CASH FLOW RATIOS AS PREDICTORS OF BUSINESS FAILURE

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We hereby certify that this Dissertation submitted by Anthony J. Zordan conforms to acceptable standards, and as such is fully adequate in scope and quality. It is therefore approved as the fulfillment of the Dissertation requirements for the degree of Doctor of Business Administration.

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CERTIFICATION STATEMENT

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Anthony J. Zordan

ABSTRACT

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Numerous studies have used ratios to predict business failure. Few of these have been industry specific or have used reported cash flows. The purpose of this study was to determine if accounting information in the form of cash flow ratios derived from the statement of cash flows (SCF) has information content, i.e., cash flow ratios can distinguish between failed and non-failed firms.

Using a matched sample of 108 failed and 108 non-failed retail/wholesale firms and a matched sample of 162 failed and 162 non-failed manufacturing firms from the Compustat database, multiple discriminant analysis was used to develop three discriminant models using cash flow and accrual ratios as independent variables. The means of the z scores calculated by applying the multivariate discriminant function models to the failed firms in the sample were significantly different from the means for non-failed firms as measured by Hotelling's T^2 test. The models were validated using a jackknife procedure and a split sample analysis. The models accurately classified 74.5% of the retail/wholesale firms, 76.5% of the manufacturing firms, and 73.9% of the two groups combined. This suggests evidence consistent with the hypothesis.

Further, the percentage of correct predictions of failed and non-failed firms by the three models (retail/wholesale, manufacturing, and combined) developed using SCF data were compared to the percentage of correct predictions of failed and non-failed firms by established accrual-only models using the firms in this sample. There were no significant differences as measured by McNemar's (1947) test. This study does not provide evidence that the SCF contains non-redundant information when used in a bankruptcy prediction model.

While the three models developed in this study were not found to be significantly better or worse predictors of failure than prior accrual-only models, the results suggest the SCF has information content and cash flow ratios can be used to predict failed vs. non-failed firms.

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CHAPTER I

INTRODUCTION

This study considers whether cash flow information can be used as a predictor of business failure. As such, it is an expansion of the stream of literature questioning whether accounting information in the required statement of cash flows (SCF) has information content, i.e., can this accounting information predict failed vs. non-failed firms.

Sufficient cash flow is critical for a firm's health. Traditionally, a failed firm was cash deficient and unable to pay creditors in a timely manner. Firms can survive a loss of earnings more easily than they can survive a loss of cash flow (Standard & Poor's, 1998). Largay & Stickney (1980), Gentry, Newbold, & Whitford (1985b) and Rujoub, Cook, & Hay (1995) suggested that inadequate levels of cash may endanger a firm or cause the firm to fail.

In this study, failure is defined as filing for federal bankruptcy protection. Although there are other causes for seeking bankruptcy protection besides a cash shortage, i.e., protection from product liability lawsuits, numerous studies used a filing for bankruptcy to identify failed firms (Altman, 1968; Deakin, 1977; Ohlson, 1980; Rose & Giroux, 1984; Casey & Bartczak, 1985; McGurr, 1996).

If cash flow ratios can be shown to predict business failure, then the underlying accounting data used to derive the ratios have value relevance and could be used to avoid failure.

Rationale for the Study

Each year thousands of businesses cease operations for various reasons. In 1996, 71,811 firms failed, resulting in some loss to creditors (Dun & Bradstreet, 1997). In the year ended September 30, 1997, 121 companies that filed with the Securities and Exchange Commission (SEC) sought Chapter 11 federal bankruptcy protection[1]. A business failure often has significant, negative consequences for many parties including creditors, investors, employees, customers, auditors, taxing bodies, and the community at large. All of these groups could benefit from knowledge of why firms fail or which firms are more likely to fail than others.

Both the retail/wholesale and manufacturing industries are important to the U.S. economy but are particularly vulnerable to failure. The retail/wholesale industry employed 23.5% of the non-agricultural workforce and contributed $1.18 trillion to the national economy in 1996 (Office of the President, 1998). While this represents 15.5% of 1996 gross domestic product (GDP), retail/wholesale firms accounted for 24.2% of 1996 business failures, a rate of 71 per 10,000 firms (Dun & Bradstreet, 1997). Manufacturing firms accounted for $1.3 trillion or 17.4% of GDP and employ 15.1% of the workforce in 1996 (Office of the President, 1998). Although manufacturing firms accounted for only 5.7% of the number of failures, their failure rate was 82 per 10,000 firms. (Dun & Bradstreet, 1997)

Numerous researchers have predicted business failure from accounting information using financial ratios (Zavgren, 1983; Jones, 1987). Many considered only accrual oriented variables. Most of the studies which considered the value-relevance of cash flow ratios used an estimate for cash flow since the reporting of cash flow was not required before 1988 (FASB, 1987). Some researchers have suggested these estimates of cash flow used in earlier studies were poor proxies for actual cash flow (Mitchell, Goh, & Forman, 1995; Ward, 1995; Cheng, Liu, & Schaefer, 1997). The few that used reported cash flow failed to

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[1]This list was obtained from the SEC under the Freedom of Information Act.

control for the failed firms' industry. This study considers the ability of ratios developed from reported cash flow to predict failure in the retail/wholesale and manufacturing industries.

Background

In order to prepare a set of financial statements in accordance with generally accepted accounting principles, four financial statements must be presented: (1) a balance sheet; (2) an income statement; (3) a statement of retained earnings; and (4) a statement of cash flows (SCF) (FASB, 1987; 1997). Statement of Financial Accounting Standard (SFAS) No. 95 required the presentation of a SCF for years ending after July 15, 1988 (FASB, 1987). The SCF replaced the statement of changes in financial position which had been required since 1971 by Accounting Principle Board Opinion No. 19 (AICPA, 1971).

The statement of changes in financial position required the presentation of "funds" but allowed funds to be variously defined as cash, cash plus temporary investments, quick assets, or working capital (AICPA, 1971). This latitude made comparisons over time and across firms difficult (Drtina & Largay, 1985). In Statement of Financial Accounting Concept (SFAC) No. 5, the Financial Accounting Standards Board (FASB) (1984) recommended the presentation of cash receipts and payments classified by major sources and uses as well as a narrower definition of funds. Such presentation is now required by SFAS No. 95. The standard requires the presentation of cash or cash equivalents, defined as short-term, highly liquid investments. The standard also requires the separation of cash flows into the areas of operating, investing, and financing activities.

Ratio Analysis

Financial ratios are derived from data presented in the financial statements to establish "useful information". Ratios have long been used to evaluate the credit worthiness and other aspects of a firm's financial and operating health, predict business failure, determine bond ratings, and evaluate stock price (Aksu, Eckstein, Greene, & Ronen, 1996). One advantage of ratios is their ability to clearly show relationships among data over time within the same firm and compared to other firms or to industry averages. Ratio analysis is an accepted way of presenting information which has been adjusted for differences in dollar magnitude.

Since any two numbers can be combined to form a ratio, it is important to know which financial ratios to consider in an analysis since there are so many to choose from. Using factor analysis several authors found that a few ratios can often convey the information contained in a much larger group of ratios (Pinches, Mingo, & Caruthers, 1973). Altman (1968) and others have developed models which use ratios and other financial and operating information to predict business failure.

Information Content of Cash Flow Information

SFAC No. 1 (FASB, 1978) stated that accrual net income "generally provides a better indication of enterprise performance than information about current cash receipts and payments" (par. 44). SFAC No. 5 (FASB, 1984) stated that net income figures "usually provide a better basis for assessing future cash flow prospects of an entity than do cash flow statements alone" (par. 24c). Several studies challenged these FASB assertions and considered to what extent cash flow ratios capture unique financial characteristics of a firm. Those few studies which used post-SFAS No. 95 data used reported cash flow. Most used pre-SFAS No. 95 data and were forced to use estimates of cash flow. Cheng et al. (1997) and others concluded these estimates were poor proxies for actual cash flow. The present study uses ratios developed from cash flow from operating, investing, and financing activities as reported in the SCF.

Industry Issues

Most business failure prediction studies have not been industry specific. The studies by Beaver (1966), Ohlson (1980), and Flagg, Giroux, & Wiggins (1991) excluded utilities, transportation, and financial services firms from their samples of industrial firms. These were excluded because their regulatory environment made it difficult to compare their financial ratios with those of unregulated industries. Altman (1968) originally considered only manufacturing firms but added retail firms in a later study (Altman, Haldeman, & Narayanan, 1977). Deakin (1972, 1977), Blum (1974), Rose & Giroux (1984), and Casey & Bartczak (1984) considered all firms listed on the Compustat industrial file. Zavgren (1985) used only manufacturing firms, McGurr (1996) only retail, and Gombola, Haskins, Ketz, & Williams (1987) used both. Neither Altman et al. (1977) nor Gombola et al. (1987) separately analyzed the retail and manufacturing firms. Fulmer, Moon, Gavin, & Erwin (1984), Gentry, Newbold, & Whitford (1985a, 1985b), Dambolena & Shulman (1988), Bukovinsky (1993), and Rujoub et al. (1995) used all industries; Gilbert, Menon, & Schwartz (1990) and Ward (1994) excluded financial firms.

Platt & Platt (1990, 1991) considered all industries but adjusted their variables by using industry-relative ratios and concluded that such an adjustment improved classification accuracy. Gombola & Ketz (1983c), Ketz, Doogar, & Jensen (1990), and McGurr (1996) suggested that ratios for retail and manufacturing firms were sufficiently different to warrant separate consideration. On the other hand, Johnson (1978), Giacomino & Mielke (1993), and Bukovinsky (1993) suggested that ratio patterns are quite stable across industries and little is gained by separate industry analysis.

Base Theory

This dissertation is based upon the theory of ratio analysis developed by Beaver (1966) in which he "viewed the firm as a reservoir of liquid assets" (p. 80). If indicators are negative, failure should follow. "Four concepts are important in drawing the relationship between the liquid-asset-flow model and the ratios" (p. 80). The probability of failure is greater (1) the smaller the reservoir, (2) the smaller the net cash flow over time, (3) the greater the amount of debt, and (4) the greater the fund expenditures for operations. The thirty ratios he analyzed had to meet one of three criteria to be selected, one of which was "that the ratio be defined in terms of a cash-flow concept" (p. 79). Beaver (1966) found the ratio of cash flow divided by total debt was the single best predictor of failure. Cash flow was defined as net income plus depreciation, depletion, and amortization (NIPD).

Altman (1968) significantly expanded on Beaver's univariate approach. He found that a multivariate combination of five specific ratios provided the greatest degree of accuracy in predicting business failure. None, however, involved cash flow. Numerous other studies followed. Some of the studies found cash flow to be a significant predictor of failure, some did not, while others did not consider cash flow (see Table 1). At the same time, several other studies discussed the difficulty in estimating cash flow from operations (CFFO), calling into question results based on those estimated amounts (Drtina & Largay, 1985; Gombola et al., 1987; and Bahnson, Miller, & Budge, 1996).

Wilcox (1971, 1976) used a "gambler's ruin" approach to failure prediction which considered liquidation value and the variability of cash flow. It assumed a firm had no access to capital markets and must sell assets to meet losses. At the other extreme, Scott (1976) developed a theory of financial distress and proposed a model based on perfect access to capital markets. Scott (1981) proposed a model which allowed for imperfect access to capital markets and compared four theoretically-derived predictors of failure. While theories of failure prediction are not as well developed as theories used in other areas of accounting (Ohlson, 1980), the attempts by Wilcox (1971, 1976) and Scott (1976, 1981) represent efforts to understand business failure rather than to merely predict it.

Table 1

Use of Cash Flow in Various Studies

Study	Cash Flow In model	Cash Flow Significant
Beaver, 1966	Yes	Yes
Altman, 1968	No	n/a
Deakin, 1972	Yes	Yes
Edmister, 1972	No	n/a
Blum, 1974	Yes	Yes
Ohlson, 1980	No	n/a
Largay & Stickney, 1980	Yes	Yes
Gombola & Ketz, 1983a	Yes	Yes
Zmijewski, 1984	No	n/a
Casey & Bartczak, 1985	Yes	No
Gentry, Newbold, & Whitford, 1985b	Yes	No
Zavgren, 1985	No	n/a
Gombola, Haskins, Ketz, Williams, 1987	Yes	No
Platt & Platt, 1990	Yes	Yes
Bukovinsky, 1993	Yes	No
Ward, 1994	Yes	Yes
Zeller & Stanko, 1994a	Yes	No
Rujoub, Cook, & Hay, 1995	Yes	Yes
Kane, Richardson, & Graybeal, 1996	No	n/a
McGurr, 1996	No	n/a

Statement of Hypotheses

The purpose of this study is to determine if accounting information in the form of cash flow ratios derived from the required SCF has information content. If cash flow ratios can be used to predict failed vs. non-failed firms, then the SCF has information content.

The following six hypotheses are tested. The first three research and null hypotheses relate to development of cash flow and accrual models; research and null hypotheses 4-6 compare the cash and accrual models developed in testing H1, H2, and H3 to previously developed accrual-only models.

Research and Null Hypotheses 1-3

H1: Cash flow ratios, when included in a multivariate discriminant model and when measured by the means of the z score produced by multiple discriminant analysis (MDA), can be used to predict failed vs. non-failed firms in the retail/wholesale industry.

$H_0$1: Cash flow ratios, when included in a multivariate discriminant model and when measured by the means of the z score produced by MDA, are not able to predict failed vs. non-failed firms in the retail/wholesale industry.

H2: Cash flow ratios, when included in a multivariate discriminant model and when measured by the means of the z score produced by MDA, can be used to predict failed vs. non-failed firms in the manufacturing industry.

$H_0$2: Cash flow ratios, when included in a multivariate discriminant model and when measured by the means of the z score produced by MDA, are not able to predict failed vs. non-failed firms in the manufacturing industry.

H3: Cash flow ratios, when included in a multivariate discriminant model and when measured by the means of the z score produced by MDA, can be used to predict failed vs. non-failed firms in the retail/wholesale and manufacturing industries combined.

$H_0 3$: Cash flow ratios, when included in a multivariate discriminant model and when measured by the means of the z score produced by MDA, are not able to predict failed vs. non-failed firms in the retail/wholesale and manufacturing industries combined.

These hypotheses are tested to evaluate if models can be developed using a combination of cash flow and accrual ratios which are useful in predicting failed vs. non-failed firms in the retail/wholesale industry, the manufacturing industry, and in the two industries combined. Development of such models would indicate the SCF has information content.

Research and Null Hypotheses 4-6

H4: Cash flow ratios, when included in a multivariate discriminant model and when measured by the percentage of correct predictions of failed vs. non-failed firms by the model developed in H1 for the retail/wholesale industry, are more accurate than accrual ratios in predicting failed vs. non-failed firms.

$H_0 4$: Cash flow ratios, when included in a multivariate discriminant model and when measured by the percentage of correct predictions of failed vs. non-failed firms by the model developed in H1 for the retail/wholesale industry, are less accurate than or equally as accurate as accrual ratios in predicting failed vs. non-failed firms.

H5: Cash flow ratios, when included in a multivariate discriminant model and when measured by the percentage of correct predictions of failed vs. non-failed firms by the model developed in H2 for the manufacturing industry, are more accurate than accrual ratios in predicting failed vs. non-failed firms.

$H_0 5$: Cash flow ratios, when included in a multivariate discriminant model and when measured by the percentage of correct predictions of failed vs. non-failed firms by the model developed in H2 for the manufacturing industry, are less accurate than or equally as accurate as accrual ratios in predicting failed vs. non-failed firms.

H6: Cash flow ratios, when included in a multivariate discriminant model and when measured by the percentage of correct predictions of failed vs. non-failed firms by the model developed in H3 for the retail/wholesale and manufacturing industries combined, are more accurate than accrual ratios in predicting failed vs. non-failed firms.

$H_0$6: Cash flow ratios, when included in a multivariate discriminant model and when measured by the percentage of correct predictions of failed vs. non-failed firms by the model developed in H3 for the retail/wholesale and manufacturing industries combined, are less accurate than or equally as accurate as accrual ratios in predicting failed vs. non-failed firms.

These hypotheses are tested to determine if cash flow and accrual oriented models developed in this study are better predictors of failure than previously developed models. More accurate prediction by the cash flow and accrual models would indicate the SCF has non-redundant information.

Overview of the Methodology

Public companies in the retail, wholesale, and manufacturing industries that have filed for bankruptcy during the period 1990-1997, excluding restaurants, are selected. A non-failed group, matched by size, industry, and year, is also selected. Separate retail/wholesale, manufacturing, and mixed industry failure prediction models are developed. Prior accrual oriented models are replicated using current data. Classification accuracies are compared to determine the significance, if any, of cash flow ratios as predictors of failure.

Organization of Study

The next chapter presents a review of the literature on ratios, cash flow, and failure prediction. Chapter 3 presents the methodology.

Chapter 4 presents the analysis and presentation of the findings and chapter 5 presents a summary, conclusions, limitations, and suggestions for future research.

CHAPTER II

LITERATURE REVIEW

The focus of this study is business failure prediction using ratios derived from financial statement data, particularly the statement of cash flows. But there are many studies which consider the tools (i.e., ratios and absolute amounts) or the data (i.e., financial and non-financial, cash flow and accrual) used in business failure prediction studies without directly considering the issue of failure. These are classified here as background studies.

In order to understand the use of financial ratios in business failure studies, this review first considers four areas of background studies. The first considers the general use of ratios in financial analysis. The second considers the value of cash flow accounting information. The third focuses on the recent development of cash flow ratios. The fourth includes factor-analytic studies, a statistical technique that can largely reduce the number of variables needed for consideration with only a small loss of information. Once this background is established, numerous business failure prediction studies are considered.

The Use of Ratios in Financial Analysis

Horrigan (1968) traced the first use of financial ratios to the 1890's when the volume and availability of financial information increased greatly. Elam (1975) cited studies from 1932-1942 which used ratio trends as indicators of failure. Walter (1957) encouraged the use of ratios for financial analysis and the determination of technical solvency. He was critical of the traditional approach which focused on the current and quick ratios to determine a firm's ability to pay and suggested that cash flow be considered.

