somers' D			.693		.577		.344

[1]Estimated ordinal parameters and standard deviations for the gross cash flows model. $SIZE_1$ = total assets, CFFO = cash flow from operating activities, CFFI = cash flow from investing activities, CFFF = cash flow from financing activities, and LFF = long-term financing flow.

[2]Score Test for the proportional odds assumption - distributed as a chi-square distribution with ten degrees of freedom.

[3]-2Log Likelihood for the covariates - distributed as a chi-square distribution with five degree of freedom.

[4]Change in -2Log Likelihood for the covariates - distributed as a chi-square distribution with one degree of freedom. This test compares the reduced model $SIZE_1$ + CFFO + CFFI + CFFF (Table D-10) to the full model $SIZE_1$ + CFFO + CFFI + CFFF + LFF and is calculated by taking the difference in the overall model (-2Log Likelihood) chi-squares for the reduced and full models.

***Significant at p-value = .001

**Significant at p-value = .01

*Significant at p-value = .05

Table D-18

Year-1, Four-State Accrual Models

		$SIZE_1$+NITA+SALESCA+CACL+OETL +CATA+CASHTA		$SIZE_1$+NITA+SALESCA+CACL+OETL	
		Parameter[1] Estimates (sd)	Wald χ^2 Statistic	Parameter Estimates (sd)	Wald χ^2 Statistic
Variable	Expected Sign				
Intercept1		1.9064	8.9569**	1.7808	11.4366***
		(.6370)		(.5266)	
Intercept2		.9526	2.3287	.8271	2.6121
		(.6243)		(.5118)	
Intercept3		-.5494	.7160	-.6927	1.6314
		(.6493)		(.5424)	
$SIZE_1$	(-)	-.000349	3.3694	-.000357	3.6506
		(.00019)		(.000187)	
NITA	(-)	-1.8939	7.6454**	-1.8619	7.3992**
		(.6850)		(.6845)	
SALESCA	(-)	-.1406	5.0145*	-.1360	5.2150*
		(.0620)		(.0595)	
CACL	(-)	-.4699	2.6113	-.5670	4.9293*
		(.2908)		(.2554)	
OETL	(-)	-1.2631	12.6981***	-1.3066	15.4479***
		(.3545)		(.3324)	
CATA	(-)	-.1934	.0523		
		(.8458)			
CASHTA	(-)	-3.4178	1.1406		
		(3.2003)			
Score Test[2]			46.8049*** (14 df)		25.8222** (10 df)
-2Log Likelihood[3]			109.585*** (7 df)		108.182*** (5 df)
AIC Criterion			317.587		314.991
Somers' D			.712		.704

[1]Estimated ordinal parameters and standard deviations for accrual models. $SIZE_1$ = total assets, NITA = net income/total assets, SALESCA = sales/current assets, CACL = current assets/current liabilities, OETL = owners' equity/total liabilities, CATA = current assets/total assets, and CASHTA = cash plus marketable securities/total assets.
[2]Score Test for the proportional odds assumption - distributed as a chi-square distribution with degrees of freedom in parentheses.
[3]-2Log Likelihood for the covariates - distributed as a chi-square distribution.
***Significant at p-value = .001
**Significant at p-value = .01
*Significant at p-value = .05

Table D-19

Year-2, Four-State Accrual Models

		$SIZE_1$+NITA+SALESCA+CACL OETL+CATA+CASHTA		$SIZE_1$+NITA+SALESCA+CACL+OETL +CASHTA	
		Parameter[1] Estimates (sd)	Wald χ^2 Statistic	Parameter Estimates (sd)	Wald χ^2 Statistic
Variable	Expected Sign				
Intercept1		1.5998	5.7320*	1.3903	6.0985**
		(.6682)		(.5630)	
Intercept2		.7754	1.3716	.5694	1.0453
		(.6621)		(.5570)	
Intercept3		-.5388	.6225	-.7483	1.6577
		(.6829)		(.5812)	
$SIZE_1$	(-)	-.000336	3.1437	-.000312	3.0203
		(.000189)		(.000187)	
NITA	(-)	-3.5135	14.1230***	-3.5924	14.9004***
		(.9349)		(.9307)	
SALESCA	(-)	-.1568	3.6053	-.1432	3.3237
		(.0826)		(.0785)	
CACL	(-)	-.3200	2.1022	-.3725	3.2868
		(.2207)		(.2055)	
OETL	(-)	-.4461	4.8780*	-.4118	4.7257*
		(.2020)		(.1894)	
CATA	(-)	-.4939	.4102		
		(.7710)			
CASHTA	(-)	-6.1731	6.0668**	-6.5187	7.0538**
		(2.5063)		(2.4544)	
Score Test[2]			39.4677*** (14 df)		30.5793** (12 df)
-2Log Likelihood[3]			84.245*** (7 df)		83.663*** (6 df)
AIC Criterion			342.928		341.510
Somers' D			.650		.653