Horrigan (1965) suggested the use of 17 ratios categorized by liquidity and profitability for the analysis of financial statements. He concluded financial ratios tended to be approximately normally distributed, a required attribute of some prediction models.

Deakin (1976), on the other hand, concluded most ratios are not normally distributed and that while ratios are good for decision making, a company's specific industry needed to be considered. He found some indication that ratios might be normally distributed within certain industries. He also suggested that normality might be achieved if the ratios were transformed.

Many other researchers considered whether ratios were normally distributed. It is an important question because many failure prediction studies use multiple discriminant analysis (MDA) as the statistical technique. Key assumptions of MDA are that the independent variables (e.g., ratios) exhibit a normal distribution and that the groups defined by the dependent variable (e.g., failed or non-failed) have unknown, but equal, dispersion and covariance structures, or matrices (Hair, Anderson, Tatham, & Black 1995, p.196). Johnson (1970) criticized the early failure prediction work of Beaver (1966) and Altman (1968) based on the argument that ratios are not normally distributed.

Ezzamel, Mar-Molinero, & Beecher (1987) looked at financial ratios for three industry groups and a mixed sample and found most ratios not to be normally distributed because of the presence of skewness and extreme outliers. The ratios for the retail food industry were most different compared to other industrial classifications.

Hopwood, McKeown, & Mutchler (1988) investigated the impact of non-normality in the application of MDA and also in logit and probit, the two other most common statistical techniques used in failure prediction studies. Classification accuracy of their model was improved by removing outliers and then applying square root transformations.

Gribbin, Lau, & Lau (1996) also concluded that financial ratios are not normally distributed but often exhibit a stable-Paretian or, sometimes, a Pearson distribution. Therefore, they concluded that outliers are legitimate and necessary members of the main population and should not be eliminated. Barnes (1987) presents a review of the analysis and use of financial ratio literature.

The Value of Cash Flow Accounting Information

Lee (1972) believed that information about past and future business activity measured on a cash basis should be provided because it was useful to financial statement users. Lee (1978) also stated the use of cash flow accounting would simplify the financial statements by requiring less disclosure, avoiding the complexities of accruals, and making them easier for potential users to understand.

Govindarajan & Shank (1984) suggested traditional strategic growth models do not place enough emphasis on cash sufficiency. The authors presented a sustainable growth model that focused on cash provided by operations.

Rock (1989) suggested using cash flow to guide stock investment strategies. She argued traditional measures of book value and the price/earnings ratio are subject to manipulation. Generally accepted accounting principles permit many alternative methods of calculation and presentation. She proposed using free cash flow, which considered capital expenditures and preferred dividends, as a more accurate measure of a stock's true worth.

From a survey of over 2,300 shareholders, Epstein & Pava (1992) concluded that investors were placing more emphasis on cash flow information compared to the results of a 1973 study by one of the authors. "Investors have refocused. Cash is king" (p. 54). They suggested that this increased emphasis on cash flow is the result of the deterioration in the credibility of the net income figure; investors rely less on net income as a measure of performance.

Deriving Cash Flow From Operations (CFFO)

Cash flow was found to be a significant variable in several early failure prediction studies (see Table 1). But U. S. firms were not required to report cash flow information until 1988 with the issuance of SFAS No. 95 (FASB 1987). Several authors considered whether the variables used to measure cash flow in pre-SFAS No. 95 studies were valid proxies.

Before SFAS No. 95, many analysts and researchers (Beaver, 1966; Deakin, 1972; Blum, 1974) used the sum of net income plus depreciation, amortization, and depletion (NIPD) as a measure of cash flow. However, Gombola & Ketz (1981a, 1981b) and Ketz & Kochanek (1982) found neither NIPD nor working capital from operations (WCFO) to be suitable proxies for cash flow from operations (CFFO) because of the material effects of accruals and deferrals other than depreciation.

WCFO could be derived from the statement of changes in financial position (SCFP). The SCFP was a required financial statement from 1981 until 1988 when it was replaced by the statement of cash flows (SCF). Both Drtina & Largay (1985) and Kochanek & Norgaard (1987) documented the difficulty in calculating CFFO from the SCFP by making adjustments to WCFO and cautioned that WCFO was a poor substitute for CFFO.

In an attempt to refine WCFO, Bowen, Burgstahler, & Daley (1986, 1987) adjusted WCFO for changes in all current accounts except cash to arrive at CFFO. They found little correlation between NIPD or WCFO and CFFO. Also, NIPD and WCFO were more highly correlated with accrual net income than was CFFO.

Schaeffer & Kennelley (1986) compared the incremental ability of three alternative measures of CFFO to explain changes in equity share prices. The three measures were: (1) NIPD; (2) NIPD adjusted for changes in current accounts except cash ($WCFO_1$); and (3) $WCFO_2$ calculated like $WCFO_1$ except that changes in the current maturity of long-term debt were ignored. They found none of the three definitions consistently outperformed the others and concluded that refining the cash flow definition provides no additional information over the crude NIPD estimation.

Franz & Thies (1988) studied financial statement data for a 13 year and a 19 year period and found that WCFO was more closely associated with accrual net income than CFFO and therefore WCFO was not a good proxy for CFFO. WCFO and CFFO were found to be less and less related over the 19 years studied. Factors cited as possible causes for this divergence between WCFO and CFFO included inflation, a movement to the last-in, first-out method of reporting for inventories, periods of business expansion and contraction, and the promulgation of numerous accounting principles which increased the difference between accrual net income and cash flow. These included standards on pensions, interperiod income tax allocation, goodwill in business combinations, intangible assets, the equity investment method, and others which had the effect, under the "all-inclusive" concept, of recognizing in income items which had no current cash flow effect.

Some researchers have considered the ability of cash flow information to predict future cash flow. These studies used pre-SFAS No. 95 information and, therefore, used estimates of CFFO. Greenberg, Johnson, & Ramesh (1986) found that accrual income was a better predictor of future cash flow than was current cash flow. Income was defined as income before extraordinary items and discontinued operations. Finger (1994) used the same definitions for earnings and cash flow as Greenberg et al. (1986) but concluded that current cash flow was a better predictor of future cash flow than earnings in the short-term (one year) and equally as good in the longer term (four to eight years).

Cheng et al. (1997) used post-SFAS No. 95 cash flow data to study the difference between reported CFFO and an estimate of CFFO. The estimate of CFFO was calculated by adjusting NIPD for changes in current accounts and plant asset gains and losses. Using unexpected security returns as a measure of the value of specific accounting measures, they found both earnings and reported CFFO provided incremental value-relevance. Even estimated CFFO had incremental information content (when compared to earnings alone), but not as much as reported CFFO. They concluded that reported CFFO in the SCF provides information above and beyond what can be derived from earnings and estimated CFFO alone.

Decomposing Cash Flow

SFAS No. 95 requires cash flow to be divided into operating, investing, and financing activities. These three are further refined into their specific components, for example, for operations - cash collected from customers and cash paid to suppliers; for investing activities - cash paid or received for buying or selling plant and equipment; for financing activities - cash received from the issuance of long-term debt, common stock, or preferred stock and cash paid for dividends. (FASB, 1987).

Studies reviewed thus far considered only cash flow from operations (CFFO). Livnat & Zarowin (1990) examined investing and financing activities in addition to CFFO and considered the components of all three. Since the authors used pre-SFAS No. 95 data, these amounts were estimated.

Usefulness of the components was measured by their association with security returns. Results indicated that the components of operating cash flow were strongly associated and financing components were weakly associated with security returns. The individual components of investing cash flow were less significant. The authors concluded that decomposing cash flow yields incremental information.

In a more theoretical analysis, Ward (1995) presented a six stage financial distress model. He suggested investing and financing cash flow from the SCF are just as important in assessing distress as CFFO. Companies in distress are more likely to have gross inflows from investing activities (sales of plant assets or investments).

Summary of the Value of Cash Flow Accounting Information

The value of cash flow accounting information has long been maintained (Lee, 1972; 1978). SFAC No. 1 (FASB, 1978) stated that providing investors and creditors with information to help assess the timing, accuracy, and uncertainty of prospective net cash inflows was one of the objectives of financial reporting. SFAC No. 5 (FASB, 1984) recommended the preparation of a statement of cash flows and SFAS No. 95 (FASB, 1987) required it. Several studies, beginning with Beaver (1966), used NIPD or WCFO as a proxy for CFFO. Others (Gombola & Ketz, 1981a, 1981b; Ketz & Kochanek, 1982; Bowen et al., 1986, 1987) found both NIPD and WCFO to be poor surrogates for CFFO. Studies which used post-SFAS No. 95 data (Ward, 1995; Cheng et al., 1997) concluded that data provided by the SCF was superior to pre-SFAS No. 95 data. Neill, Schaefer, Bahnson, & Bradbury (1991) presented a review of the literature regarding the usefulness of cash flow data.

The Development of Cash Flow Ratios

Several studies explored the use of ratios developed from the SCF. Figlewicz & Zeller (1991) derived three performance, four liquidity and coverage, and four investing and financing ratios for financial analysis. Carslaw & Mills (1991) identified eleven different ratios, all based on CFFO, for analyzing a firm's financial strength and profitability. They recommended three cash coverage, two quality of income, two capital expenditure, and four cash flow return ratios for financial analysis.

Giacomino and Mielke (1993) derived nine different cash flow ratios for analyzing financial statements. They offered six sufficiency and three efficiency ratios using CFFO. Calculating the ratios for the three years 1986-1988 for the electronics, food, and chemical industries the authors concluded the ratios did not exhibit significant differences between industries.

Berton (1994) described cash flow adequacy, a measure of a firm's earnings available to meet future debt obligations after paying for capital expenditures, interest, and taxes. Wise (1994) described a weighting scheme based on industry-specific cash flow risk factors which were used to determine the certainty and stability of cash flow.

Until the issuance of SFAS 117 (FASB, 1993), hospitals and other not-for-profit companies were not required to prepare a statement of cash flows. Zeller, Stanko, & Cleverley (1996) suggested five CFFO ratios: two sufficiency ratios - to assess a hospital's ability to fund future operations and repay long-term debt; and three efficiency ratios - to measure cash recovery from operations. The ratios considered features unique to hospitals.

While several cash flow ratios have been proposed, there is no consensus on which ones are most useful for financial analysis.

<u>Factor-Analytic Studies</u>

Factor analysis identifies similarities in the basic construct of a set of variables. It permits reduction of the variable space to a smaller number of factors. The factors contain much of the information in the original data set. In other words, a large number of variables can be reduced to a smaller number while still explaining most of the variance (Hair et al., 1995). The variable with the highest correlation (factor loading) within each factor (dimension) can then be used to represent this dimension (Chen & Shimerda, 1981). Several factor-analytic studies attempted to identify the set of financial ratios which would best describe a firm's activities.

Pinches, Mingo, & Caruthers (1973)

Pinches et al. (1973) developed an empirically based classification of financial ratios. Using factor analysis and the Standard and Poor's Compustat database from 1951, 1957, 1963, and 1969 for 221 industrial firms they concluded that 48 financial ratios loaded on seven distinct factors. The seven factors represented between 87% and

92% of the information contained in the original 48 ratios. The following seven factors patterns were identified: (1) return on investment; (2) capital intensiveness; (3) inventory intensiveness; (4) financial leverage; (5) receivables intensiveness; (6) short-term liquidity; and (7) cash position.

Cash position emerged as a separate factor, distinct from short-term liquidity. Also, of the four cash flow variables, three loaded on the return on investment factor and one on capital intensiveness. Cash flow was defined as NIPD plus non-recurring items. As discussed above, several authors (Gombola & Ketz, 1981a; Bowen et al., 1986; Schaeffer & Kennelley, 1986) have shown this to be a poor proxy for CFFO.

Pinches, Eubank, Mingo, & Caruthers (1975)

Using a similar approach to Pinches et al. (1973) and more current data, Pinches, Eubank, Mingo, and Caruthers (1975) found the same seven factors exhibited short-term stability over the period 1966-1969. They suggested a hierarchy for analysis composed of three second-order factors: (1) return on invested capital, made up of the return on investment and financial leverage factors; (2) overall liquidity, comprised of the capital turnover, short-term liquidity, and cash position factors; and (3) short-term capital turnover, made up of the inventory and receivable turnover factors. "A few carefully chosen financial ratios could then be selected which would represent virtually all the different aspects of a firm's operations" yet are independent of each other (p. 306).

In this study, eight of the original 48 ratios did not load on any of the seven factors including cash flow/total debt, the ratio Beaver (1966) identified as the "best" univariate predictor of failure. The authors suggested that ratios excluded from the seven factors, but found to be useful in prior studies, may still be useful in future failure (and other) prediction studies.

Johnson (1978)

Johnson (1978) used factor analysis to replicate the study of Pinches et al. (1973) using 306 industrial and manufacturing and 159 retail firms. He analyzed 61 ratios. In addition to the seven factors identified by Pinches et al. (1973) an eighth, decompositional and ninth factor entitled "loose ends", which included cash flow/net worth, were identified. The factors accounted for 86% of the industrial and manufacturing group's and 87% of the retail group's variance in the original data. The author concluded that his study and that of Pinches et al. (1973), taken together, indicate that meaningful empirically-based classifications of financial ratios can be determined and the composition of these groups is reasonably stable across industry classification and over time.

Gombola & Ketz (1983a, 1983b, 1983c)

Gombola & Ketz (1983a) used factor analysis to consider the impact of cash flow measurement on classification patterns of financial ratios. The study used 40 ratios from 119 firms from Compustat for the period 1962-1980. Almost all of the ratios included either net income (NI), NIPD, WCFO, or CFFO. CFFO was defined as WCFO adjusted for all changes in current accounts except cash, short-term debt, and short-term marketable securities. The seven factors reported by Pinches et al. (1973) were observed but the authors found the cash flow ratios loaded on a separate and distinct eighth factor. This separate cash flow factor was not captured by any other ratio group.

While the NIPD and WCFO ratios were highly correlated, those based on CFFO were only moderately correlated with NIPD or WCFO. The authors concluded that using NIPD or WCFO as a surrogate for CFFO is inappropriate.

In another study (1983b) the authors analyzed seven variables for 597 firms from Compustat for the period 1960-1977. The seven were: (1) NI, (2) operating income, (3) NIPD, (4) operating income plus depreciation, (5) WCFO, (6) quick flow from operations (QFFO), and (7) CFFO. A correlation matrix revealed that the first five were all correlated above .85. The last two, QFFO and CFFO, were not highly correlated to the first five but to each other at .856. The authors concluded that NIPD, while often used as a measure of solvency, is more accurately considered a measure of profitability and that the results support the view that NIPD is not a surrogate for CFFO.

In a further study, Gombola & Ketz (1983c) considered the cross-sectional factor stability between retail and manufacturing firms. They concluded the structure of financial ratios does differ between the two. Ratios for retail and manufacturing firms were sufficiently different to warrant separate consideration.

Ketz, Doogar, & Jensen (1990)

Perhaps the most exhaustive factor-analytic study was by Ketz, Doogar, and Jensen (1990). They found 32 financial ratios loaded on seven factors which explained between 89% and 92% of overall variance. Their study looked at seven industries and concluded the seven factors were stable across industries for the period 1978-1987.

The seven factors were: (1) return; (2) inventory; (3) liquidity; (4) cash flow; (5) cash position; (6) sales; and (7) debt. Compared to the factors identified by Pinches et al. (1973) this study identified a separate cash flow factor. Cash flow variables were primarily included in Pinches et al.'s return on investment factor. Pinches et al. also showed a separate receivables intensiveness factor. Ketz et al. found the ratios to be stable not only across time for the economy as a whole but for each of the seven industries examined. With the exception of the retail industry, their "findings indicate a very high degree of comparability across industries" (p.15).

Stanko & Zeller (1993) and Zeller & Stanko (1994a, 1994b)

In a study of the transportation manufacturing industry, Stanko &

Zeller (1993) used factor analysis on 34 ratios including four which utilized CFFO from the SCF. As with Ketz et al. (1990), a unique cash flow factor was identified.

Zeller & Stanko performed factor analysis on 36 ratios of manufacturing (1994a) and retail (1994b) firms for the years 1988-1991. Contrary to the earlier findings of Gombola & Ketz (1983a) and others, the cash flow ratios did not load on a separate factor but loaded with other accrual return ratios. The accrual return ratios and the cash flow ratios appeared to measure the same operating characteristics of a firm's activities. The authors surmised that results of earlier studies showing a separate cash flow factor were the result of confounding introduced by having to estimate CFFO from the statement of changes in financial position. Cash flow ratios did not load with the traditional measures of liquidity - the current ratio and the quick ratio. The authors concluded that ratios based on CFFO provide unique insight into a firm's ability to pay its debts as they come due.

Summary of Factor-Analytic Studies

Theoretically, there is an unlimited number of ratios which can be used when analyzing a firm's financial statements. Factor analysis has been used to reduce that set of ratios to a manageable number. While cash flow appeared as a separate factor in some studies, it did not in others. No guiding theory has emerged. The determination of the most useful ratios seems to be dependent upon the time period studied and the initial set of ratios considered.

Numerous failure prediction studies were conducted beginning in the 1960s. These have been grouped into the following categories: (1) univariate; (2) multivariate accrual oriented; (3) cash flow oriented; (4) international; and (5) other.

Univariate Failure Studies

The first studies to consider the use financial ratios as predictors of business failure attempted to identify a single ratio with predictive ability.

Beaver (1966)

Beaver's (1966) work is considered the beginning of the modern, statistical oriented work using ratios as predictors of business failure. He sought to verify the usefulness of accounting data and defined usefulness as predictive ability. While most recent studies define business failure as the filing for bankruptcy protection, Beaver considered bankruptcy, nonpayment of preferred stock dividends, bond default, or an overdrawn bank account as evidence of failure.