[1]Estimated ordinal parameters and standard deviations for accrual models. $SIZE_1$ = total assets, NITA = net income/total assets, SALESCA = sales/current assets, CACL = current assets/current liabilities, OETL = owners' equity/total liabilities, CATA = current assets/total assets, and CASHTA = cash plus marketable securities/total assets.
[2]Score Test for the proportional odds assumption - distributed as a chi-square distribution with degrees of freedom in parentheses.
[3]-2Log Likelihood for the covariates - distributed as a chi-square distribution.
***Significant at p-value = .001
**Significant at p-value = .01
*Significant at p-value = .05

Table D-20

Year-3, Four-State Accrual Models

		$SIZE_1$+NITA+SALESCA+CACL OETL+CATA+CASHTA		$SIZE_1$+NITA+SALESCA+CASHTA	
		Parameter[1] Estimates (sd)	Wald χ^2 Statistic	Parameter Estimates (sd)	Wald χ^2 Statistic
Variable	Expected Sign				
Intercept1		.5370 (.5026)	1.1415	.0819 (.3439)	.0567
Intercept2		-.1091 (.5042)	.0468	-.5552 (.3496)	2.5223
Intercept3		-1.1545 (.5315)	4.7185*	-1.5872 (.3903)	16.5339***
$SIZE_1$	(-)	-.000335 (.00017)	3.8933*	-.000298 (.000162)	3.3772
NITA	(-)	-1.4054 (.7922)	3.1470	-1.7454 (.7808)	4.9970*
SALESCA	(-)	-.1358 (.0770)	3.1078	-.1030 (.0711)	2.1019
CACL	(-)	-.1965 (.1897)	1.0729		
OETL	(-)	-.1239 (.1700)	.5312		
CATA	(-)	.1607 (.2729)	.3469		
CASHTA	(-)	-3.5959 (2.0156)	3.1859	-5.6335 (1.8046)	9.7449**
Score Test[2]			28.4785* (14 df)		24.6264** (8 df)
-2Log Likelihood[3]			34.429*** (7 df)		30.236*** (4 df)
AIC Criterion			392.743		390.936
Somers' D			.442		.430

[1]Estimated ordinal parameters and standard deviations for accrual models. $SIZE_1$ = total assets, NITA = net income/total assets, SALESCA = sales/current assets, CACL = current assets/current liabilities, OETL = owners' equity/total liabilities, CATA = current assets/total assets, and CASHTA = cash plus marketable securities/total assets.
[2]Score Test for the proportional odds assumption - distributed as a chi-square distribution with degrees in parentheses.
[3]-2Log Likelihood for the covariates - distributed as a chi-square distribution.
***Significant at p-value = .001
**Significant at p-value = .01
*Significant at p-value = .05

Table D-21
Correlation Matrices for the Parameter Estimates of the Four-State Accrual Model $SIZE_1$ + NITA + SALESCA + CACL + OETL + CATA + CASHTA

Year - 1 Estimated Correlation Matrix

Variable	INT1	INT2	INT3	$SIZE_1$	NITA	SALESCA	CACL	OETL	CATA	CASHTA
INT1	1.0000	.9591	.8687	-.3072	.3657	-.601	-.2798	-.2516	-.5437	-.0724
INT2		1.0000	.8975	-.2973	.3998	-.5892	-.2650	-.2275	-.5530	-.0701
INT3			1.0000	-.2741	.4665	-.5403	-.2301	-.1849	-.5312	-.0687
$SIZE_1$				1.0000	-.1940	.0942	.0109	.0610	.1844	-.0958
NITA					1.0000	-.1025	-.2569	-.0915	-.0759	.0931
SALESCA						1.0000	.0481	.0862	.2728	.0194
CACL							1.0000	-.4210	-.4172	-.1331
OETL								1.0000	.3031	-.1514
CATA									1.0000	-.0892
CASHTA										1.0000

Year - 2 Estimated Correlation Matrix

Variable	INT1	INT2	INT3	$SIZE_1$	NITA	SALESCA	CACL	OETL	CATA	CASHTA
INT1	1.0000	.9716	.9065	-.3330	.3266	-.7274	-.3185	-.3198	-.5384	-.0271
INT2		1.0000	.9272	-.3266	.3587	-.7205	-.3095	-.3100	-.5396	-.01444
INT3			1.0000	-.3097	.4032	-.6810	-.2803	-.2861	-.5231	-.0032
$SIZE_1$				1.0000	-.2225	.1577	-.0005	.1309	.2021	-.0782
NITA					1.0000	-.2759	-.2008	-.0281	-.0984	.2161
SALESCA						1.0000	.1604	.1341	.2929	-.0030
CACL							1.0000	-.3170	-.3747	-.1796
OETL								1.0000	.3249	-.1041
CATA									1.0000	-.1345
CASHTA										1.0000