Using Moody's Industrial Manual and a list of failed companies from Dun & Bradstreet, Beaver selected 79 firms which failed between 1954-1964 for which financial statement data could be obtained for the first year before failure. Five years of data were used, where available. A sample of 79 non-failed firms was pair-matched based on the company's three-digit SIC code and asset size. All were publicly owned, industrial (manufacturing and non-manufacturing) corporations excluding public utilities, transportation companies, and financial institutions.

Dichotomous (failed or non-failed) classification tests were performed using thirty ratios. The ratios were picked based on popularity in the literature, performance in prior studies, and whether the ratio was defined in terms of a cash flow concept. Cash flow was defined as net income plus depreciation, depletion, and amortization (NIPD). The ratios were classified into six "common element" categories: (1) cash flow; (2) net income; (3) debt to total assets; (4) liquid assets to total assets; (5) liquid assets to current debt; and (6) turnover.

For each of the thirty ratios, the ratio values were arrayed in ascending order and a cutoff point that minimized the percent of incorrect prediction was visually selected. The ratio with the lowest percentage error in each of the six groups was selected. In descending order of accuracy these ratios were: (1) cash flow/total debt; (2) net income/total assets, (3) total debt/total assets, (4) the current ratio (current assets/current liabilities), (5) no-credit interval (quick assets - current liabilities/fund expenditures for operations); and (6) working capital/total assets. Ratio values of non-failed firms were quite stable throughout the five years before failure whereas the ratio values of failed firms exhibited a marked deterioration.

The best predictor ratio, cash flow/total debt, was 87% accurate one year prior to failure. Accuracy dropped to 78% in the fifth year before failure. The other ratios had first year accuracy rates between 76% and 87% and fifth year rates between 55% and 82%. Type I and Type II errors were also compared[2]. The chance of a Type I error was about four times greater than a Type II error in the first or second year before failure. This disparity grew to ten to one in the fourth and fifth years. Despite the deterioration in predictive accuracy moving from one to five years before failure, Beaver concluded ratio analysis was useful for at least five years before failure.

Beaver (1968)

Using the data from the study cited above, Beaver (1968) examined the predictive ability of 14 ratios. He found cash position ratios performed better as predictors of failure than the more commonly used current or quick ratios. One explanation offered was that while failed firms may have less cash, they tend to have more receivables. Measures

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[2]Throughout this study a Type I error refers to classifying a firm as non-failed when, in fact, it has failed. A Type II error refers to misclassifying a non-failed firm. Only Flagg et al. (1991) and Edmister (1972) reversed the definitions. All other authors reviewed in this study considered misclassifying a failed firm as a Type I error.

like the current and quick ratios which add cash and receivables together tend to obscure the differences between failed and non-failed firms. Beaver also suggested that failing firms may intentionally window dress the financial ratios which are most likely to be used to assess liquidity.

Beaver's univariate analyses examined the predictive ability of each ratio singularly. Although subsequent studies used a multivariate approach, they often adopted Beaver's design and methodology.

Multivariate Accrual Oriented Business Failure Studies

Altman (1968)

Altman (1968) considered univariate ratio analysis potentially confusing and susceptible to faulty interpretation. For example, a univariate analysis of a firm with poor solvency or profitability could indicate potential failure when in fact the firm may be in good condition as evidenced by other ratios. Altman was the first to address this shortcoming by using multivariate analysis and Multiple Discriminant Analysis (MDA). The MDA technique has the advantage of considering an entire profile of characteristics (in this case, ratios) common to relevant firms as well as their interaction. MDA "attempts to derive a linear combination of these characteristics which 'best' discriminates between groups" (Altman 1968, p 592.) MDA determines a set of coefficients which, when applied to the actual ratios for a given company, allows for classification into one of the mutually exclusive groups of failed or non-failed.

Considering only manufacturing firms, Altman selected a sample of 33 corporations which filed for Chapter 10 bankruptcy protection between 1946-1965. He also randomly selected 33 non-failed firms pair-matched on the basis of industry and asset size. Twenty-two ratios were utilized. Most were selected based on popularity in the literature and potential relevancy but a few were created by Altman.

MDA reduced the 22 variables to a five variable combination which best classified the 66 firms into failed and non-failed categories. This reduction in variables was arrived at by: (1) observing the statistical significance of various combinations of variables including the relative contribution of each variable independently, (2) evaluating the inter-correlations between variables, (3) observing the predictive accuracy of the various ratios, and (4) judgment. While not claiming that the process resulted in an optimal solution, Altman arrived at the final discriminant function shown in Table 2.

Table 2

Altman's (1968) Multiple Discriminant Analysis Model

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

where

X_1 = working capital/total assets

X_2 = retained earnings/total assets

X_3 = earnings before interest, taxes/total assets

X_4 = market value of equity/total liabilities

X_5 = sales/total assets

Z = overall index

Note. From "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy" by E. I. Altman, 1968, *Journal of Finance, 22*, p. 594.

The model correctly classified 95% of the firms in the year prior to failure. The type I error rate was 6% and the type II error rate was 3%. Two years prior to failure the error rate rose to 17% (Type I = 28%, Type II = 6%). Error rates increased to 52%, 71%, and 64% in the third, fourth, and fifth years, respectively, prior to failure.

The model was validated by using a secondary sample of 25 failed firms and 66 non-failed but distressed firms. Distressed firms were those reporting a net loss in 1958 and 1961. Only one of the 25 failed firms (4%) was misclassified one year prior to failure. Fourteen, or 22%, of the non-failed but distressed firms were misclassified. The model was further validated by performing five replications on subsets of the original sample of 66 firms as suggested by Frank, Massy, & Morrison (1965). This resulted in error rates of 3%-9% one year prior to failure.

Altman found that firms having an overall index (Z score) greater than 2.99 clearly fell into the "non-failed" category, while all firms with a Z score below 1.81 had filed for bankruptcy. Sample firms with scores between 1.81 and 2.99, called the "zone of ignorance", were susceptible to misclassification. Altman considered a Z score of 2.675 as a practical cutoff point. Altman suggested the model, along with other variables not explicitly considered in the model, could be used to make credit decisions. For example, a loan applicant with a Z score over 3.0 would have little likelihood of default and therefore require less time and effort. Applicants with low Z scores would require a more thorough investigation.

Edmister (1972)

Most failure prediction studies were based on large firm data because the information was publicly available. Since earlier studies considered only large, publicly traded companies, conclusions drawn from those studies could not be generalized to smaller firms.

Edmister (1972) was the first to analyze smaller businesses in a failure prediction study. He drew two samples from recipients of Small Business Administration (SBA) loans during 1954-1969. The smaller sample of 21 failed and 21 non-failed companies included three years of data; a larger sample of 281 failed and 281 non-failed companies contained only one year of data. Failure was defined as loan loss. The non-failed firms were selected randomly with no attempt to pair-match for industry or size.

Edmister selected 19 ratios used in prior studies but was the first to consider the ratio value relative to the industry average, the three-year average of the ratio, the three-year trend of the ratio, and the combination of the industry-relative trend and the industry-relative value of the ratio. All the ratios were converted to dichotomous variables. An individual ratio was assigned a value of one if it was less than the lower quartile for the industry and zero otherwise. Trend dummy variables were created by assigning a one for the expected direction (increasing or decreasing) and zero otherwise.

To limit multicollinearity, no variable was allowed to enter the model if its correlation coefficient with a variable already in the model was greater than .31. The large, one-year sample was split into developmental and validation subsamples. The final MDA model, based on this smaller sample, contained seven variables and is provided in Table 3.

The model achieved an overall classification accuracy of 93% (39 of 42 firms correctly classified). Similar to Altman's (1968) "zone of ignorance", Edmister suggested a "black-gray-white" classification scheme. Only failed firms had a Z score below .47 and no failed firm had a score above .53. It was recommended that lenders using the model consider firms scoring between .47 and .53 as being in the gray area and these firms would require more analysis than those in the black or white areas. This was seen as a more practical alternative to trying to determine the cost of Type I and Type II errors because of the difficulty in estimating the marginal opportunity cost of rejecting a loan to a successful firm and the marginal actual cost of making a loan to a firm that eventually fails.

Edmister found that standardizing the ratios and converting them, and trend variables, to dichotomous variables improved the model. Like Altman (1968) he found that small groups of ratios predict better than any individual ratio. A limitation, noted by Edmister and Joy &

Table 3

Edmister's (1972) Small Firm Multiple Discriminant Analysis Model

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

where

Z = overall index

X_1 = 1 if annual funds flow/current liabilities < .05; 0 otherwise

X_2 = 1 if equity/sales < .07, 0 otherwise

X_3 = 1 if (net working capital/sales)/industry average < -0.02; 0 otherwise

X_4 = 1 if (current liabilities/equity)/industry average < .48; 0 otherwise

X_5 = 1 if (inventory/sales)/industry average < .04 and trends upward; 0 otherwise

X_6 = 1 if quick ratio/industry average < .34 and trends downward; 0 otherwise

X_7 = 1 if quick ratio/industry average trends upward; 0 otherwise

Note. From "An Empirical Test of Financial Ratio Analysis for Small Business Failure Prediction" by R. O. Edmister, 1972, in Journal of Financial and Quantitative Analysis, 7, p. 1487-1488.

Tollefson (1975), is that the samples were drawn from SBA loans granted, presumably a financially healthier group than firms whose loan applications had been rejected. The results are, therefore, not generalizable to all small businesses.

Deakin (1972)

Deakin (1972) attempted to apply Altman's (1968) method of MDA to the 14 ratios used by Beaver (1968) to classify failed and non-failed firms because the method used by Altman had more intuitive appeal.

Defining failure as the filing for bankruptcy protection, insolvency, or liquidation for the benefit of creditors, Deakin selected

32 firms which failed between 1964-1970 and 32 firms pair-matched on the basis of industry, year, and asset size from Moody's Industrial Manual. Five years of data were used for each firm. Deakin was able to replicate Beaver's results using Beaver's univariate analysis method when applied to the 64 firms selected. The ratio cash flow/total debt was again the best single predictor of failure or non-failure.

Deakin then applied MDA to the group of 32 failed firms and a different sample of 32 non-failed firms. In analyzing the scaled vector which indicates the relative contribution of each ratio to the discriminant function, Deakin determined that classification errors increased substantially when variables that only provided a small contribution to the model were eliminated. He argued this would support the use of more, rather than fewer, variables in models used to predict business failure.

Classification error rates were 3.1%, 4.7%, 4.7%, 20.3%, and 17.2% for each of the five years prior to failure. When validated on a sample of eleven failed and 23 non-failed firms, these error rates rose to 22%, 6%, 12%, 23%, and 15%. While some deterioration is expected when applying a statistical test to a population different than that from which the model was drawn, "the deterioration of the first year is rather severe and cannot be explained by the presence of any unusual events peculiar to the sample used" (p. 176).

Blum (1974)

The Failing Company Doctrine is an argument used to justify a merger between two companies even though the merger may result in decreased competition. First formulated by the Supreme Court in 1930, it can be invoked when it is thought that prohibiting a merger will likely result in the failure of one of the companies. The rationale is that more harm would be caused by a company's failure than by a reduction in competition. Blum (1974) developed a "Failing Company Model" to predict failure as defined by the courts, that is, "an inability to pay debts as they come due, entrance into bankruptcy proceeding, or an explicit agreement with creditors to reduce debt" (p. 3). The first courtroom use of the business failure model was in 1976 in United States vs. Black and Decker. The defendant used the model to support its claim that it should be allowed to acquire a company despite the acquisition's potential for reducing competition (Blum, 1977).

Blum (1974) collected three to eight years of data for 115 industrial firms which failed between 1954-1968. Only large firms (liabilities over $1,000,000) were selected since smaller firms are rarely subject to antitrust policy. The 115 were pair-matched on the basis of industry, sales, number of employees, and fiscal year. One-half of the sample was used to develop the model and the other half was used for validation.

Blum used trend variables, a procedure introduced by Edmister (1972). Instead of allowing the MDA procedure to select the variables as Altman (1968) had, Blum selected twelve ratio and trend variables which he felt best measured short-term and long-term liquidity, profitability, and variability of profitability and short-term liquidity.

Since some firms had as few as three years, and some as many as eight years of data, several models were developed. Similar to previous studies, classification accuracy was best one year prior to failure. Models using four and six years of data had 95% predictive accuracy one year before failure. Blum noted that the variable cash flow/total debt was rated among the three most significant ($p < .01$) variables in 17 of the 21 models. Variable coefficients were not reported.

Deakin (1977)

Deakin (1977) expanded his 1972 study in two ways. First he added 31 firms that failed in 1970 and 1971 to his original group of 32 failed firms. Eighty non-failed companies were randomly selected from Moody's Industrial Manual. Deakin did not attempt to pair-match this group on the basis of industry, size or any other criteria believing that such matching, although used in prior studies, could confound the results.

Secondly, he used the five ratios which Libby (1975) had reduced through factor analysis from the original 14 used by both Beaver (1968) and Deakin (1972). Only two years of data were gathered for each firm. The Lachenbruch (1967) hold out method was used to validate the model. Often referred to as the "jackknife" technique, this method validates a developmental sample by holding out one member of the sample and recalculating the model. This is repeated until each member is held out one time. It is particularly useful when samples are too small to be split. MDA was used and the linear model provided in Table 4 was obtained.

Table 4

Deakin's (1977) Multiple Discriminant Analysis Model

$$I = -1.369 + 13.855X_1 + .06X_2 - .601X_3 + .396X_4 + .194X_5$$

where

I = overall index

X_1 = net income/total assets (TA)

X_2 = current assets (CA)/ TA

X_3 = cash/TA

X_4 = CA/current liabilities

X_5 = sales/CA

Note. From "Business Failure Prediction: An Empirical Analysis" by E. B. Deakin, 1977, in E. I. Altman & A. W. Sametz (Eds.) Financial Crises: Institutions and Markets in a Fragile Environment, New York: John Wiley & Sons, p.79.

The model resulted in an overall classification error rate of 5.6% (Type I error = 11.1%; Type II error = 1.2%). In an effort to improve upon the linear classification rule, a quadratic model was also developed which resulted in an overall classification error rate of 16.1% (Type I error = 1.6%; Type II error = 27.5%). The quadratic model resulted in a much higher Type II error. Deakin was unable to resolve the trade-off between the costs of these two errors but suggested applying both models and investigating firms which were classified differently by the two models. Firms classified consistently using both models as either failed or non-failed would not require further analysis.

The adopted classification rule involved applying both the linear and quadratic models. A firm would be classified as failing if both models indicated failure and as non-failing if both models indicated non-failure. If the models were in conflict, further investigation was required. This adopted classification rule was then applied to the entire set of 1,780 companies in the 1971 Compustat file. Two hundred ninety firms were classified as failing. These were tracked for the next 3-1/2 years. Of the 290, 18 failed and another 206 experienced some type of pre-failure event, such as a dividend omission or reduction, default, or a major disposal of assets. A control group of 100 firms classified as non-failing was also tracked for the same period and had a statistically significant ($p < .001$) fewer number of these pre-failure events and no bankruptcies or preferred dividend omissions.

As a further test, Deakin applied the two model classification rule to 47 firms that failed in 1972-1974. Of these, seven fell in the gray area where the two equations yielded different results (needed further investigation), 39 were correctly classified (83%), and one was misclassified as non-failing.

Altman, Haldeman, & Narayanan (1977)

Altman, Haldeman, & Narayanan (1977) updated Altman's 1968 study by creating a new MDA model which they called the ZETA™ model. One major change was to adjust firms' reported data by capitalizing all non-cancelable operating and financing leases. Adjustments were also made to net reserves and minority interest against assets, to consolidate all subsidiaries, and to write off goodwill, intangibles, research and development, and interest which had been capitalized.

Fifty-three failed firms and a matched sample, based on industry and year, of 58 non-failed firms were selected primarily from 1969-1975. Only failed firms where no known fraud was involved were selected. The authors maintained that fraudulent financial data could not be expected to predict failure since it had been deliberately manipulated. Almost half of the firms were retail concerns; the rest were in manufacturing.

Twenty-seven variables were considered for inclusion including several new variables not used in prior studies. Two variables were expressed in logarithmic form "in order to reduce outlier possibilities and to adhere to statistical assumptions" (p. 32). An iterative process reduced the 27 variables to a seven variable model. Since the model is used for proprietary purposes, relative weights were not disclosed. The variables appear in Table 5.

Table 5

Variables Included in Altman, Haldeman, & Narayanan's (1977) MDA Model

X_1 Return on assets	EBIT/total assets (TA)
X_2 Stability of earnings	Standard error of estimate of EBIT/TA for a 10 year trend
X_3 Debt service	EBIT/total interest payments (including capitalized leases and transposed by taking the log 10)
X_4 Cumulative profitability	Retained earnings/TA
X_5 Liquidity	Current assets/current liabilities
X_6 Capitalization	Market value (MV) of common equity/MV of total capital (common and preferred stock, long-term debt, and capitalized leases)
X_7 Size	Log of TA

Note. From "ZETA™ Analysis" by E. I. Altman, R. G. Haldeman, and P. Narayanan, 1977, Journal of Banking and Finance, 1, p. 34-35.

As with Deakin's (1977) study, both linear and quadratic structures were analyzed. Overall accuracy results were essentially equal for the two, but the linear model proved superior in the Lachenbruch (1967) holdout sample, used for validation purposes. For one year to five years prior to failure, classification accuracy ranged from 96.2% to 69.8% for failed firms, 89.7% to 82.1% for non-failed firms, and 92.8% to 76.8% overall.

Altman et al. were also the first to explicitly consider and incorporate estimates of the relative costs of misclassification. Recognizing that the decision-maker's role (auditor, creditor, banker, management) would affect the estimate of costs, the authors surveyed 26 major bank and 33 regional bank officers to estimate Type I and Type II error costs from a commercial bank loan officer's perspective. They estimated Type I error costs as 70% of the amount loaned. Opportunity costs of refusing a loan to a non-failing firm were estimated at 2%. Hence, Type I errors were deemed to be 35 times more costly than Type II errors. Their model, therefore, attempted to minimize Type I errors because of their higher estimated costs.