Year - 3 Estimated Correlation Matrix

Variable	INT1	INT2	INT3	$SIZE_1$	NITA	SALESCA	CACL	OETL	CATA	CASHTA
INT1	1.0000	.9670	.8937	-.2773	.2906	-.7280	-.5326	.0348	-.2673	-.0961
INT2		1.0000	.9185	-.2674	.3043	-.7157	-.5241	.0365	-.2718	-.0868
INT3			1.0000	-.2464	.3198	-.6694	-.4891	.0330	-.2657	-.0742
$SIZE_1$				1.0000	-.1330	.1048	.0357	.0763	.0933	-.0169
NITA					1.0000	-.1854	-.1630	-.0589	-.0290	-.0154
SALESCA						1.0000	.2615	-.0469	.1008	.0538
CACL							1.0000	-.5438	-.1826	-.2895
OETL								1.0000	.0803	-.1192
CATA									1.0000	.04992
CASHTA										1.0000

Table D-22

Mixed Four-State Models for Year-1 - Cash Flows CFFO, CFFI, and LFF Added to the Accrual Model $SIZE_1$ + NITA + SALESCA + CACL + OETL

		$SIZE_1$+NITA+SALESCA+CACL +OETL+CFFO+CFFI+LFF		$SIZE_1$+NITA+SALESCA+CACL +OETL+CFFO+LFF	
		Parameter[1] Estimates (sd)	Wald χ^2 Statistic	Parameter Estimates (sd)	Wald χ^2 Statistic
Variable	Expected Sign				
Intercept1		1.5380 (.5351)	8.2617**	1.4542 (.5217)	7.7693**
Intercept2		.4420 (.5225)	.7155	.3613 (.5102)	.5014
Intercept3		-1.2514 (.5606)	4.9831*	-1.3342 (.4409)	5.8663*
$SIZE_1$	(-)	-.000215 (.000168)	1.6372	-.000217 (.000169)	1.6426
NITA	(-)	-1.2136 (.6583)	3.3988	-1.2452 (.6442)	3.61117
SALESCA	(-)	-.0779 (.0601)	1.6771	-.0803 (.0600)	1.7923
CACL	(-)	-.4059 (.2622)	2.3963	-.3676 (.2548)	2.0823
OETL	(-)	-1.1646 (.3815)	9.3206**	-1.2461 (.3577)	12.1350***
CFFO	(-)	-3.6768 (1.0278	12.7975***	-3.6958 (1.0261)	12.9719***
CFFI	(+)	.6081 (1.0241)	.3525		
LFF	(-)	-2.2061 (.7956)	7.6896**	-2.3897 (.7562)	9.9866**
Score Test[2]			28.0258* (16 df)		27.6902* (14 df)
-2Log Likelihood[3]			131.108*** (8 df)		130.759*** (7 df)
Change in -2Log Likelihood[4]			22.926*** (3 df)		22.577*** (2 df)
AIC Criterion			298.065		296.414
Somers' D			.760		.759

[1]Estimated ordinal parameters and standard deviations for the appropriate mixed models.
[2]Score Test for the proportional odds assumption - distributed as a chi-square distribution.
[3]-2Log Likelihood for the covariates - distributed as a chi-square distribution.
[4]Change in -2Log Likelihood for the covariates - distributed as a chi-square distribution. This test compares the model with the cash flows added to the base accrual model $SIZE_1$ + NITA + SALESCA + CACL + OETL.
***Significant at p-value = .001
**Significant at p-value = .01
*Significant at p-value = .05

Table D-23

Mixed Four-State Models for Year-2 - Cash Flows CFFO, CFFI, SFF, and EFF Added to the Accrual Model $SIZE_1$ + NITA + SALESCA + CACL + OETL + CASHTA

		$SIZE_1$+NITA+SALESCA+CACL +CASHTA+CFFO+CFFI+SFF+EFF		$SIZE_1$+NITA+SALESCA+CACL+OETL +CASHTA+CFFO+CFFI+SFF	
Variable	Expected Sign	Parameter Estimates	Wald χ^2 Statistic	Parameter Estimates	Wald χ^2 Statistic
Intercept1		1.3285 (.6267)	4.4935*	1.3237 (.6049)	4.7887*
Intercept2		.4090 (.6224)	.4317	.4042 (.6007)	.4529
Intercept3		-1.1195 (.6538)	2.9324	-1.1244 (.6318)	3.1675
$SIZE_1$	(-)	-.000317 (.000184)	2.9765	-.000317 (.000184)	2.9799
NITA	(-)	-2.5567 (1.0832)	5.5713*	-2.5642 (1.0580)	5.8740*
SALESCA	(-)	-.0533 (.0809)	.4350	-.0531 (.0803)	.4373
CACL	(-)	-.3372 (.2445)	1.9010	-.3360 (.2413)	1.9386
OETL	(-)	-.2373 (.2670)	.7905	-.2368 (.2663)	.7908
CASHTA	(-)	-6.0365 (2.6226)	5.2981*	-6.0156 (2.5206)	5.6954*
CFFO	(-)	-.7341 (.6998)	1.1004	-.7458 (.5786)	1.6614
CFFI	(+)	2.5495 (1.0803)	5.5692*	2.5356 (.9823)	6.6635**
SFF	(+)	3.3444 (1.1206)	8.9080**	3.3361 (1.0867)	9.4241**
EFF	(+)	.0225 (.7968)	.0008		
Score Test			35.6279* (20 df)		30.7813* (18 df)
-2Log Likelihood			104.715*** (10 df)		104.714*** (9 df)
Change in -2Log Likelihood[1]			21.052*** (4 df)		21.051*** (3 df)
AIC Criterion			328.458		326.459
Somers' D			.691		.692