Ohlson (1980)

Ohlson was the first to use the conditional logit methodology instead of MDA to predict failure. Logit does not require that the predictor variables be normally distributed or that the two groups (failed and non-failed) have equal variance-covariance matrices as does MDA. Also, logit produces a score which represents the probability that a firm will experience failure within a given time period compared to MDA which produces a Z score which is an index score used to predict either failure or non-failure.

The Wall Street Journal Index was used to identify 105 publicly-traded industrial firms which declared Chapter 10 or 11 bankruptcy between 1970-1976. Three years of data were collected from the firms' 10-K reports. Care was taken to ensure that the most recent report used was filed prior to the filing for bankruptcy. The non-failed group was made up of one year's data, also from 1970-1976, for the 2,058 remaining industrial firms on the Compustat file. The year for any given firm was randomly selected. Ohlson's use of a much larger sample of non-failed firms represented an attempt to more closely match the ratio of failed to non-failed firms in the general population.

In selecting variables to include in the analysis, "no attempt was made to select predictors on the basis of rigorous theory. To put it mildly, the state of the art seems to preclude such an approach" (p. 118). Nine variables were selected based on their use in prior literature and simplicity. The variables and their coefficients are found in Table 6.

Four factors were found to be statistically significant: (1) size; (2) the amount of leverage in the financial structure - total liabilities/total assets; (3) a performance measure - NITA; and (4) a measure of current liquidity - WCTA.

A cut-off point of .038 minimized the combined number of Type I and Type II errors. At that point the model had a Type I error rate of 12.4%, a Type II error rate of 17.4%, and an overall error rate of 14.9%. Ohlson noted that a naive model which classified all firms as non-failed would have an error rate of only 4.85% [105/(105+2058)].

Ohlson offered several possible explanations for the model's apparently poorer results compared to prior MDA studies. First, controlling to ensure that the financial statement date preceded the bankruptcy filing date resulted in longer lead times. Ohlson suggested that data in earlier studies may have already been adjusted for an actual bankruptcy in cases where bankruptcy was declared prior to the issuance of the financial statements. Other factors may have been the use of data from the 1970s instead of the 1950s and 1960s, the choice of predictor variables, and the use of logit instead of MDA or Beaver's univariate methodology.

Table 6

Ohlson's (1980) Logistic Regression Model

$$y_i = -1.32 - .407\ \text{SIZE} + 6.03\ \text{TLTA} - 1.43\ \text{WCTA} + .0757\ \text{CLCA} - 2.37\ \text{NITA} - 1.83\ \text{FUTL} + .285\ \text{INTWO} - 1.72\ \text{OENEG} - .521\ \text{CHIN}$$

and $P = (1 + \exp(-y_i)^{-1})$ so that $y_i = \log[P/(1-P)]$.

where

P	=	Overall probability of failure
SIZE	=	Log (total assets/GNP price-level index)
TLTA	=	Total liabilities (TL)/total assets (TA)
WCTA	=	Working capital/TA
CLCA	=	Current liabilities/current assets
NITA	=	Net income/TA
FUTL	=	Funds from operations/TL
INTWO	=	1 if net income was negative for the last two years; 0 otherwise
OENEG	=	1 if TL > TA; 0 otherwise
CHIN	=	a measure of the change in net income

Note. From "Financial Ratios and the Probabilistic Prediction of Bankruptcy" by J. A. Ohlson, 1980, Journal of Accounting Research, 18, p. 121.

Rose & Giroux (1984)

Rose & Giroux's (1984) study was unique in its consideration of a large number of predictor variables. Three to seven years of data and over 130 ratios obtained from the Compustat data file were tested for statistically significant differences between a group of 46 firms that filed for Chapter 10 or 11 bankruptcy protection and 46 non-failed firms between 1970 and 1978. Of the 130 ratios, 34 proved to be statistically significant ($p < .10$) in separating the failed from the non-failed groups. These, along with 27 variables identified in prior literature, were entered into an MDA stepwise regression to produce an 18-variable model. The Lachenbruch (1967) holdout method was used for validation.

Like Altman et al. (1977) both quadratic and linear models were prepared. While the linear model showed greater classification accuracy, the quadratic model was preferred because it was more accurate in classifying failed firms, thus giving implicit recognition to the higher cost of Type I errors and because "an F test indicated that the variance co-variance matrices of the two groups are not identical" (p. 10). While model coefficients were not provided, overall classification accuracy for the quadratic model ranged from 86.7% to 74.5% over the seven years examined.

Measures of profitability and liquidity displayed substantial explanatory power, as did a number of activity ratios. The authors concluded that only by looking at a large number of variables could they see that bankrupt companies have (1) higher expenses, especially selling, general, and administrative, (2) smaller cash flow margins, (3) higher receivable and inventory turnovers, (4) lower earnings, (5) higher financial leverage, (6) lower liquidity, and (7) lower dividend yield on common equity.

Zmijewski (1984)

Zmijewski (1984) developed a failure prediction model in order to demonstrate two methodological issues rather than to develop a premier prediction model. Zmijewski was concerned that earlier distress prediction studies were biased as a result of oversampling distressed firms and from excluding firms with incomplete data.

Most studies used a 1:1 matched sample of failed and healthy firms (Beaver, 1966; Altman, 1968; Blum, 1974; Rose & Giroux, 1984) even though the true proportion of failed firms in the population is very small (Ohlson, 1980). Zmijewski argued such matching results in a higher Type I error rate and suggested the use of the weighted exogenous sample maximum likelihood (WESML) technique to reduce this bias.

Zmijewski showed that excluding firms with incomplete data, his other methodological concern, introduced "sample selection bias" since firms with incomplete data had a greater likelihood of failure than the population as a whole. However both the "choice-based sample bias" from oversampling and the sample selection bias from selecting only firms with complete data "do not indicate significant changes in overall classification and prediction rates, nor do they indicate different qualitative results (statistical inferences) for the financial distress model tested" (p.63).

Zavgren (1985)

Like Ohlson (1980), Zavgren (1985) used conditional logit methodology instead of MDA because she believed the earlier studies "play loose with the assumptions of discriminant analysis" (p. 20). Unlike Ohlson, she thought it was important to pair-match samples in order to control for size and industry effects. Her sample included 45 manufacturing firms which filed for Chapter 10 or 11 bankruptcy protection between 1972 to 1978 identified in the F and S Index of Corporate Changes. These were matched by industry and asset size with 45 randomly selected healthy firms. Five years of data were gathered for each firm.

The variables selected were based on those identified by Pinches et al. (1973, 1975) who used factor analysis to develop an empirically based classification of financial ratios. A few carefully chosen financial ratios were selected which represented virtually all the different aspects of a firm's operations.

Zavgren used the quick ratio instead of the current ratio believing that a firm with falling sales would experience an unwanted build-up in inventory and report a misleading current ratio. She believed the quick ratio, by ignoring inventory, would provide a clearer picture of liquidity. The ratios, coefficients, and related factors of Zavgren's model are provided in Table 7.

Table 7

Zavgren's (1985) Logistic Regression Model

$y_i = -0.23883 - .00108X_1 + .01583X_2 + .1078X_3 - .03074X_4 - .00486X_5 + .0435X_6 - .0011X_7$ and

$P = (1 + \exp(-y_i)^{-1})$ so that $y_i = \log[P/(1-P)]$.

	where	Factor
P =	Overall probability of failure	
X_1 =	Inventory/sales	Inventory turnover
X_2 =	Receivable/inventory	Receivables turnover
X_3 =	Cash/total assets	Cash position
X_4 =	Quick assets/current liabilities	Short-term liquidity
X_5 =	Total income/total capital	Return on investment
X_6 =	Debt/total capital	Financial leverage
X_7 =	Sales/net plant	Capital turnover

Note. From "Assessing the Vulnerability to Failure of American Industrial Firms: A Logistic Analysis" by C. V. Zavgren, 1985, Journal of Business Finance & Accounting, 12, p. 24, 29.

Results suggested that the efficiency ratios, X_1, X_2, and X_7, are significant in distinguishing failing and healthy firms in the long-run but not in the short-run. In all years, financial leverage was significant (X_6) and, in the first and second years before failure, the cash position and quick ratio (X_3 and X_4) were significant ($p < .05$). Unexpectedly, the income/capital ratio (X_5) was marginally significant in only the fourth year ($p < .10$). Zavgren suggested earnings (1) may have been "managed", (2) result from the application of different GAAP, or (3) really do not differ between failing and healthy firms. She noted Ohlson (1980) found many of his failed firms reported a profit in the year of failure.

Without attempting to estimate the relative costs of Type I and Type II errors, a cutoff probability was used which minimized the total error rate. The classification error rates were 18%, 17%, 28%, 27%, and

20% for one to five years, respectively, prior to failure. Similar to Ohlson's (1980) logit based study, these error rates were higher than those found in MDA studies. The model was validated on a sample of 16 New York Stock Exchange firms which failed in 1979 and 1980 pair-matched with 16 healthy firms. Error rates were 31% for years one to five, respectively, prior to failure.

Zavgren concluded financial ratios can be very useful in assessing failure risk but was hesitant to compare her results to other studies because of differences in variables, validation methods, and statistical methodology.

Platt & Platt (1990, 1991)

In their initial study, Platt & Platt (1990) considered the effect of including various industries in a single failure study. They thought such inclusion was one possible explanation for the substantial decrease in accuracy noted by many researchers when validating their models. Another potential reason offered was that ratios might not be stable over time. Pinches et al. (1973) had indicated that some financial ratios were not stable over time.

Ketz et al. (1990) found financial ratios vary by industry. Platt & Platt (1990) believed that may be why ex ante (out of sample) classification results were often much worse than ex post (within sample) results in failure prediction studies. They attempted to account for this variation by using industry-relative ratios, defined as "the ratio of a firm's financial ratio relative to the mean value for that ratio in the firm's industry at a point in time" (p.34). An industry-relative ratio was derived by dividing a specific firm's ratio by the product of the mean ratio for that firm's industry times 100. [firm ratio/(industry ratio * 100)] The industry average ratios were taken from The Internal Revenue Service Statistics of Income.

Platt & Platt also tried to account for an industry's relative health, believing that relatively healthy firms in weak industries may fail and, conversely, relatively weak firms have a better chance of survival if they are in healthy industries. They used a variable composed of the change in sales compared to the change in industry output in an attempt to test for this effect.

Fifty-seven firms from Compustat which filed for Chapter 11 bankruptcy protection between 1971-1986 were pair-matched by industry, size, and year with 57 healthy firms. Numerous industries, including retail and transportation, were included. Two years of data were used. Three firms, identified through the Wall Street Journal Index as having filed for bankruptcy due to lawsuits, fraud, or union conflicts, were excluded.

Ratio selection was based on factors identified by Pinches et al. (1973). Two to four ratios (including cash flow (CF)/sales) for each of the seven factors plus five additional ratios were selected (including CF/interest and CF/total debt). The 26 ratios were entered into a logistic regression. The final model contained seven variables. The model with coefficients is shown in Table 8.

Table 8

Platt & Platt's (1990) Industry-Relative Logistic Regression Model

Independent Variable	Coefficient
Sales growth	- 0.01337
CF/sales	- 1.11952
Total debt (TD)/total assets (TA)	2.01995
Net fixed assets/TA	0.32614
Short-term debt/TD	0.18413
Output * CF/sales	- 8.83057
Output * TD/TA	11.18168

Note. From "Development of a Class of Stable Predictive Variables: The Case of Bankruptcy Prediction" by H. D. Platt & M. B. Platt, 1990, *Journal of Business Finance & Accounting, 17*, p. 43.

The effects of both CF/sales and TD/TA were found to depend on the growth or decline of a company's industry. Classification accuracy was higher (90% overall) when industry-relative ratios were used than when unadjusted ratios were used (78% overall). The industry-relative ratio model was validated using both the Lachenbruch (1967) jackknife procedure and a matched holdout sample of 34 failed and 34 non-failed firms from 1986-1987. Overall accuracy dropped only slightly for the jackknife procedure and remained the same for the ex ante holdout sample.

The authors concluded the use of industry-relative ratios is useful in multi-industry failure studies to help stabilize forecasts and offers several advantages over unadjusted ratios.

Platt & Platt (1991) reported similar results in a follow-up study. Compustat, instead of IRS, industry averages were used to improve uniformity of variable definitions, aggregation methods, and industry selection and because they were more readily available and more current. Again, the industry-relative model accuracy exceeded that of the unadjusted model.

Flagg, Giroux, & Wiggins (1991)

The Flagg, Giroux, & Wiggins (1991) study differed from other failure prediction studies in that their sample only included distressed firms in order to determine if it was possible to predict which firms would fail from a group that only included financially distressed firms.

A firm was considered distressed if any one of the following four "events" had occurred: (1) reduction in (common stock) dividends, (2) violation of debt covenants, (3) troubled debt restructuring, or (4) an audit opinion reflecting a "going concern" qualification. Using Compustat data from 1975-1981, 202 firms, excluding utilities, transportation, and financial services, were selected which had experienced at least one of these events. Financial data for five years after the event date were examined. In that period, 26 (13%) firms filed for Chapter 11 bankruptcy protection and 176 survived.

The four events were entered as dichotomous variables (1 or 0). Six other ratios, popular in the literature, were also selected. Table 9 contains Flagg et al.'s ten-variable logistic regression analysis model.

Table 9

Flagg, Giroux, & Wiggins' (1991) Logistic Regression Model

y_i = .1161 - 3.3786 DIV + .4126 C - 1.5318 TDR + 2.189 QUAL + 5.0463 L - 1.5974 CA - 22.4225 NT - 7.5352 CF - .419 LN + 6.193 RT

and

P = $(1 + \exp(-y_i)^{-1})$ so that $y_i = \log[P/(1-P)]$.

where

P	=	overall probability of failure
DIV	=	1 if dividend reduction; 0 otherwise
C	=	1 if violation of debt covenants; 0 otherwise
TDR	=	1 if troubled debt restructuring; 0 otherwise
QUAL	=	1 if qualified auditor's opinion; 0 otherwise
L	=	Total debt/total assets (TA) (leverage)
CA	=	current assets/current liabilities
NT	=	net income/TA
CF	=	cash flow/TA
LN	=	log of TA
RT	=	retained earnings/TA

Note. From "Predicting Corporate Bankruptcy Using Failed Firms" by J. C. Flagg, G. A. Giroux, & C. E. Wiggins, Jr., 1991, Review of Financial Economics, 1, p. 71-72, 75.

The model had an overall classification accuracy of 94%. It misclassified failed firms 27% of the time but misclassified non-failed firms only 3% of the time. The variable representing receipt of a going concern opinion qualification was highly significant ($p < .01$). The variable's coefficient was positive, as expected. The authors suggested that auditors were somewhat accurate in their predictions of failure. Other research (Hopwood, McKeown, & Mutchler, 1994) suggested that auditor opinions are poor predictors of failure. The dividend coefficient was also highly significant ($p < .01$). Contrary to the authors' expectations, the variable's coefficient was negative suggesting that a reduction in dividends reduces the probability of failure, possibly by conserving cash.

The authors concluded that the use of non-financial ratios and a focus on events of distress may improve understanding of the failure process and failure prediction.

McGurr (1996)

McGurr (1996) restricted his study to the retail industry and sought to determine if a retail prediction model that was superior to previous models could be developed. No previous model considered only retail firms.

Two years of Compustat data for 66 retail firms that filed for Chapter 7, 11, or 13 bankruptcy protection between 1989-1996 was pair-matched by size and year with 66 non-failed retail firms. Because of inventory and other operating differences, eating and drinking establishments were excluded. Thirty-five ratios, many specifically related to the retail industry (e.g., sales per employee) but none including cash flow, were selected from Beaver (1966), Gifford (1986), and Ou & Penman (1989) for initial consideration. Tests for multicollinearity eliminated eleven ratios. The remaining variables were entered into multiple iterations. Analysis of the mean vectors using Hotelling's T^2 resulted in the seven-variable model provided in Table 10.

The model achieved an overall classification accuracy of 78%. Type I and II misclassification errors were almost equal; Type I, 21% and Type II, 23%. McGurr, like most authors, did not estimate the costs of misclassification.

Table 10

McGurr's (1996) Retail Prediction Model

$$Z = -3.421169 + 5.947315X_1 + 1.185424X_2 + .013X_3 + 3.923027X_4 + .01072X_5 + .437459X_6 - 1.49685X_7$$

where:

Z = overall index: if < 0, failure is predicted; if > 0, non-failure is predicted

X_1 = net income (NI)/total assets (TA)

X_2 = 1 if working capital increased; 0 otherwise

X_3 = sales (in thousands)/number of employees

X_4 = gross margin/sales

X_5 = % change in long-term debt (LTD)

X_6 = current assets/current liabilities

X_7 = LTD/TA

Note. From Failure Prediction of Retail Firms Through Use of Financial Ratios by Paul T. McGurr, 1996, Unpublished doctoral dissertation, Purdue University, p. 102.

Accuracy dropped to 76% when validated using the jackknife procedure. The model was further validated by performing seven replications using a split sample procedure suggested by Frank et al. (1965). The model's ability to predict failure was statistically significant ($p < .001$).

Data collected in this study were then used to replicate the studies of Zavgren (1985), who used only manufacturing firms to develop her model, and Deakin (1972) who used a mixed-industry sample to develop his model. The retail prediction model was found to better classify firms than Zavgren's non-retail, single industry model but not significantly better than Deakin's mixed-industry model.

Cash Flow Oriented Failure Studies

Early failure prediction studies defined cash flow as net income plus depreciation (NIPD) (Beaver, 1966; Deakin, 1972; Blum, 1974). Beginning in the early 1980s, several researchers challenged the common assumption that NIPD was a suitable proxy for cash flow from operations (Gombola & Ketz, 1981a, 1981b; Ketz & Kochanek, 1982; Drtina & Largay, 1985). Several cash flow oriented studies were conducted which were similar to previous accrual oriented studies in terms of sample selection and statistical methodologies. Because the present study will explore the ability of cash flow ratios to predict business failure, these cash flow failure studies are considered separately in this section.