[1]Change in -2Log Likelihood for the covariates - distributed as a chi-square distribution. This test compares the model with the cash flows added to the base accrual model $SIZE_1$ + NITA + SALESCA + CACL + OETL + CASHTA.
***Significant at p-value = .001
**Significant at p-value = .01
*Significant at p-value = .05

Table D-24

Mixed Four-State Models for Year-3 - Cash Flows CFFO and CFFI Added to the Accrual Model $SIZE_1$ + NITA + SALESCA + CASHTA

		$SIZE_1$+NITA+SALESCA+CASHTA+CFFO+CFFI		$SIZE_1$+NITA+SALESCA+CASHTA+CFFI	
		Parameter[1] Estimates (sd)	Wald χ^2 Statistic	Parameter[2] Estimates (sd)	Wald χ^2 Statistic
Variable	Expected Sign				
Intercept1		.2980 (.3748)	.6322	.3061 (.3778)	.6567
Intercept2		-.3422 (.3785)	.8171	-.3336 (.3814)	.7650
Intercept3		-1.3775 (.4154)	10.9988***	-1.3665 (.4176)	10.7081**
$SIZE_1$	(-)	-.000312 (.000167)	3.4728	-.000311 (.000167)	3.4691
NITA	(-)	-1.2391 (.8692)	2.0323	-1.5889 (.7689)	4.2699*
SALESCA	(-)	-.0900 (.0737)	1.4907	-.1018 (.0740)	1.8918
CASHTA	(-)	-5.7818 (1.8727)	9.5324**	-6.1219 (1.8543)	10.8997***
CFFO	(-)	-.2620 (.3225)	.6598		
CFFI	(+)	.7737 (.4829)	2.5675	.7526 (.4754)	2.5065
Score Test[2]			31.6158** (12 df)		29.1535** (10 df)
-2Log Likelihood[3]			33.801*** (6 df)		33.044*** (5 df)
Change in -2Log Likelihood[4]			3.565 (2 df)		2.808 (1 df)
AIC Criterion			391.372		390.128
Somers' D			.429		.432

[1]Estimated ordinal parameters and standard deviations for the appropriate mixed models.
[2]Score Test for the proportional odds assumption - distributed as a chi-square distribution.
[3]-2Log Likelihood for the covariates - distributed as a chi-square distribution.
[4]Change in -2Log Likelihood for the covariates - distributed as a chi-square distribution. This test compares the model with the cash flows added to the base accrual model $SIZE_1$ + NITA + SALESCA + CASHTA.
***Significant at p-value = .001
**Significant at p-value = .01
*Significant at p-value = .05

Table D-25

Incremental Predictive Power of NOF: the Addition of NOF to the Relevant Four-State Gross Cash Flows Models

Year Lagged	-2Log L[1] (Base)	-2Log L[2] (Added)	Δ -2Log L[3]	Degrees of Freedom	P -Values
Year - 1: Base Cash Flow Model from Table D-12, $SIZE_1$+CFFO+CFFI+LFF					
NOF added	88.159	99.330	11.171***	1	.0008
Year - 2: Base Cash Flow Model from Table D-13, $SIZE_1$+CFFO+CFFI+SFF+EFF					
NOF added	69.398	87.740	18.342***	1	.0001
Year - 3: Base Cash Flow Model from Table D-14, $SIZE_1$+CFFO+CFFI					
NOF added	18.333	21.462	3.129	1	.0769

[1]-2Log Likelihood for the covariates for the gross cash flows models of interest- distributed as a chi-square distribution with four degrees of freedom for Year - 1 model, five degrees of freedom for Year - 2 model, and three degrees of freedom for Year - 3 model.
[2]-2Log Likelihood for the covariates for each model with NOF added to the base gross cash flows model - distributed as a chi-square distribution with five degrees of freedom for Year - 1 model, six degrees of freedom for Year - 2 model, and four degrees of freedom for Year - 3 model.
[3]The change in the -2Log Likelihood chi-square for the base cash flows model and the -2Log Likelihood chi-square for the cash flows model with NOF added.
***Significant at p-value = .001
**Significant at p-value = .01
*Significant at p-value = .05

Table D-26

Estimated Correlations of the Parameter Estimates of NOF With the Parameter Estimates of CFFO and NOF for the Relevant OLR Models Tested