Largay & Stickney (1980)

When it filed for bankruptcy in 1975, W. T. Grant was the nation's largest retailer. Largay & Stickney (1980) used this company as an example of how an analysis of cash flow ratios, as opposed to traditional accrual ratios, might have revealed its impending failure. Both working capital from operations (WCFO) and net income increased in 1973 before falling in 1974. Cash flow from operations (CFFO), on the other hand, began falling in 1970 and was negative for the period 1970-1973. Although based on only one company's data, this study was one of the first to call into question the prevailing use of NIPD as a surrogate for CFFO and raised the suspicion that accrual numbers are more easily manipulated and "window-dressed" than cash flow measures.

Casey & Bartczak (1984)

As support was growing for a cash flow oriented definition of funds over the traditional accrual working capital definition, Casey & Bartczak (1984) undertook a study of the relationship between CFFO and financial distress. Selecting 60 industrial firms that had filed for bankruptcy protection and 230 healthy industrial firms from Compustat for the period 1971-1982, they calculated three variables: (1) CFFO, (2) CFFO/current liabilities (CL), and (3) CFFO/total liabilities (TL). Since U.S. firms did not begin reporting CFFO until 1988, Casey & Bartczak used WCFO adjusted for changes in the non-cash working capital accounts except for short-term debt as a proxy for CFFO.

Although the mean values of each variable for the failed group were significantly lower than for the healthy group, univariate analysis of the classification accuracy for CFFO ranged from only 60% to 49% one year to five years before failure, respectively. CFFO/CL and CFFO/TL were only slightly better but still never exceeded 75· classification accuracy in any year. These low accuracy rates seemed to be a result of a high number of healthy firms whose cash flow variables resembled those of failed firms causing a high number of Type II errors.

Using the same sample, the authors constructed a MDA model using six conventional accrual ratios. Overall classification accuracy improved to 86%-61% one year to five years before failure, respectively. When the cash flow variables were added, one at a time, to the accrual oriented model, there was no improvement in accuracy.

Casey & Bartczak (1985)

In a follow-up study in 1985 Casey & Bartczak used the same data as their 1984 study but focused on the marginal improvement in classification accuracy from using CFFO (again defined as an adjustment to WCFO). The same six accrual ratios and three cash flow-based ratios, in various combinations, were analyzed using MDA and logit. The ratios were standardized and log-transformed. Filing for bankruptcy protection was used as evidence of failure because of the high direct and indirect costs of bankruptcy, better comparability with previous studies, and lower data gathering costs. While the failed firms were matched with at least one healthy firm from the same industry, no effort was made to control for size. Although size was found to be a significant discriminator in other research (Ohlson, 1980), it did not appear as such in this study.

Both MDA and logit results were significant for the three years prior to failure ($p < .05$) but there was no marginal improvement in classification accuracy from using any of the cash flow variables. CFFO did not appear to assist in predicting failure. Classification accuracy did not improve, confirming the findings of the authors' 1984 study that CFFO, calculated in both studies as an adjustment to WCFO, did not improve their model's predictive accuracy. They suggested that other measures of cash flow, such as the variability of CFFO or total cash flow (including those from investing and financing activities) may have predictive power.

Gentry, Newbold, & Whitford (1985a)

Noting that the empirical findings of prior failure studies tended to be sample specific due to a lack of a theoretical basis, Gentry, Newbold, & Whitford (1985a) used a cash-based funds flow model developed by Helfert (1982) as a basis for selection of the eight variables in their study.

Their sample included 33 failed and 33 non-failed firms from Compustat for the period 1970-1981. Twenty-one firms in each group were industrials; the remaining twelve from a variety of industries. The groups were pair-matched by size, industry, and year.

MDA, probit, and logit analyses were performed to examine the predictive ability of the funds flow components. Only the results from the logit analysis were reported since the MDA and probit models gave similar results. The logit model consisted of eight variables. They were: (1) net funds flow from operations/total net flow (TNF), (2) net working capital/TNF, (3) other asset and liability flow/TNF, (4) financing flow/TNF, (5) fixed coverage expenses/TNF, (6) capital expenditures/TNF, (7) dividends/TNF, and (8) a scale measure, total net flow/total assets.

The logit model had an overall classification accuracy of 83% one year before failure and 77% when the mean of each variable three years before failure was used. Only the dividend variable was significant at the .05 level for both time periods. Consistent with the findings of Casey & Bartczak (1984, 1985) the variables comprising CFFO (variables 1, 2, and 5) were not significant. The model was validated using a secondary sample of 23 weak (but not failed) and 23 healthy firms. Classification accuracy dropped to 72% one year before failure and 74% when the mean of each variable three years before failure was used.

Gentry, Newbold, & Whitford (1985b)

Using the same 66-firm sample, Gentry, Newbold, & Whitford (1985b) reported three variations. First, probit instead of logit results were reported. Second, one of the eight variables in their earlier model (Gentry et al., 1985a) was modified. The working capital variable was divided into five parts for a better picture of funds flow: (1) receivables, (2) inventory, (3) other current assets, (4) payables, and (5) other current liabilities. The final model was composed of these five working capital variables plus the remaining seven reported earlier for a total of twelve variables. Third, a new model composed of the twelve funds flow components and nine ratios was tested.

Overall classification accuracy for the twelve variable probit model was 83% one year before failure and 79% when the mean of the variables three years before failure was used - almost identical to the earlier results. Again, only the dividend variable was significant at the .05 level for both time periods. For healthy firms, dividends averaged 9.2% of funds flow; six of the 33 healthy firms did not pay dividends. Dividends averaged 1.8% of funds flow for the ten failed firms that paid a dividend. The remaining 23 failed firms paid no dividend. The authors concluded that, overall, there appeared to be some benefit to disaggregating cash flows into their component parts.

In a further effort to determine the relative advantage of funds flow components and ratios, Gentry et al. (1985b) developed a model using the twelve funds flow components and nine additional ratios - seven common ratios, the log of total assets, and a market value measure. Adding the nine ratios did increase the explanatory power of the model even though none of the nine was individually significant. The authors concluded that adding cash-based funds flow components to traditional financial ratio models improved predictive performance.

Since funds flow components capture the dynamics of the flow of cash through a firm, the authors believed that insights and signals about potential failure can be gained by measuring or observing the trend of components that generate or use cash. In a further article based on the same data, Gentry, Newbold, & Whitford (1987) discussed the results of a log likelihood test and arrived at the same conclusion - the use of funds flow components significantly improves the classification of failed and non-failed firms.

Gombola, Haskins, Ketz, & Williams (1987)

During the 1970s, the FASB and its predecessor, the Accounting Principles Board, issued numerous statements and opinions, including ones on deferred taxes, equity earnings, capitalization of interest, recognition of foreign currency items, and extraordinary items. Believing that the cumulative effect of these pronouncements was to reduce the correlation between CFFO and net income, Gombola, Haskins, Ketz, & Williams (1987) considered two separate periods, 1967-1972 and 1973-1981, in their study of whether CFFO was a good predictor of failure.

Twenty-four financial ratios were selected based on their use in previous failure literature. Variables included ratios based on NIPD, WCFO (working capital from operations), and CFFO. CFFO was calculated as in prior Gombola & Ketz studies (1981a, 1983a) as WCFO adjusted for changes in all current accounts except cash, short-term debt, and short-term marketable securities.

The 24 ratios were factor analyzed over the two separate time periods for 442 Compustat industrial firms. A separate factor for cash flow appeared in the late period but not in the early period. This suggested "that earnings and cash flow are similar in the early period but dissimilar in the late period" (p.61) and, in the late period, cash flow ratios contain information not found in NIPD or WCFO ratios. The authors concluded that studies during the early period which used NIPD as a surrogate for CFFO (e.g., Beaver, 1966) may have been valid at the time but are not generalizable to future periods.

To test the classification accuracy of cash flow ratios, 77 retail and manufacturing firms that had filed for bankruptcy protection and 77 healthy firms pair-matched by industry and size were selected. The six accrual ratios which had the highest loadings in the factor-analytic study comprised the base model. These were cash/total asset (TA), current assets/sales, current liabilities/total liabilities (TL), sales/TA, TA/TL, and net income/TA. Three additional models were constructed by adding the ratios CFFO/TA, NIPD/TA, and working capital from operations (WCFO)/TA individually to the base model. No attempt was made to separately analyze the retail and manufacturing firms.

Linear MDA was reported as the results from quadratic MDA and probit analysis were approximately the same. Validation was performed using the Lachenbruch (1967) technique. Believing the costs to be user specific, no adjustment was made for the relative costs of Type I and Type II errors. The models were run for the early, late, and combined time periods and for one through four years prior to failure. CFFO did not improve the classification accuracy of the models. On the other hand, NIPD appeared in the model with the highest classification accuracy.

The results reaffirmed those of Casey & Bartczak (1985) - CFFO is not an important predictor of failure. Gombola et al. noted that the use of actual cash flow, as opposed to CFFO derived from making adjustments to the reported WCFO may alter the results and suggested "our study might be replicated at a later time when firms report cash flow from operations" (p. 64).

Dambolena & Shulman (1988)

Believing that the higher the level of a firm's net liquid balance, the less liquidity risk, and, therefore, the lower the chance of failure, Dambolena & Shulman (1988) tested whether adding a net liquid component to failure prediction models would improve their accuracy. They argued that only part of net working capital, that part not tied up in operations, is truly liquid. Net liquid assets are the difference between cash plus marketable securities (liquid current assets) and short-term notes payable plus the current portion of long-term debt (liquid current payables).

Fifty failed firms from 1977-1980 with at least two years of data from a variety of industries were pair-matched with 50 healthy firms on the basis of industry, size, and year. A holdout sample of 25 from each group was used for validation.

Using the Altman (1968) and Gentry et al. (1985b) models as benchmarks, the authors developed two "best" stepwise logit models and then developed two additional models by adding a net liquid balance variable to the Altman and Gentry et al. models. Coefficients for the models were not given. Overall classification accuracy improved from 85% to 92% and 82% to 84% for one year and two years before failure, respectively, using the model based on Altman and from 74% to 89% and 68% to 76% using the Gentry et al. model. The net liquid balance ratio was the single best predictor of failure. Also, adding this ratio increased the Chi-square goodness-of-fit from .68 to .94 in the Altman model and from .61 to .99 in the Gentry et al. model. The authors concluded that inclusion of the net liquid balance in failure models resulted in a consistent improvement in predictive ability.

Gahlon & Vigeland (1988)

Gahlon & Vigeland (1988) were the first to consider whether the components of cash flow obtained from the direct method of reporting cash flow were significantly different between failed and non-failed firms. They used the Uniform Credit Analysis (UCA) format to identify components of cash flow. The UCA format is similar to the direct method of reporting cash flow from operations (CFFO) recommended by the FASB. Sixty industrial firms (excluding utility, transportation, and financial services firms) that filed for bankruptcy protection between 1973-1985 were selected from Compustat. A non-matched sample of 204 non-failed firms was also selected.

UCA cash flow statements and selected ratios were calculated for each firm for five years. Items in the UCA cash flow statements were scaled for size using total assets since the non-failed group was, on average, larger than the failed group.

Because the means of several variables exhibited considerable skewness, the authors used the Mann-Whitney test. This nonparametric test involves using the ranks of the variables instead of the variables themselves and is not affected by skewness of the data (Zar, 1974). The authors concluded that the following seven variables had significant differences between failed and non-failed firms as much as five years before failure: (1) cash operating income, (2) cash income taxes, (3) CFFO, (4) cash net income, (5) cash flow after debt retirement, (6) age of accounts payable, and (7) cash coverage ratio [CFFO/(total financing cost + mandatory debt retirement)]. Gahlon & Vigeland did not derive a classification or prediction model but suggested that the above variables should be considered for such a model.

Aziz & Lawson (1989)

Aziz & Lawson (1989) compared classification and predictive accuracy of four models: (1) Altman (1968) Z; (2) Zeta™ (Altman et al., 1977); (3) cash flow-based (CFB); and (4) a mixed model containing Z and CFB variables. Variables in the CFB model were based on Lawson's (1985) cash flow identity and included CFFO, taxes paid, net capital improvements, lender flows, and shareholder flows as components of cash flow. Data were derived from the statement of changes in financial position. Book value was used as a scale factor.

Aziz & Lawson sought to determine if CFB and mixed models were superior to Z and Zeta™ models in terms of classification, prediction, and number of Type II errors. Five years of data from Compustat for 49 industrials (excluding utilities and financial services) that filed for bankruptcy protection between 1973-1982 were pair-matched with 49 healthy firms. The authors did not apply the data used in this study to the Zeta™ model since that model's coefficients were not publicly available. In comparing classification accuracies, the error rates used for Zeta™ were those originally reported by Altman et al. (1977).

A holdout sample was used. The results suggested the four models were about the same in their ability to discriminate between failed and non-failed firms. The CFB and mixed models, however, were better able to predict failure several years in advance. Overall, the authors concluded that cash flow variables were important in failure prediction.

Gilbert, Menon, & Schwartz (1990)

Models had been developed which could distinguish failed from healthy firms. Gilbert, Menon, & Schwartz (1990) attempted to develop a model using cash flow variables which could distinguish between failed firms and stressed but non-failed firms.

Seventy-six firms that filed for Chapter 11 bankruptcy protection between 1974-1983 were selected from Compustat. Only financial firms were excluded. Unique to this study was the method of selecting non-failed firms. Two groups were identified using both the Compustat Annual Industrial and the Compustat Research files. The Research files contained firms removed from the Annual file because of merger, liquidation, bankruptcy, or other reason. Gilbert et al. believed that not using this data source in prior studies understated the population of distressed firms. The first non-failed group consisted of 304 (four for each failed firm) randomly selected firms. The second group of 304 was selected from all firms considered distressed, i.e., they had negative cumulative income from operations over any consecutive three year period between 1972-1983 but did not file for bankruptcy protection. Non-failed firms were matched to the failed group by year only. Approximately 32% of each group was used as a holdout sample.

Two models were developed; the first based on the failed and random groups, the second based on the failed and distressed groups. Variables considered for inclusion were the five used by Altman (1968) and the nine (including three cash flow) used by Casey & Bartczak (1985). A stepwise procedure was used to reduce the number of variables entering the logit models.

For the failed/random sample, only three variables were significant: (1) earnings before interest and taxes (EBIT)/total assets (TA); (2) cash flow from operations (CFFO)/total liabilities (TL); and (3) stockholders' equity (SE)/TL. As with Casey & Bartczak (1985) CFFO was defined as working capital from operations adjusted for current account changes. Overall classification accuracy was 89% and 91% in the estimation and holdout samples, respectively. Type I errors were 33% and 38%, Type II errors were below 7%.

Four variables entered the failed/distressed model: (1) CFFO/current liabilities; (2) cash/TA; (3) SE/TL; and (4) retained earnings/TA. Classification accuracies, while still statistically significant ($p < .001$), were not as high reaching 82% and 78% overall for the estimation and holdout samples. Type II errors were below 10% but Type I errors rose to 70%.

CFFO appeared in both models (as the numerator in one variable in each model) which led the authors to conclude, contrary to Casey & Bartczak (1985), that CFFO was significant and should be included in failure studies. Still, only one variable (SE/TL) appeared in both models. The authors suggested "the financial dimensions that set apart bankrupt from healthy firms may be different from those that separate bankrupt from distressed, but not bankrupt, firms" (p. 169).

Bukovinsky (1993)

SFAS No. 95, issued in November, 1987, required the presentation of a statement of cash flows (SCF) for all public companies reporting on financial statements for fiscal years ending after July 15, 1988 (FASB, 1987). Bukovinsky was one of the first to study the prediction of failure using cash flow ratios developed from the new statement. He sought to determine if: (1) a useful model could be developed using only cash flow variables, (2) a cash flow oriented model was more accurate than accrual oriented models, and (3) a mixed-model was superior to either cash flow-only or accrual-only models.

Bukovinsky (1993) selected 54 firms which filed for Chapter 11 bankruptcy protection between October, 1988 - January, 1991. Two years of Compustat data was used and no industry was excluded. Two samples of non-failed firms were selected from the Compustat current (Annual) and Research files. The first included 500 firms matched by year and two-digit SIC code (approximately 10 firms for each of the 54 failed firms). A second sample of 100 firms, used to test generalizability to all industries, not just those represented in the failed group, was matched only by year. Each of the three groups was split into an 80% developmental sample and a 20% validation sample.

Forty cash flow ratios were selected based on prior use or were developed by the researcher. The ratios were factor analyzed to produce a more parsimonious set of noncollinear variables which still captured most of the information contained in the original variable set. The variables loaded on eleven factors. One variable from each factor (usually the one with the highest loading) was selected for use in both MDA and logit eleven-variable models. The eleven variables are shown in Table 11.

Table 11

<u>Bukovinsky's (1993) Variables</u>

(1) CFFO/ average total assets

(2) Cash paid for inventory/CFFO

(3) CFFO/cash paid for interest, long-term debt (LTD), and other financing uses

(4) Cash received from LTD/average LTD

(5) Cash received from the sale of stock, LTD, and other financing sources/total cash flow

(6) Cash paid for investing activities/net cash flow from investing activities (CFFI)

(7) Cash paid for inventory/cost of goods sold

(8) Cash received from sale of plant assets and other investing sources/average plant assets (Avg PA)

(9) CFFI/Avg PA

(10) Cash paid for dividends/net cash flow from financing activities

(11) Cash/current liabilities

<u>Note</u>. From "Cash Flow and Cash Position Measures in the Prediction of Business Failure: An Empirical Study" by D. M. Bukovinsky, 1993, <u>University Microfilms International</u>, 9319949, p. 81-84, 127-128.

Additional MDA and logit models were developed using the two most significant variables (# 8 and 11 above) for a total of four models. Classification accuracy rates of all four models were between 87% and 91%. Type I error rates were three per cent or less in the validation samples. Type II error rates were between 90% to 100%.

Since these results were similar to what a naive model would predict (i.e., all non-failed), Bukovinsky concluded that a cash flow model could not be used to accurately predict failure.