Year	Model	Correlation of the Parameter Estimates for NOF and CFFO	Correlation of the Parameter Estimates for NOF and NITA
Section 1 of Table D-26			
[1]Year-1	$SIZE_1$+CFFO+CFFI+LFF+NOF	-.44152	
[2]Year-2	$SIZE_1$+CFFO+CFFI+SFF+EFF+NOF	-.39976	
[3]Year-3	$SIZE_1$+CFFO+CFFI+NOF	-.42172	
Section 2 of Table D-26			
[4]Year-1	$SIZE_1$+NITA+SALESCA+CACL+OETL+NOF		-.73681
[5]Year-2	$SIZE_1$+NITA+SALESCA+CACL+OETL+CASHTA+NOF		-.78542
[6]Year-3	$SIZE_1$+NITA+SALESCA+CASHTA+NOF		-.81562

[1]NOF added to the reduced cash flow model from Table D-12.
[2]NOF added to the reduced cash flow model from Table D-13.
[3]NOF added to the reduced cash flow model from Table D-14.
[4]NOF added to the reduced accrual model from Table D-18.
[5]NOF added to the reduced accrual model from Table D-19.
[6]NOF added to the reduced accrual model from Table D-20.

Table D-27

Four-State OLR Models With Both NITA and NOF Included

		Year - 1 Model		Year - 2 Model		Year - 3 Model	
		Parameter[1] Estimates (sd)	Wald χ^2 Statistic	Parameter Estimates (sd)	Wald χ^2 Statistic	Parameter Estimate (sd)	Wald χ^2 Statistic
Variable	Expected Sign						
Intercept1		1.8085 (.5246)	11.8854***	1.7608 (.5966)	8.7105**	.1535 (.3486)	.1938
Intercept2		.8543 (.5085)	2.8228	.9043 (.5867)	2.3756	-.4812 (.3536)	1.8518
Intercept3		-.6630 (.5349)	1.5366	-.4694 (.6080)	.5961	-1.5096 (.3920)	14.7927***
$SIZE_1$	(-)	-.000349 (.000188)	3.4382	-.000323 (.000185)	3.0565	-.000317 (.000167)	3.6265
NITA	(-)	-.7286 (.9875)	.5444	.1489 (1.4187)	.0110	-.3332 (1.4062)	.0562
SALESCA	(-)	-.1217 (.0595)	4.1910*	-.1049 (.0781)	1.8006	-.0889 (.0712)	1.5566
CACL	(-)	-.5228 (.2541)	4.2336*	-.3380 (.2151)	3.2539		
OETL	(-)	-1.3404 (.3524)	14.4658***	-.7284 (.2210)	10.8623***		
CASHTA	(-)			-5.2949 (2.4830)	4.5473*	-5.3241 (1.7960)	8.7880**
NOF	(-)	-1.2783 (.7315)	3.0536	-2.6444 (.8869)	8.8904**	-.7483 (.6190)	1.4612
Score Test[2]			34.7209***		33.9210**		24.6264**
-2Log Likelihood[3]			110.593***		95.798***		30.236***
AIC Criterion			314.580		331.375		390.936
Somers' D			.708		.670		.433

[1]Estimated ordinal parameters and standard deviations for the relevant models from Tables D-18, D-19, and D-20 with NOF added. Year - 1 model = $SIZE_1$ + NITA + SALESCA + CACL + OETL + NOF. Year - 2 model = $SIZE_1$ + NITA + SALESCA + CACL + OETL + CASHTA + NOF. Year - 3 model = $SIZE_1$ + NITA + SALESCA + CASHTA + NOF.

[2]Score Test for the proportional odds assumption - distributed as a chi-square distribution with twelve degrees of freedom for the Year - 1 model, fourteen degrees of freedom for the Year - 2 model, and ten degrees of freedom for the Year - 3 model.

[3]-2Log Likelihood for the covariates - distributed as a chi-square distribution with six degrees of freedom for the Year - 1 model, seven degrees of freedom for the Year - 2 model, and five degrees of freedom for the Year - 3 model.

***Significant at p-value = .001
**Significant at p-value = .01
*Significant at p-value = .05

Table D-28

Score Test Chi-Squares for the Four-State Univariate OLR Accrual Models

	Chi-Square Reported for Each Proportional Odds Test		
Variable	Year - 1	Year - 2	Year - 3
NITA	8.7809*	20.1733***	11.2635**
SALESCA	5.4586	1.5219	3.1883
CACL	7.9728*	5.7238	1.7113
OETL	8.0504*	.8523	.1417
CATA	5.2040	4.8165	1.3732
CASHTA	.5776	.9553	2.6304
NOF	8.2774*	12.9829**	4.4167

[1]Each univariate test has 2 df - chi-square distribution.
***Significant (rejected) at p-value = .001
**Significant (rejected) at p-value = .01
*Significant (rejected) at p-value = .05

Table D-29

Rank Order (RPS) Scores for the Four-State OLR Models of Interest: Test of the Predictive Power of the Relevant Models

	1988 Sample		Holdout Sample	
YearModel	[1]SS_m	SS_{naive}	SS_m	SS_{naive}
Year - 1:				
[2]Net cash flows	206.262	197.029	135.719	134.097
[3]Gross cash flows	207.470	197.029	135.729	134.097
[4]Accrual	210.302	197.029	140.193	134.097
[5]Mixed	211.878	197.029	139.569	134.097
[6]NOF added	209.036	197.029	137.074	134.097
Year - 2:				
Net cash flows	203.528	197.029	136.098	134.097
Gross cash flows	205.529	197.029	135.169	134.097
Accrual	207.045	197.029	139.812	134.097
Mixed	209.666	197.029	138.680	134.097
NOF added	208.325	197.029	138.622	134.097
Year - 3:				
Net cash flows	199.042	197.029	135.297	134.097
Gross cash flows	198.929	197.029	135.386	134.097
Accrual	200.373	197.029	134.633	134.097
Mixed	200.508	197.029	135.373	134.097
NOF added	199.226	197.029	132.863	134.097

[1]Sum of Rank Score (RPS) for 1988 and 1989 models - n = 229 for 1988 sample and n = 158 for 1989 (holdout) sample.

[2]$SIZE_1$ + CFFO + CFFI + CFFF for all three years.

[3]Year - 1: $SIZE_1$ + CFFO + CFFI + LFF. Year - 2: $SIZE_1$ + CFFO + CFFI + SFF + EFF. Year - 3: $SIZE_1$ + CFFO + CFFI.

[4]Year - 1: $SIZE_1$ + NITA + SALESCA + CACL + OETL. Year - 2: $SIZE_1$ + NITA + SALESCA + CACL + OETL + CASHTA. Year - 3: $SIZE_1$ + NITA + SALESCA + CASHTA.

[5]Gross cash flows and accrual models added together. See Tables D-22, D-23, and D-24 for the final mixed models tested.

[6]NOF added to the final gross cash flows models.

Table D-30

Comparison of the Results of the Accrual and Mixed Four-State OLR Models With Lau's Best Multi-State Nominal Model Using RPS Scores: Test of the Predictive Power of the Relevant Models

	Original Sample		Holdout Sample	
YearModel	[1]SS_m	SS_{naive}	SS_m	SS_{naive}
Year - 1:				
Accrual	210.302	197.029	140.193	134.097
Mixed	211.878	197.029	139.567	134.097
Lau's model	396.300	377.280	376.100	377.280
Year - 2:				
Accrual	207.045	197.029	139.812	134.097
Mixed	209.666	197.029	138.680	134.097
Lau's model	390.500	377.280	373.700	377.280
Year - 3:				
Accrual	200.373	197.029	134.633	134.097
Mixed	200.508	197.029	135.373	134.097
Lau's model	388.10	377.280	374.200	377.280

[1]Sum of Rank Score (RPS) for 1988 and 1989 accrual and mixed models tested in this study and Lau's best ten variable model (working capital model). Total possible SS_m = number of observations. Total possible score for accrual and mixed models = 229 for original sample and 158 for holdout sample. Total possible score for Lau's model = 400 for both the original and holdout sample (Lau sampled 400 firms for each group).

Table D-31

RPS Scores, Broken Down by State of Distress, for Four-State OLR and Nominal Logistic Accrual and Mixed Models: Comparison of the Predictive Power of OLR Models With Nominal Models for Models Where the Proportional Odds Assumption Was Violated

	Original Sample of 1988 Firms[1] (n = 229)			Holdout Sample of 1989 Firms[2] (n = 158)		
	Year - 1 SS_m	Year - 2 SS_m	Year - 3 SS_m	Year - 1 SS_m	Year - 2 SS_m	Year - 3 SS_m
Ordinal Logistic Models (OLR):						
Accrual model						
Overall RPS Score[3]	210.30	207.05	200.37	140.19	139.81	134.63
State-0	161.25	160.32	159.53	107.47	106.40	105.98
State-1	17.60	17.80	17.81	13.61	13.75	13.68
State-2	18.83	18.04	16.39	10.91	10.11	9.17
State-3	12.62	10.89	6.64	8.20	9.55	5.80
Mixed model:						
Overall RPS Score	211.87	209.66	200.51	139.57	138.68	135.37
State-0	161.56	161.37	159.40	107.29	106.72	106.47
State-1	17.75	17.79	17.91	13.43	13.42	13.66
State-2	19.41	17.85	16.28	11.40	10.31	9.21
State-3	13.15	12.65	6.92	7.45	8.23	6.03
Nominal Logistic Models:						
Accrual model:						
Overall RPS Score	212.49	208.98	200.70	140.12	139.22	133.67
State-0	161.89	160.40	158.89	107.14	106.44	104.60
State-1	17.13	17.44	17.62	13.31	13.55	13.57
State-2	19.64	19.36	17.38	11.09	9.97	9.39
State-3	13.83	11.78	6.81	8.58	9.26	6.11
Mixed model:						
Overall RPS Score	213.50	213.22	200.91	138.84	138.00	134.17
State-0	162.10	161.98	158.79	106.85	106.10	104.73
State-1	17.28	17.30	17.78	13.24	13.23	13.58
State-2	19.79	19.63	17.21	11.23	9.75	9.66
State-3	14.33	14.31	7.13	7.52	8.92	6.19

[1]The total 1988 sample size of 229 firms is composed of 166 State 0, 22 State 1, 23 State 2, and 18 State 3 firms.
[2]The total 1989 sample size of 158 firms is composed of 111 State 0, 17 State 1, 14 State 2, and 16 State 3 firms.
[3]Total possible score for each state of distress equals the sample size for each state. State 0 = healthy firms. State 1 = dividend reduction firms. State 2 = loan default/accommodation firms. State 3 = bankrupt firms.