The data in this study were also used to replicate the accrual oriented studies of Beaver (1966), Altman (1968), Deakin (1972), Ohlson (1980), and Zavgren (1985). The two-variable logit model was compared to these five accrual models. Overall classification accuracy of the replication of the five accrual models ranged from 87% to 94% but none was significantly more accurate (at the 5% level) than the accuracy of a naive model which classified all firms as non-failed. While Type II error rates were low (2% or less), Type I rates were 53%-100%. Finally, mixed models (created by adding cash flow variables to the accrual models) showed no improvement in classification accuracy or Type I or II error rates.

It appears that the disappointing results were almost entirely a result of the proportion of failed to non-failed firms used in the study (approximately 10%). Since the models developed and replicated were all about 90% accurate, they could not be shown to be significantly different than the naive model which was also 90% accurate.

Still, other conclusions could be drawn from the study. The factor analysis did identify ratios which might be useful in future cash flow failure prediction studies. Also, results from the second holdout sample - those firms from all industries - were similar to the industry-matched holdout sample suggesting that "cash flow patterns and accrual measures may not differ greatly across industries" (p. 177). In addition, the study raised doubt about the generalizability of past accrual oriented studies across time. Changing conditions may have rendered them less useful.

Ward (1994)

Early failure studies found that net income plus depreciation (NIPD) divided by total debt was a good predictor of failure (Beaver, 1966; Blum, 1974; and Deakin, 1977). Ward (1994) suggested that "the justification for the strong predictive ability was attributed to the belief that [NIPD] was a naive measure of operating cash flow" (p.547). Several studies in the 1980s, which defined cash flow from operations (CFFO) as working capital from operations adjusted for current account changes, found CFFO did not improve predictive ability (Casey &

Bartczak, 1984, 1985; Gentry et al., 1985a, 1985b). But none of these earlier studies tested the incremental predictive ability of NIPD over CFFO because they failed to test NIPD and CFFO in the same model. Ward's study considered both NIPD and CFFO.

Most failure studies consider a dichotomous dependent variable, usually failed or non-failed. Ward, using "events" similar to Flagg et al. (1991) and Lau (1987), developed a four-state classification: (1) healthy; (2) dividend reduction of at least 40%; (3) loan default or debt accommodation; and (4) Chapter 11 bankruptcy filing.

Three years of data for 227 non-financial firms were collected from 1984/85 to 1986/87. A holdout sample consisted of 1989 data for 158 firms. Compustat Annual and Research files were used. Approximately 70% of the firms in each group were healthy and 10% were in each of the three increasingly distressed groups. Two ordinal four-state logistic regression models were considered. Each contained the six accrual variables used by Casey & Bartczak (1984, 1985), Gentry et al. (1985a, 1985b) and Gilbert et al. (1990) and CFFO/total liabilities (TL). CFFO was estimated since pre-SFAS No. 95 data was used. One model also contained NIPD/TL.

Both models had strong predictive power based on their Ranked Probability Scores. For one and two years before failure, CFFO was the strongest predictor followed by net income/total assets (NI/TA). Further, NIPD was much more highly correlated with NI/TA than CFFO suggesting NIPD "is a significant ($p < .01$) predictor of financial distress because [NIPD] is a better measure of economic income than NI/TA not because [NIPD] is a naive measure of operating cash flow" (p. 553).

Rujoub, Cook, & Hay (1995)

Rujoub, Cook, & Hay (1995) studied cash flow as reported in the statement of cash flows (SCF). They used three years of Compustat data for 33 firms which had filed for Chapter 11 bankruptcy protection and 33 non-bankrupt firms, pair-matched by size, industry, and year. No industry was excluded. Eighteen cash flow ratios, created by the authors or by Giacomino & Mielke (1988), were identified. The eight most significant ratios were selected for inclusion in a model using stepwise discriminant procedures. In addition to the cash flow ratios, thirty conventional accrual accounting ratios used by Beaver (1966, 1968) and Altman & Spivack (1983) were identified and divided into six groups. A single ratio in each group found to be significant in previous studies was selected for use in this study.

Three models were developed using MDA: (1) an eight-variable cash flow oriented model; (2) a six-variable accrual oriented model; and (3) a 14-variable mixed model. Coefficients were not disclosed; table 12 contains the cash flow and accrual ratios included in the final models.

Highest classification accuracy rates were reported with the third model composed of cash flow and accrual ratios followed by the first model composed of only cash flow ratios. The authors concluded that cash flow ratios are useful by themselves or as a supplement to accrual accounting data in predicting business failure.

International Failure Studies

Several failure studies have been performed in other countries, often using U.S. research as a base. An international survey by Altman (1984) cites studies done in Japan, Germany, Switzerland, Brazil, Australia, England, Ireland, Canada, The Netherlands, and France. Three studies are presented here. Because of differences between U.S. and foreign GAAP, care should be used in drawing conclusions.

Takahashi, Kurokawa, & Watase (1984)

Takahashi, Kurokawa, & Watase (1984) collected three years of data for 40 failed, 40 pair-matched non-failed, and 40 randomly selected non-failed Japanese firms. Seventy-five accrual variables (61 ratios and 14

Table 12

Rujoub, Cook, & Hay's (1995) Variables

Cash flow variables		Accrual variables	
1.	CFFO/TA (total assets)	1.	NI/TA
2.	CFFO/TL (total liab.)	2.	NIPD/TD
3.	CFFO/NI	3.	CA/CL
4.	CFFO/TSC	4.	(CA-CL)/TA
5.	CFFF/TA	5.	TL/TA
6.	CFFF/TSC	6.	Quick assets-CL/CUO
7.	CUO/TSC		
8.	Cash used to reduce LTD/cash received from issuance of LTD		

where:

CFFO = cash flow from operations

CFFF = cash flow from financing activities

TSC = total sources of cash

NI = net income

CUO = cash used in operations

LTD = long-term debt

CA = current assets

CL = current liabilities

NIPD = NI + depreciation + depletion + amortization

Note. From "Using Cash Flow Ratios to Predict Business Failure" by M. A. Rujoub, D. M. Cook, & L. E. Hay, 1995, Journal of Managerial Issues, 7(1), p. 80-85.

absolute amounts) and 54 cash flow variables (45 ratios and nine absolute amounts) were included in their original variable set. Several models were developed which varied by the following characteristics: (1) data which had or had not been adjusted for reported exceptions, reservations, and/or qualifications; (2) accrual or cash flow data; (3) data from one year or three years before failure; and (4) ratios alone or a combination of ratios and absolute amounts.

The more accurate models were those that used three-year, adjusted, accrual data. There was no significant difference between using ratios with or without absolute amounts. The most accurate model, using stepwise linear MDA, consisted of eight variables: (1) net worth/fixed assets; (2) current liabilities ratio; (3) voluntary reserves plus unappropriated retained earnings (RE)/total assets (TA); (4) borrowed expenses/sales; (5) RE; (6) net operating plus other income/cash sales; (7) CFFO (cash flow from operations)/TA; and (8) cash sales minus cash purchases. A holdout sample consisting of four failed, four matched non-failed and the 40 random non-failed firms was used for validation. The authors noted the probability of "window dressing" resulting from Japan's incomplete system of disclosure.

Peel & Peel (1987)

Unique to the Peel & Peel (1987) study was their attempt to shed light on the "gray area" or "zone of ignorance" between the clearly failed and clearly non-failed firms where most misclassifications occur. Instead of studying only failed and non-failed UK firms, both profitable and unprofitable non-failed, private, industrial firms were selected.

A total of 85 variables were considered. Both logit and MDA models were developed. Variables entering the most accurate models were: (1) size; (2) working capital/TA; (3) quick assets/current liabilities (CL); (4) income before tax/sales; (5) total liabilities/CL; and (6) number of months between year end and issuance of financial statements.

Classification errors were relatively high, especially when unprofitable firms were included. The authors suggested future model building explicitly consider these problematic, unprofitable firms, as well as additional non-financial variables. The lag variable (6) is unique in failure prediction studies reviewed thus far and was significant ($p < .05$) in this study. Also of interest was that a dummy variable indicating whether the firm received a going concern qualification had a positive association with non-failure, i.e., firms in poor enough shape to receive the qualified audit opinion were actually more likely not to fail than to fail. The authors did not expect this result and suggested it as an area of further research.

Laitinen (1991)

Laitinen (1991) believed understanding of failure prediction would be enhanced by first identifying the different failure processes. He also wanted to select financial ratios based on a theoretical model instead of popularity or intuition.

Variable selection was based on a model that analyzed the relationship between the accounting and economic rates of return which assumed a steady growth rate and identical investment alternatives. Profitability, growth rate, capital intensiveness, financial leverage, and asset structure were the five factors identified as having the most effect on failure prediction. The author noted the similarity to the seven factors identified by Pinches et al. (1973) through factor analysis. From this, six ratios were selected: (1) return on investment; (2) total asset (TA) growth rate; (3) sales/TA; (4) cash flow/sales; (5) total liabilities/TA; (6) current ratio.

Laitinen split his sample of 40 failed Finnish firms into three groups. Signs of failure were evident as much as four years in advance for the "chronic failure" group. The "revenue financing failure" group exhibited low net sales to total assets and low cash flow to net sales. Failure could be predicted two years in advance. Providing the least amount of warning was the "acute failure" group. Indicators of failure appeared only one year in advance. This grouping was based on the work of Argenti (1976) who also identified three types of failure.

No validation procedure was reported. Classification accuracies ranged from 84% to 95% and were highest for the "revenue financing failure" group. The author concluded that failure prediction is improved when a theoretical basis is used for selecting the independent variables and when firms are first classified by probable type of failure process.

Other Failure Studies

Fulmer, Moon, Gavin, & Erwin (1984) studied firms with less than $10 million in total assets who filed for voluntary or involuntary bankruptcy protection. Their MDA failure prediction model included the variable cash flow/total liabilities and resulted in overall classification accuracy rates of 98% and 81% for one and two years prior to failure.

Henebry (1994, 1996) used a Cox proportional hazard model, instead of MDA, probit, or logit, to determine if cash flow variables improved bank failure models. She used a 1:1 matched sample of banks that failed between 1986-1990. Five years of data were collected. She concluded that adding cash flow variables improved predictive ability three to five years before failure.

Zmijewski (1984) refers to failure studies in the insurance, railroad, education, and securities industries. Ball & Foster (1982), Zavgren (1983), and Jones (1987) provided reviews of the failure prediction literature.

Summary of Literature Review

This literature review has summarized the development of failure prediction studies. Selected studies have shown that accounting information can be used in discriminating between failed and non-failed firms.

Financial reporting has evolved over the years. Although some early studies included a measure labeled "cash flow", most focused on the use of accrual variables. The introduction of the statement of changes in financial position, with its focus on "funds", led to the use of various measures of funds in the failure prediction literature. This led to studies which attempted to determine the information content of various measures of funds. Several studies concluded that measures commonly used for cash flow were poor surrogates for cash flow. These studies, in conjunction with the required change to a statement of cash flows (SCF), focused attention on the information content of cash flow information in failure studies.

The results of both the accrual and cash flow studies are mixed. Several have resulted in relatively high predictive and classification accuracies. Many studies, especially those involving cash flow, introduced new variables. While a few variables are common in many studies, none are common to all and there is no consensus regarding which variables are the most effective predictors of failure. Few of the prior failure prediction studies used post-SFAC No. 95 data. The two which did (Bukovinsky, 1993; Rujoub et al., 1995) used mixed industry samples. These same two were also the only studies that considered cash flow from investing and financing activities in addition to cash flow from operations.

The present study differs from prior research in that it uses post-SFAS No. 95 information from the statement of cash flows applied to two separate industry groups - the retail/wholesale industry and the manufacturing industry. Only one failure prediction study (McGurr, 1996) focused solely on the retail industry. Only two (Altman, 1968; Zavgren, 1985) limited their study to manufacturing firms. None of these three considered cash flow variables. No other failure prediction study isolated a specific industry. (Both Altman et al., 1977 and Gombola et al. 1987 examined manufacturing and retail firms but reported the results as one group.) The studies of Gombola & Ketz (1983c), Ketz, Doogar, & Jensen (1990), Zeller & Stanko (1994a, 1994b) and McGurr (1996) suggested that ratios for retail and manufacturing firms were sufficiently different to warrant separate consideration.

Using reported data from the SCF eliminates the need to develop a proxy for cash flow. Cash flow ratios based on all three components - operating, investing, and financing activities - will be examined. Finally, the present study uses ten years of SCF data, a longer period than other post-SFAC No. 95 studies. Financial statement data from 1988, when the SCF was first required, through 1997 will be used to study firms which failed from 1990 through 1997.

The next chapter explains the proposed methodology for the study. Data to be used and tests to be performed are identified.

CHAPTER III

METHODOLOGY

This chapter describes the design of this study: the research and null hypotheses, the statistical variables for these hypotheses, the data for these variables, and the statistical procedures employed.

Statement of Hypotheses

As stated in Chapter 1 the purpose of this study is to determine if accounting information in the form of cash flow ratios derived from the SCF has information content. If cash flow ratios can be used to predict failed vs. non-failed firms, then the SCF has information content.

The following six hypotheses were developed. The first three research and null hypotheses relate to development of cash flow and accrual models; research and null hypotheses 4-6 compare the cash and accrual models to previously developed accrual-only models.

Research and Null Hypotheses 1-3

H1: Cash flow ratios, when included in a multivariate discriminant model and when measured by the means of the z score produced by MDA, can be used to predict failed vs. non-failed firms in the retail/wholesale industry.

$H_0$1: Cash flow ratios, when included in a multivariate discriminant model and when measured by the means of the z score produced by MDA, are not able to predict failed vs. non-failed firms in the retail/wholesale industry.

H2: Cash flow ratios, when included in a multivariate discriminant model and when measured by the means of the z score produced by MDA, can be used to predict failed vs. non-failed firms in the manufacturing industry.

$H_0 2$: Cash flow ratios, when included in a multivariate discriminant model and when measured by the means of the z score produced by MDA, are not able to predict failed vs. non-failed firms in the manufacturing industry.

H3: Cash flow ratios, when included in a multivariate discriminant model and when measured by the means of the z score produced by MDA, can be used to predict failed vs. non-failed firms in the retail/wholesale and manufacturing industries combined.

$H_0 3$: Cash flow ratios, when included in a multivariate discriminant model and when measured by the means of the z score produced by MDA, are not able to predict failed vs. non-failed firms in the retail/wholesale and manufacturing industries combined.

These hypotheses were tested to evaluate if models can be developed using a combination of cash flow and accrual ratios which are useful in predicting failed vs. non-failed firms in the retail/wholesale industry, the manufacturing industry, and in the two industries combined. Development of such models would indicate the SCF has information content.

Research and Null Hypotheses 4-6

H4: Cash flow ratios, when included in a multivariate discriminant model and when measured by the percentage of correct predictions of failed vs. non-failed firms by the model developed in H1 for the retail/wholesale industry, are more accurate than accrual ratios in predicting failed vs. non-failed firms.

$H_0 4$: Cash flow ratios, when included in a multivariate discriminant model and when measured by the percentage of correct predictions of failed vs. non-failed firms by the model developed in H1 for the retail/wholesale industry, are less accurate than or equally as accurate as accrual ratios in predicting failed vs. non-failed firms.

H5: Cash flow ratios, when included in a multivariate discriminant model and when measured by the percentage of correct predictions of failed vs. non-failed firms by the model developed in H2 for the manufacturing industry, are more accurate than accrual ratios in predicting failed vs. non-failed firms.

$H_0$5: Cash flow ratios, when included in a multivariate discriminant model and when measured by the percentage of correct predictions of failed vs. non-failed firms by the model developed in H2 for the manufacturing industry, are less accurate than or equally as accurate as accrual ratios in predicting failed vs. non-failed firms.

H6: Cash flow ratios, when included in a multivariate discriminant model and when measured by the percentage of correct predictions of failed vs. non-failed firms by the model developed in H3 for the retail/wholesale and manufacturing industries combined, are more accurate than accrual ratios in predicting failed vs. non-failed firms.

$H_0$6: Cash flow ratios, when included in a multivariate discriminant model and when measured by the percentage of correct predictions of failed vs. non-failed firms by the model developed in H3 for the retail/wholesale and manufacturing industries combined, are less accurate than or equally as accurate as accrual ratios in predicting failed vs. non-failed firms.

These hypotheses were tested to determine if new cash flow and accrual oriented models are better predictors of failure than previously developed models. More accurate prediction by the cash flow and accrual models would indicate the SCF has non-redundant information.

Statistical Variables

Dependent Variable

The event of interest was whether a firm filed for bankruptcy protection. Casey & Bartczak (1985), among others, used filing for bankruptcy protection, as opposed to loan default or some other event, as evidence of failure because of the high direct and indirect costs of bankruptcy, better comparability with previous studies, and lower data gathering costs. For the same reasons, filing for bankruptcy protection was selected in this study. Therefore, the dependent variable was dichotomous - if a firm filed for bankruptcy, the firm was considered failed; if no filing was made, the firm was considered non-failed. A firm was placed in the failed group if it filed for bankruptcy between January 1, 1990 and December 31, 1997. A firm was placed in the non-failed group if no such filing was made.