Table D-32

Percentage of Firms Classified Correctly by the OLR Four-State Models

	Original Sample of 1988 Firms[1] (n = 229)			Holdout Sample of 1989 Firms[2] (n = 158)		
Model State of Distress	Year - 1	Year - 2	Year - 3	Year - 1	Year - 2	Year - 3
Net Cash Flows Model:						
Overall Percentage[3]	64.6%	54.2%	45.8%	59.5%	47.5%	43.2%
State-0	72.9	62.0	50.6	72.1	56.8	49.5
State-1	40.9	27.3	40.9	29.4	00.0	00.0
State-2	60.9	56.2	52.2	50.0	85.7	85.7
State-3	22.2	11.1	00.0	12.5	00.0	00.0
Gross Cash Flows Model:						
Overall Percentage	64.6%	59.4%	46.7%	60.8%	50.6%	39.9%
State-0	73.5	65.7	51.8	73.9	61.3	45.0
State-1	31.9	45.5	36.4	35.3	00.0	00.0
State-2	56.5	47.8	56.4	50.0	85.7	92.9
State-3	33.3	33.3	00.0	6.2	00.0	00.0
NOF Added To Gross Cash Flows Model:						
Overall Percentage	65.5%	62.45%	48.9%	57.6%	61.4%	40.5%
State-0	74.1	69.9	53.0	73.9	74.8	46.8
State-1	45.4	40.9	50.0	11.8	29.4	00.0
State-2	52.2	52.2	56.5	42.9	42.9	85.7
State-3	50.0	53.3	00.0	6.2	18.7	00.0
Accrual Model:						
Overall Percentage	62.0%	58.9%	52.8%	65.2%	58.2%	50.6
State-0	69.3	64.5	57.2	76.6	71.2	45.1
State-1	45.4	54.5	45.4	35.3	17.6	00.0
State-2	47.8	56.5	62.2	71.4	50.0	71.4
State-3	33.3	16.7	5.6	12.5	18.7	00.0
Mixed Model:						
Overall Percentage	66.8%	59.4%	52.0%	65.2%	58.9%	48.1%
State-0	72.9	65.7	57.2	78.4	74.8	42.4
State-1	59.1	50.0	45.4	47.1	17.6	00.0
State-2	59.1	47.8	56.5	42.8	42.8	64.3
State-3	33.3	27.8	5.6	12.5	6.2	00.0

[1]The total 1988 sample size of 229 firms is composed of 166 State-0, 22 State-1, 23 State-2, and 18 State-3 firms.
[2]The total 1989 sample size of 158 firms is composed of 111 State-0, 17 State-1, 14 State-2, and 16 State-3 firms.
[3]State-0 = healthy firms. State-1 = dividend reduction firms. State-2 = loan default/accommodation firms. State-3 = bankrupt firms.

Table D-33

Comparison of the Predictive Power of the Four-State OLR and Nominal Logistic Accrual and Mixed Models: the Percentage of Firms Classified Correctly

	Original Sample of 1988 Firms[1] (n = 229)			Holdout Sample of 1989 Firms[2] (n = 158)		
Model State of Distress	Year - 1	Year - 2	Year - 3	Year - 1	Year - 2	Year - 3
Ordinal Logistic Regression (OLR)						
Accrual Model:						
Overall Percentage[3]	62.0%	58.9%	52.8%	65.2%	58.2%	50.6
State-0	69.3	64.5	57.2	76.6	71.2	45.1
State-1	45.4	54.5	45.4	35.3	17.6	00.0
State-2	47.8	56.5	62.2	71.4	50.0	71.4
State-3	33.3	16.7	5.6	12.5	18.7	00.0
Mixed Model:						
Overall Percentage	66.8%	59.4%	52.0%	65.2%	58.9%	48.1%
State-0	72.9	65.7	57.2	78.4	74.8	42.4
State-1	59.1	50.0	45.4	47.1	17.6	00.0
State-2	59.1	47.8	56.5	42.8	42.8	64.3
State-3	33.3	27.8	5.6	12.5	6.2	00.0
Nominal Logistic Regression						
Accrual Model:						
Overall Percentage	66.4%	59.4%	59.4%	69.0%	61.4%	50.6
State-0	75.3	65.7	63.2	83.8	76.6	62.2
State-1	40.9	40.9	31.8	17.6	29.4	11.8
State-2	60.9	60.9	82.6	57.1	35.7	50.0
State-3	22.2	22.2	27.8	31.2	12.5	12.5
Mixed Model:						
Overall Percentage	69.0%	66.8%	55.4%	70.2%	62.0%	48.1%
State-0	80.7	71.7	59.6	85.6	79.3	59.5
State-1	18.2	31.8	27.3	29.4	23.5	17.6
State-2	60.9	73.9	82.6	50.0	14.3	35.7
State-3	33.3	55.5	16.7	25.0	25.0	12.5

[1]The total 1988 sample size of 229 firms is composed of 166 State-0, 22 State-1, 23 State-2, and 18 State-3 firms.
[2]The total 1989 sample size of 158 firms is composed of 111 State-0, 17 State-1, 14 State-2, and 16 State-3 firms.
[3]State-0 = healthy firms. State-1 = dividend reduction firms. State-2 = loan default/accommodation firms. State-3 = bankrupt firms.