Independent Variables

Cash flow and accrual financial ratios and trend variables calculated from financial statement information were the independent variables. Firm industry is also an independent variable controlled for in testing hypotheses 1, 2, 4, and 5. All the variables needed to replicate the findings of Altman (1968), Deakin (1977), and McGurr (1996) were calculated. These variables and additional cash flow and accrual variables selected are found in Table 13 and include the cash flow variables used in the recent failure prediction studies of Bukovinsky (1993), Rujoub et al. (1995), and Ward (1995). Also included are variables from Zavgren's (1985) study which used the Pinches et al. (1973) factor-analytic study as a base and the cash flow variables

Table 13

Variables Selected for Analysis

#	Source	Variable	Description
1	AR	WC/TA	Working capital/total assets
2	A	RE/TA	Retained earnings/total assets
3	A	EBIT/TA	Earnings before interest, taxes/total assets
4	A	MV EQ/TL	Market value of equity/total liabilities
5	A	Sales/TA	Sales/total assets

Table 13

Variables Selected for Analysis

#	Source	Variable	Description
6	DGMRW	NI/TA	Net income/total assets
7	DW	CA/TA	Current assets/total assets
8	DGZ	Cash/TA	Cash/total assets
9	W	CA/TL	Current assets/total liabilities
10	DWG	Sales/CA	Sales/current assets
11	M	WC TRND	1 if WC $CY (current year)>WC$PY (prior year)
12	M	Sales/# EMP	Sales/number of employees
13	M	GM/Sales	Gross margin/sales
14	M	%CHG LTD	(Long-term debt (LTD)CY-LTD PY)/LTD PY
15	DMRW	CA/CL	Current ratio
16	M	LTD/TA	Long term debt/total assets
17	SZ	INV/Sales	Inventory/sales
18	Z	REC/INV	Receivables/inventory
19	SZ	QA/CL	Quick assets/current liabilities
20	WZ	TL/SE	Total liabilities/stockholders' equity
21	Z	Sales/PA	Sales/plant assets
22	BGR	CFFO/TA	Cash flow from operations/total assets
23	B	Cash PD INV/CFFO	Cash paid for inventory/CFFO
24	B	CFFO/Cash PD INT+LTD+FIN	CFFO/cash paid for interest, LTD, other financing uses
25	B	Cash RD LTD/LTD	Cash received from LTD/Average LTD
26	B	Cash RD STK+LTD+FIN/TCF	Cash received from sale of stock, LTD, other fin sources/total cash flow
27	B	Cash PD ALL CFFI/CFFI	Cash paid for investing activities/net cash flow from investing activities
28	B	Cash PD INV/CGS	Cash paid for inventory/cost of goods sold
29	B	Cash RD	Cash received from sale of plant assets+

Table 13

Variables Selected for Analysis

#	Source	Variable	Description
		PA+INVST/AVG PA	other investing sources/average plant assets
30	B	CFFI/AVG PA	CFFI/average plant assets
31	B	DIV/CFFF	Cash paid for dividends/net cash flow from financing activities
32	BR	Cash/CL	Cash/current liabilities
33	GR	TA/TL	Total assets/total liabilities
34	G	NIPD/TA	Net income + depreciation + depletion + amortization/total assets
35	RW	NIPD/TL	NIPD/total liabilities
36	RSW	CFFO/TL	CFFO/total liabilities
37	R	CFFO/NI	CFFO/net income
38	R	CFFO/TCF	CFFO/total cash flow
39	R	CFFF/TA	Cash flow from financing activities/total assets
40	R	CFFF/TCF	CFFF/total cash flow
41	S	OIPD/TA	Operating income + depreciation/total assets
42	S	OI/TA	Operating income/total assets
43	S	REC/Sales	Receivables/sales
44	S	CL/TL	Current liabilities/total liabilities
45	S	(CFFO-DIV)/TL	(CFFO-cash paid for dividends)/total liabilities
46	S	CFFOBIT/INT	CFFO before interest, taxes/interest paid

Note 1. A = Altman (1968), B = Bukovinsky (1993), D = Deakin (1977), G = Gombola et al. (1987), M = McGurr (1996), R = Rujoub et al. (1995), S = Stanko & Zeller (1993) or Zeller & Stanko (1994a or 1994b), W = Ward (1994), Z = Zavgren (1985).

derived through factor analysis used by Gombola et al. (1987), Stanko & Zeller (1993), and Zeller & Stanko (1994a, 1994b).

Industry Effects

A model which could be generalized to firms in all industries would have a high level of practical and theoretical applicability. However, Gombola & Ketz (1983c) found ratios for retailing and manufacturing firms were sufficiently different to warrant separate consideration. Platt & Platt (1990, 1991) also found significant differences between industries. In order to analyze industry effects, two subsets of the failed and non-failed groups were created. The first was retail and wholesale firms except eating and drinking establishments (SIC codes 5000-5799 and 5900-5999); the second was manufacturing firms (SIC codes 2000-3999). The lack of inventory in eating and drinking places warrants their exclusion (McGurr, 1996).

Data

The data used in the study were amounts taken from the balance sheet, income statement, statement of retained earnings, and statement of cash flows of public companies listed on the Standard & Poor's Compustat PC Plus database. This database contains active and inactive (research) files. For each company selected, two years of data were obtained.

Sample Selection

This study followed Altman (1968), Deakin (1977), Ohlson (1980), Rose & Giroux (1984), Gombola et al. (1987), Rujoub et al. (1995), Kane et al. (1996), McGurr (1996), and others in using the filing for bankruptcy as the condition for sample selection of failed firms.

Companies that filed for Chapter 7 or 11[3] bankruptcy protection between January 1, 1990 and December 31, 1997 were identified by reviewing the Wall Street Journal Index and from a listing of SEC bankruptcy filings. All manufacturing firms (SIC codes 2000-3999), wholesale firms (SIC codes 5000-5199), and retail firms (SIC codes 5200-5999) except eating and drinking places (SIC codes 5800-5899) were used. Only data from financial statements issued before the date of bankruptcy filing were used to ensure that the financial statements were prepared under a "going concern" assumption. These firms constituted the "failed" group.

For each failed firm, a non-failed firm matched by four digit SIC code and size was selected. A list of the failed and matching non-failed firms used in this study is in Appendix A. Use of a one to one matched sample has been criticized by Joy & Tollefson (1975) and others for introducing a choice-based bias into the sample because the true proportion of failed firms in the population is very small (Ohlson, 1980). However, Zmijewski (1984) reports that this choice-based bias from oversampling did not significantly change the overall classification or prediction accuracy rates. One to one matched samples have been used by Beaver (1966), Altman (1968), Deakin (1972), Blum (1974), Rose & Giroux (1984), Zavgren (1985), Gombola et al. (1987), Platt & Platt (1990), Rujoub et al. (1995), McGurr (1996), and others.

These efforts resulted in finding a total of 108 retail/wholesale and 162 manufacturing firms in the Compustat database with sufficient data which filed for Chapter 7 or 11 bankruptcy protection between January 1, 1990 and December 31, 1997. The retail/wholesale sample consisted of 108 failed and 108 non-failed retail/wholesale firms; the manufacturing sample consisted of 162 failed and 162 non-failed manufacturing firms; and the combined sample totaled 270 failed and 270 non-failed firms for a total of 540 firms. The failed group sample size

[3]In 1979 the U. S. Bankruptcy Code consolidated Chapters 10, 11, and 12 into a single Chapter 11.

of studies reviewed in Chapter 2 ranged from 21 (Edmister, 1972) to 115 (Blum, 1974).

Statistical Procedures

Multiple discriminant analysis (MDA) was used to develop the models. "MDA is appropriate when the dependent variable is categorical (nominal or nonmetric) and the independent variables are metric [i.e., interval or ratio data]" (Hair et al., 1995, p.181). Use of MDA in failure prediction studies was supported by Gentry et al. (1985a) who found that MDA, logit, and probit produced similar results. Gombola et al. (1987) found MDA and probit produced similar results. MDA has been used in numerous failure prediction studies including the recent studies by Bukovinsky (1993), Rujoub et al. (1995), and McGurr (1996). It was also found to provide superior classification results than neural networks (Altman, Marco, & Varetto, 1994).

In this study, several metric independent variables were used to discriminate between two groups. The original group of continuous variables were tested for collinearity using Pearson's correlation (Tabachnick & Fidell, 1989). Only one variable was selected from each group of highly correlated variables. The remaining variables were entered into the analysis and a stepwise technique was used to determine which variables discriminate between failed and non-failed groups.

Three separate models were developed, one each for the retail/wholesale industry, the manufacturing industry, and a mixed-industry model. Each industry group consisted of failed and pair-matched non-failed firms. The MDA produced a linear function in the form of:

$$Z = a + b_1X_1 + b_2X_2 + b_3X_3 + \ldots b_nX_n$$

where Z = the result from applying the model; scores > 0 suggest the firm will not fail, < 0 that it will.

a = a constant to force the cut-off point to 0

b_n= coefficients produced by the model

X_n= independent variables

Tests of Hypotheses 1-3

As stated earlier, the following research and null hypotheses were tested:

H1: Cash flow ratios, when included in a multivariate discriminant model and when measured by the means of the z score produced by MDA, can be used to predict failed vs. non-failed firms in the retail/wholesale industry.

$H_0$1: Cash flow ratios, when included in a multivariate discriminant model and when measured by the means of the z score produced by MDA, are not able to predict failed vs. non-failed firms in the retail/wholesale industry.

H2: Cash flow ratios, when included in a multivariate discriminant model and when measured by the means of the z score produced by MDA, can be used to predict failed vs. non-failed firms in the manufacturing industry.

$H_0$2: Cash flow ratios, when included in a multivariate discriminant model and when measured by the means of the z score produced by MDA, are not able to predict failed vs. non-failed firms in the manufacturing industry.

H3: Cash flow ratios, when included in a multivariate discriminant model and when measured by the means of the z score produced by MDA, can be used to predict failed vs. non-failed firms in the retail/wholesale and manufacturing industries combined.

$H_0$3: Cash flow ratios, when included in a multivariate discriminant model and when measured by the means of the z score produced by MDA, are not able to predict failed vs. non-failed firms in the retail/wholesale and manufacturing industries combined.

These hypotheses were tested to evaluate if models can be developed using a combination of cash flow and accrual ratios which are useful in predicting failed vs. non-failed firms in the retail/wholesale industry, the manufacturing industry, and in the two industries combined. Development of such models would indicate the SCF has information content.

Each of the three models developed to test the above hypotheses were used to classify firms as failed or non-failed. MDA determined the mean vectors for the failed and non-failed groups. Hotelling's T^2 test was used to determine that the mean vectors of the two groups were significantly different (Rencher, 1995). Classification accuracy was determined by comparing the predicted outcome to the actual classification and to the naive model which would be 50% accurate based on the proportional chance criterion (Huberty, 1994).

Validation

The models were validated using two methods. The jackknife method, proposed by Lachenbruch (1967), validates a developmental sample by holding out one member of the sample and recalculating the model. The recalculated model is used to classify the one member held out. This is repeated until each member is held out one time.

The second method, suggested by Frank et al. (1965) and used by Altman (1968) and McGurr (1996), involves splitting each failed and its matched non-failed group into analysis and validation samples. "This procedure uses the coefficients generated by the analysis sample to predict group membership for each member of the validation sample" (Frank et al., 1965, p.254). Chi-square tests were used to compare the proportion of failed to non-failed firms accurately predicted to the population proportion (50%).

Frank et al. (1965) also suggested that this validation procedure "be repeated several times. Each time the results are generated by using a different convention for randomly assigning [firms] to the analysis and validation samples" (p.254). Therefore, the iterations in Table 14 were performed. Iterations 1-4 were suggested by Altman (1968). Iterations 5 and 6 consider whether firm size affects ratios and iteration 7 considers whether the passage of time affects ratios and were suggested by McGurr (1996).

Table 14

Split Sample Validation

1. Firms were randomly assigned, in equal number, to the analysis and validation samples.
2. Firms were randomly assigned, in a two to one ratio, to the analysis and validation samples.
3. From the original list of sample companies (which was in alphabetical order), placed every other firm, beginning with the first, in the analysis sample; every other firm, beginning with the second, in the validation sample.
4. From the original list of sample companies (which was in alphabetical order), placed two out of three firms, beginning with the first, in the analysis sample; every third firm, beginning with the third, in the validation sample.
5. Using a median split of sales, placed large firms in the analysis sample and small firms in the validation sample.
6. Using a median split of sales, placed small firms in the analysis sample and large firms in the validation sample.
7. Firms with financial statements dated prior to August, 1992 were placed in the analysis sample and all other firms in the validation sample.

Reporting of Results

The overall significance of the models and of the individual predictor variables is reported as well as overall, Type I and Type II error rates. Since the relative costs of these two types of errors is user-specific (Altman et al., 1977), no weighting or distinction between them is offered.

Tests of Hypothesis 4-6 - Replication of Other Models

Research and null hypotheses 4-6 compare the cash flow and accrual models developed in testing hypotheses 1-3 to previously developed accrual-only models.

H4: Cash flow ratios, when included in a multivariate discriminant model and when measured by the percentage of correct predictions of failed vs. non-failed firms by the model developed in H1 for the retail/wholesale industry, are more accurate than accrual ratios in predicting failed vs. non-failed firms.

H_o4: Cash flow ratios, when included in a multivariate discriminant model and when measured by the percentage of correct predictions of failed vs. non-failed firms by the model developed in H1 for the retail/wholesale industry, are less accurate than or equally as accurate as accrual ratios in predicting failed vs. non-failed firms.

H5: Cash flow ratios, when included in a multivariate discriminant model and when measured by the percentage of correct predictions of failed vs. non-failed firms by the model developed in H2 for the manufacturing industry, are more accurate than accrual ratios in predicting failed vs. non-failed firms.

H_o5: Cash flow ratios, when included in a multivariate discriminant model and when measured by the percentage of correct predictions of failed vs. non-failed firms by the model developed in H2 for the manufacturing industry, are less accurate than or equally as accurate as accrual ratios in predicting failed vs. non-failed firms.

H6: Cash flow ratios, when included in a multivariate discriminant model and when measured by the percentage of correct predictions of failed vs. non-failed firms by the model developed in H3 for the retail/wholesale and manufacturing industries combined, are more accurate than accrual ratios in predicting failed vs. non-failed firms.

H_o6: Cash flow ratios, when included in a multivariate discriminant model and when measured by the percentage of correct predictions of failed vs. non-failed firms by the model developed in H3 for the retail/wholesale and manufacturing industries combined, are less accurate than or equally as accurate as accrual ratios in predicting failed vs. non-failed firms.

These hypotheses (4-6) were tested to determine if new cash flow and accrual oriented models are better predictors of failure than previously developed models. More accurate prediction by the cash flow and accrual models would indicate the SCF has non-redundant information. To test these hypotheses, the classification accuracy of the cash flow and accrual oriented models developed to test hypotheses 1-3 were compared to the classification accuracy obtained from replicating the accrual oriented models.

The base models were chosen for several reasons. Their classification accuracy and reliance on commonly available information make them easy and practical to use. The older models (Altman and Deakin) are often referred to in the business failure prediction literature. Altman's is the only MDA model limited to manufacturing firms. His model has been replicated by Dambolena & Shulman (1988), Bukovinsky (1993), Kane et al. (1996), and others. Deakin's MDA model has been replicated by Bukovinsky (1993) and McGurr (1996). McGurr's is the only model limited to retail firms. No cash flow oriented studies were replicated because most used pre-SFAS No. 95 data, coefficients necessary for replication were not reported, or classification accuracy rates were less than those of accrual studies.

The cash flow and accrual retail/wholesale industry model (developed in H1) was tested by applying the coefficients and variables of McGurr's (1996) retail prediction model to the retail and wholesale firms used in this study. This allowed a direct comparison of error rates. McNemar's (1947) test was used to compare the results from using the current study's data with McGurr's model and the cash flow and accrual retail/wholesale model results. McNemar's test uses a Chi-square goodness-of-fit to analyze differences in predicted outcomes. Overall, Type I, and Type II error rates, the Chi-square values and related levels of significance are reported.

The cash flow and accrual manufacturing industry model (developed in H2) was tested by applying the coefficients and variables of Altman's (1968) model to the manufacturing firms used in this study. McNemar's test was used to compare the results. Overall, Type I, and Type II error rates, the Chi-square values, and related levels of significance are reported.

The cash flow and accrual mixed industry model (developed in H3) was tested by applying the coefficients and variables of Deakin's (1977) model to all the firms used in this study. Again, McNemar's test was used to compare the results. Overall, Type I, and Type II error rates, the Chi-square values, and related levels of significance are reported.

The next chapter presents the analysis and presentation of the findings.

CHAPTER IV

ANALYSIS AND PRESENTATION OF FINDINGS

An analysis of the data and results are presented in this chapter.

Summary Statistics

There were 108 retail/wholesale and 162 manufacturing firms in the Compustat database with sufficient data which filed for Chapter 7 or 11 bankruptcy protection between January 1, 1990 and December 31, 1997. The retail/wholesale sample consisted of 108 failed and 108 non-failed retail/wholesale firms; the manufacturing sample consisted of 162 failed and 162 non-failed manufacturing firms; and the combined sample totaled 270 failed and 270 non-failed firms for a total of 540 firms. The initial list of variables included 47 financial statement ratios and one trend variable. Summary statistics were determined for the financial statement data and variables.