Table D-34

The Percentage of Firms Correctly Classified by Four-State Regression Models When Classified by a Dichotomous Classification Scheme

	Original Sample of 1988 Firms[1] (n = 229)			Holdout Sample of 1989 Firms[2] (n = 158)		
Model State of Distress	Year - 1	Year - 2	Year - 3	Year - 1	Year - 2	Year - 3
Ordinal Logistic Regression (OLR)						
Net Cash Flows Model:						
Overall Percentage[3]	90.4%	84.7%	67.6%	76.6%	60.8%	57.0%
States 0 + 1	93.6	86.2	71.3	82.0	55.5	48.4
States 2 + 3	75.6	78.0	51.2	53.3	83.3	93.3
Gross Cash Flows Model:						
Overall Percentage	90.4%	86.9%	70.3%	79.1%	63.3%	54.4%
States 0 + 1	94.1	89.9	72.3	85.9	59.4	44.5
States 2 + 3	73.2	73.2	61.0	50.0	80.0	96.7
NOF Added:						
Overall Percentage	91.7%	92.6%	79.0%	79.5%	84.2%	54.4%
States 0 + 1	94.1	95.2	81.9	85.1	88.3	46.1
States 2 + 3	80.5	80.5	65.9	56.7	66.7	90.0
Accrual Model:						
Overall Percentage	91.7%	92.6%	75.5%	85.4%	84.9%	62.7
States 0 + 1	94.2	95.7	79.2	89.8	85.9	60.9
States 2 + 3	80.5	80.5	58.5	66.7	76.7	70.0
Mixed Model:						
Overall Percentage	95.6%	93.5%	78.2%	84.8%	81.7%	60.1%
States 0 + 1	97.9	95.7	81.4	93.0	86.7	58.6
States 2 + 3	85.4	82.9	63.4	50.0	60.0	66.7
Nominal Logistic Regression						
Accrual Model:						
Overall Percentage	92.1%	89.1%	73.8%	82.9%	85.4%	65.8%
States 0 + 1	93.1	91.0	72.3	86.7	90.6	67.9
States 2 + 3	87.8	80.5	80.5	66.7	63.3	56.7
Mixed Model:						
Overall Percentage	93.1%	90.8%	72.9%	82.9%	82.3%	68.3%
States 0 + 1	93.1	91.0	73.4	89.1	87.5	71.9
States 2 + 3	92.7	90.2	70.73	56.7	60.0	53.3

[1]The total 1988 sample size of 229 firms is composed of 166 State-0, 22 State-1, 23 State-2, and 18 State-3 firms.
[2]The total 1989 sample size of 158 firms is composed of 111 State-0, 17 State-1, 14 State-2, and 16 State-3 firms.
[3]A State 0 or 1 firm is considered correctly classified if the firm is either a healthy or dividend reduction firm. A State 2 or 3 firm is considered correctly classified if the firm is either a loan default/accommodation or bankrupt firm. State-0 = healthy firms. State-1 = dividend reduction firms. State-2 = loan default/accommodation firms. State-3 = bankrupt firms.

Table D-35

Parameter Estimates for Univariate Two-State OLR Financial Distress Models For Only States 2 (Loan Default/Accommodation) and 3 (Bankrupt) Firms

Variable	Expected Sign	Year - 1[1]	Year - 2	Year - 3
Accrual Ratios:[2]				
NITA	(-)	.0926	1.5769	5.4014**
SALESCA	(-)	.2362	-.0377	.1959
CACL	(-)	-.1692	-.2469	-.1796
OETL	(-)	-.4439	-.1864	-.1437
CATA	(-)	2.6121*	2.2462*	-.1983
CASHTA	(-)	4.4359	.6569	5.2200
Cash Flows:				
CFFO	(-)	1.4359	-.462	.7911
CFFI	(+)	-.8722	1.0723	.8069
LFF	(-)	-.8766	.8090	.9887
SFF	(+)	-1.2904	.4764	.3888
EFF	(+)	.8458	-.6928	-.0772
Other Variables:				
NOF	(-)	-1.4648	.6972	1.2712
$SIZE_1$	(-)	.00007	.00024	.00022

[1]Parameter estimates for the univariate two-state (states 2 and 3) models.
[2]Each variable was run by itself in a two-state OLR model based on only the loan default/accommodation and bankrupt firms (states 2 and 3).
**Significant (rejected) at p-value = .05
*Significant (rejected) at p-value = .10

VITA

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