Financial Statements

Summary statistics for financial statement items are presented in Table 15 for the retail/wholesale industry sample, Table 16 for the manufacturing industry sample, and Table 17 for the mixed retail/wholesale and manufacturing industries sample. The mixed industry sample's failed firms' average total assets were approximately 8% higher than the mixed industry sample's non-failed firms' yet their average sales were about 10% lower. Failed firms in all three samples had higher average liabilities and lower average stockholders' equity. The sample's failed manufacturing firms reported an average negative mean

Table 15

Summary Statistics - Retail/Wholesale Industry Financial Statements
(in $millions except number of employees)

	Retail/Wholesale		
	Failed n=108 Mean	Non-failed n=108 Mean	All Ret/Whl n=216 Mean
Balance Sheet			
Cash & equivalents	$ 11.961	$ 25.752	$ 18.856
Receivables	32.874	59.733	46.304
Inventories	131.476	134.473	132.975
Other current	15.276	11.159	13.217
Total current assets	191.587	231.117	211.352
Net plant assets	151.539	134.129	142.874
Other assets	91.787	30.177	60.942
Total assets	$ 434.913	$ 395.423	$ 415.168
Current liabilities	$ 163.619	$ 115.650	$ 139.634
Non-current liabilities	221.813	120.477	171.146
Total liabilities	385.432	236.127	310.780
Stockholders' equity	49.481	159.296	104.388
Total liab + equity	$ 434.913	$ 395.423	$ 415.168
Income Statement			
Sales	$ 726.366	$ 807.452	$ 766.909
Cost of Sales	516.143	595.615	555.879
Gross Margin	210.223	211.837	211.030
Operating expenses	202.352	171.830	187.091
Operating margin	7.871	40.007	23.939
Other income/expense	41.953	9.503	25.728
Income before tax	-34.082	30.504	-1.789
Taxes	-2.864	11.637	4.387
Net income	$ -31.218	$ 18.867	$ -6.176
Statement of Cash Flows			
Net CF-Operating	$ 3.763	$ 22.884	$ 13.323
Net CF-Investing	1.124	-22.729	-10.803
Net CF-Financing	-7.175	1.694	-2.740
Exchange rate effect	-.028	.103	.038
Net cash flow	$ -2.316	$ 1.952	$ -.182
# of employees (000's)	7.320	6.657	6.985

Table 16

Summary Statistics - Manufacturing Industry Financial Statements

(in $millions except number of employees)

	Failed n=162 Mean	Manufacturing Non-failed n=162 Mean	All Mfg n=324 Mean
Balance Sheet			
Cash & equivalents	$ 10.616	$ 15.874	$ 13.245
Receivables	28.532	35.883	32.208
Inventories	29.121	31.949	30.535
Other current	9.297	4.878	7.087
Total current assets	77.566	88.584	83.075
Net plant assets	51.766	57.757	54.762
Other assets	53.563	27.950	40.756
Total assets	$ 182.895	$ 174.291	$ 178.593
Current liabilities	$ 106.655	$ 42.012	$ 74.334
Non-current liabilities	77.608	50.054	63.831
Total liabilities	184.263	92.066	138.165
Stockholders' equity	-1.368	82.225	40.428
Total liab + equity	$ 182.895	$ 174.291	$ 178.593
Income Statement			
Sales	$ 190.079	$ 211.376	$ 200.727
Cost of Sales	146.856	144.448	145.652
Gross Margin	43.223	66.928	55.075
Operating expenses	43.792	47.908	45.850
Operating margin	-.569	19.020	9.225
Other income/expense	24.194	4.010	-14.101
Income before tax	-24.763	15.010	-4.876
Taxes	1.264	5.537	3.401
Net income	$ -26.027	$ 9.473	$ -8.277
Statement of Cash Flows			
Net CF-Operating	$ -3.829	$ 13.406	$ 4.789
Net CF-Investing	-5.534	-13.589	-9.561
Net CF-Financing	7.156	1.434	4.295
Exchange rate effect	-.013	-.185	-.100
Net cash flow	$ -2.220	$ 1.066	$ -.577
# of employees (000's)	1.461	1.844	1.654

Table 17

Summary Statistics - Mixed Industry Financial Statements

(in $millions except number of employees)

	Mixed Industry Failed n=270 Mean	Mixed Industry Non-failed n=270 Mean	Total n=540 Mean
Balance Sheet			
Cash & equivalents	$ 11.154	$ 19.825	$ 15.490
Receivables	30.269	45.423	37.846
Inventories	70.063	72.959	71.511
Other current	11.688	7.390	9.539
Total current assets	123.174	145.597	134.386
Net plant assets	91.675	88.135	89.909
Other assets	68.854	29.012	48.928
Total assets	$ 283.703	$ 262.744	$ 273.223
Current liabilities	$ 129.440	$ 71.467	$ 100.454
Non-current liabilities	135.291	78.224	106.756
Total liabilities	264.731	149.691	207.210
Stockholders' equity	18.972	113.053	66.013
Total liab + equity	$ 283.703	$ 262.744	$ 273.223
Income Statement			
Sales	$ 404.594	$ 449.806	$ 427.200
Cost of Sales	294.571	324.915	309.743
Gross Margin	110.023	124.891	117.457
Operating expenses	107.216	97.476	102.346
Operating margin	2.807	27.415	15.111
Other income/expense	31.298	6.207	18.752
Income before tax	-28.491	21.208	-3.641
Taxes	-.387	7.977	3.796
Net income	$ -28.104	$ 13.231	$ -7.437
Statement of Cash Flows			
Net CF-Operating	$ -.792	$ 17.197	$ 8.203
Net CF-Investing	-2.870	-17.245	-10.058
Net CF-Financing	1.423	1.538	1.481
Exchange rate effect	-.019	-.069	-.044
Net cash flow	$ -2.258	$ 1.421	$ -.418
# of employees (000's)	3.845	3.809	3.827

stockholders' equity. Both retail/wholesale and manufacturing firms in the sample experienced average negative cash flow but the components differed. Failed retail/wholesale firms in the sample had positive cash flow from operating and investing activities and negative cash flow from financing activities; failed manufacturing firms in the sample experienced the opposite component net flows with only financing cash flows being positive. Sample failed retail/wholesale firms had almost 10% more employees as their non-failed counterpart. On the other hand, failed manufacturing firms in the sample had over 20% fewer employees on average than non-failed manufacturing firms.

Variables

Ratios are an accepted way of presenting information which has been adjusted for differences in dollar magnitude. All variables needed to replicate the findings of Altman (1968), Deakin (1977), and McGurr(1996) were calculated. Other cash flow and accrual oriented variables were also included. The variables, their source, and their definitions were provided in Table 13. Summary statistics of the 46 variables considered for analysis are presented in Table 18 for the retail/wholesale sample, Table 19 for the manufacturing sample, and Table 20 for the mixed industry sample.

Tests for Multicollinearity

If the variables included in MDA are highly correlated, it is difficult to determine the contribution of each independent variable thus confounding the results (Hair et al., 1995). Tabachnick & Fidell (1987) suggest eliminating highly correlated variables. A Pearson correlation matrix was developed for the 46 variables (See Appendix B). All variables with a Pearson correlation over 0.65 (McGurr, 1996) were considered highly correlated and were examined in order to determine

Table 18

Summary Statistics - Retail/Wholesale Industry Variables

VAR	LABEL	Failed n=108 Mean	Non-failed n=108 Mean	All Ret/Whl n=216 Mean
V01	WC/TA	.12	.33	.23
V02	RE/TA	-.16	.04	-.06
V03	EBIT/TA	-.09	.07	-.01
V04	MV EQ/TL	.74	2.38	1.56
V05	SALES/TA	2.16	2.28	2.22
V06	NI/TA	-.15	.02	-.06
V07	CA/TA	.60	.64	.62
V08	CASH/TA	.05	.10	.08
V09	CA/TL	.88	1.50	1.19
V10	SALES/CA	4.07	3.89	3.98
V11	WC TRND	.31	.68	.49
V12	SALES/# EMP	149.66	185.82	167.91
V13	GM/SALES	28.66	29.11	28.88
V14	%CHG LTD	7.57	4.69	6.13
V15	CA/CL	1.51	2.48	1.99
V16	LTD/TA	.26	.20	.23
V17	INV/SALES	.22	.20	.21
V18	REC/INV	.42	.47	.45
V19	QA/CL	.38	.97	.67
V20	TL/SE	-33.05	4.00	-14.53
V21	SALES/AVG PPE	12.56	14.39	13.47
V22	CFFO/TA	-.02	.04	.01
V23	CP INV/CFFO	-4.56	29.74	12.59
V24	CFFO/CP INT+LTD+OFIN	-.65	-1.37	-1.01
V25	CR LTD/AVG LTD	.91	2.39	1.65
V26	CR STK+LTD+OFIN/TCF	-15.54	13.36	-1.09
V27	CP ALL FIN/CFFI	-1.29	-1.19	-1.24
V28	CP INV/CGS	.98	1.03	1.00
V29	CR PPE+INVST/AVG PPE	.04	.09	.06
V30	CFFI/AVG PPE	-.28	-.36	-.32
V31	DIV/CFFF	-.04	-.13	-.08
V32	CASH/CL	.14	.49	.32
V33	TA/TL	1.47	2.25	1.86
V34	NIPD/TA	-.09	.05	-.02
V35	NIPD/TL	-.08	.15	.04
V36	CFFO/TL	-.01	.11	.05
V37	CFFO/NI	.50	6.03	3.27
V38	CFFO/TCF	-10.98	5.88	-2.55
V39	CFFF/TA	.06	.04	.05
V40	CFFF/TCF	18.42	9.87	14.15
V41	OIPD/TA	-.01	.11	.05
V42	OI/TA	-.06	.07	.01
V43	REC/SALES	.06	.07	.07
V44	CL/TL	.62	.62	.62
V45	(CFFO-DIV)/TL	-.01	.09	.04
V46	CFFOBIT/INT	-.89	.91	.01

Table 19

Summary Statistics - Manufacturing Industry Variables

VAR	LABEL	Failed n=162 Mean	Non-failed n=162 Mean	All Mfg n=324 Mean
V01	WC/TA	-.17	.33	.08
V02	RE/TA	-2.04	-.31	-1.17
V03	EBIT/TA	-.41	.01	-.20
V04	MV EQ/TL	2.17	7.91	5.05
V05	SALES/TA	1.38	1.38	1.38
V06	NI/TA	-.52	-.03	-.27
V07	CA/TA	.57	.63	.60
V08	CASH/TA	.08	.16	.12
V09	CA/TL	.86	2.30	1.58
V10	SALES/CA	2.62	2.32	2.47
V11	WC TRND	.25	.65	.45
V12	SALES/# EMP	191.44	153.97	172.65
V13	GM/SALES	-100.63	27.45	-36.59
V14	%CHG LTD	3.71	.84	2.28
V15	CA/CL	1.39	3.25	2.32
V16	LTD/TA	.20	.15	.18
V17	INV/SALES	.25	.19	.22
V18	REC/INV	1.30	1.42	1.36
V19	QA/CL	.67	2.17	1.42
V20	TL/SE	-.60	1.60	.50
V21	SALES/AVG PPE	10.29	11.18	10.74
V22	CFFO/TA	-.15	.00	-.07
V23	CP INV/CFFO	193.59	.07	96.83
V24	CFFO/CP INT+LTD+OFIN	-7.75	-2.84	-5.30
V25	CR LTD/AVG LTD	1.51	.36	.93
V26	CR STK+LTD+OFIN/TCF	-7.40	27.07	9.84
V27	CP ALL FIN/CFFI	.22	-1.15	-.47
V28	CP INV/CGS	1.08	1.09	1.08
V29	CR PPE+INVST/AVG PPE	.21	.04	.13
V30	CFFI/AVG PPE	.02	-.39	-.19
V31	DIV/CFFF	.02	.07	.04
V32	CASH/CL	.25	1.23	.74
V33	TA/TL	1.50	3.47	2.49
V34	NIPD/TA	-.45	.01	-.22
V35	NIPD/TL	-.41	-.13	-.27
V36	CFFO/TL	-.29	-.15	-.22
V37	CFFO/NI	-.07	1.39	.66
V38	CFFO/TCF	16.83	19.43	18.13
V39	CFFF/TA	.13	.07	.10
V40	CFFF/TCF	-13.07	-18.68	-15.88
V41	OIPD/TA	-.26	.05	-.11
V42	OI/TA	-.33	.01	-.16
V43	REC/SALES	.17	.18	.18
V44	CL/TL	.70	.66	.68
V45	(CFFO-DIV)/TL	-.30	-.19	-.25
V46	CFFOBIT/INT	-11.62	19.79	4.08

Table 20

Summary Statistics - Mixed Industry Variables

VAR	LABEL	Failed n=270 Mean	Non-failed n=270 Mean	All firms n=540 Mean
V01	WC/TA	-.06	.33	.14
V02	RE/TA	-1.28	-.17	-.73
V03	EBIT/TA	-.28	.03	-.12
V04	MV EQ/TL	1.59	5.70	3.65
V05	SALES/TA	1.69	1.74	1.71
V06	NI/TA	-.37	-.01	-.19
V07	CA/TA	.58	.63	.61
V08	CASH/TA	.07	.14	.10
V09	CA/TL	.87	1.98	1.42
V10	SALES/CA	3.20	2.95	3.08
V11	WC TRND	.27	.66	.47
V12	SALES/# EMP	174.44	167.03	170.71
V13	GM/SALES	-48.92	28.11	-10.40
V14	%CHG LTD	5.26	2.38	3.82
V15	CA/CL	1.44	2.94	2.19
V16	LTD/TA	.22	.17	.20
V17	INV/SALES	.24	.19	.22
V18	REC/INV	.95	1.04	1.00
V19	QA/CL	.55	1.69	1.12
V20	TL/SE	-13.58	2.56	-5.51
V21	SALES/AVG PPE	11.20	12.46	11.83
V22	CFFO/TA	-.10	.02	-.04
V23	CP INV/CFFO	114.33	11.94	63.13
V24	CFFO/CP INT+LTD+OFIN	-4.91	-2.25	-3.58
V25	CR LTD/AVG LTD	1.27	1.17	1.22
V26	CR STK+LTD+OFIN/TCF	-10.66	21.59	5.46
V27	CP ALL FIN/CFFI	-.38	-1.17	-.78
V28	CP INV/CGS	1.04	1.06	1.05
V29	CR PPE+INVST/AVG PPE	.15	.06	.10
V30	CFFI/AVG PPE	-.10	-.38	-.24
V31	DIV/CFFF	.00	-.01	-.01
V32	CASH/CL	.20	.93	.57
V33	TA/TL	1.49	2.99	2.24
V34	NIPD/TA	-.31	.03	-.14
V35	NIPD/TL	-.28	-.02	-.15
V36	CFFO/TL	-.18	-.05	-.11
V37	CFFO/NI	.16	3.25	1.70
V38	CFFO/TCF	5.71	14.01	9.86
V39	CFFF/TA	.11	.06	.08
V40	CFFF/TCF	-.47	-7.26	-3.87
V41	OIPD/TA	-.16	.07	-.04
V42	OI/TA	-.22	.03	-.09
V43	REC/SALES	.13	.14	.13
V44	CL/TL	.67	.64	.66
V45	(CFFO-DIV)/TL	-.18	-.08	-.13
V46	CFFOBIT/INT	-7.33	12.24	2.46

which variables would be included in the analysis.

Variables 1, 2, 3, 6, 34, 41, and 42 were highly correlated and had total assets as their denominator. Variable 6, net income/total assets (return on assets or ROA) was retained because net income is the most common measure of firm performance and ROA is commonly used in financial analysis (Helfert, 1994). Variables 4, 9, 15, 19, 32, and 33 were highly correlated and contained either total or current liabilities in the denominator. Variable 15, current assets/current liabilities or current ratio, was retained because the current ratio is the most common measure of liquidity (Helfert, 1994).

Variables 5 and 10, which were both asset turnover ratios, were highly correlated. Variable 5, total asset turnover, was retained because it resulted in a slightly higher classification accuracy in preliminary tests. ROA (variable 6) and cash flow from financing activities/total assets (variable 39) were highly correlated. Variable 6 was retained based on preliminary tests.

Variables 8, 19, and 32, which all had cash, a quick asset, in the numerator, were highly correlated. Since variables 19 and 32 were eliminated above, variable 8 (cash percentage) was retained. Variables 16 (long term debt/total liabilities) and 44 (current liabilities/total liabilities) were highly correlated. Variable 44 was eliminated because current liabilities were already reflected in variables 11 and 15.

Variable 22's high correlation with variables 39, 41, and 42 became irrelevant as these three were eliminated above. Variables 35, 36, and 45, which had total liabilities as the denominator, were highly correlated. Variable 36 was retained because it was used by more studies cited in Table 13 and contained a cash flow component. Variables 35 and 45 were eliminated.

As a result of the above, sixteen variables were eliminated due to high correlation leaving 30 variables to be entered into the multiple discriminant analysis. These are listed in Table 21.

Table 21

Variables Used in the Multiple Discriminant Analysis

#	Variable	Description
5	Sales/TA	Sales/total assets (sales turnover)
6	NI/TA	Net income/total assets (return on assets)
7	CA/TA	Current assets/total assets
8	Cash/TA	Cash/total assets
11	WC TRND	1 if WC \$CY (current year)>WC\$PY (prior year)
12	Sales/# EMP	Sales/number of employees
13	GM/Sales	Gross margin/sales
14	%CHG LTD	{Long-term debt (LTD)CY-LTD PY}/LTD PY
15	CA/CL	Current assets/current liabilities (current ratio)
16	LTD/TA	Long term debt/total assets
17	INV/Sales	Inventory/sales
18	REC/INV	Receivables/inventory
20	TL/SE	Total liabilities/stockholders' equity
21	Sales/PA	Sales/plant assets (capital turnover)
22[a]	CFFO/TA	Cash flow from operations/total assets
23[a]	Cash PD INV/CFFO	Cash paid for inventory[b]/CFFO
24[a]	CFFO/Cash PD INT+LTD+FIN	CFFO/cash paid for interest, LTD, other financing uses
25[a]	Cash RD LTD/LTD	Cash received from LTD/Average LTD
26[a]	Cash RD STK+LTD+FIN/TCF	Cash received from sale of stock, LTD, other fin sources/total cash flow
27[a]	Cash PD ALL CFFI/CFFI	Cash paid for investing activities/net cash flow from investing activities
28[a]	Cash PD INV/CGS	Cash paid for inventory/cost of goods sold
29[a]	Cash RD PA+INVST/AVG PA	Cash received from sale of plant assets+ other investing sources/average plant assets
30[a]	CFFI/AVG PA	CFFI/average plant assets
31[a]	DIV/CFFF	Cash paid for dividends/net cash flow from financing activities
36[a]	CFFO/TL	CFFO/total liabilities
37[a]	CFFO/NI	CFFO/net income
38[a]	CFFO/TCF	CFFO/total cash flow
40[a]	CFFF/TCF	CFFF/total cash flow
43	REC/Sales	Receivables/sales
46[a]	CFFOBIT/INT	CFFO before interest, taxes/interest paid

[a] Cash flow oriented variables. [b] Calculated as the cost of goods sold + change in inventory - change in accounts payable.

Hypotheses 1-3

The first three research hypotheses posited that cash flow ratios, when included in a multivariate discriminant model and when measured by the means of the z score produced by multiple discriminant analysis (MDA), can be used to predict failed vs. non-failed firms in the retail/wholesale industry, the manufacturing industry, and in the two industries combined. MDA was used to test the hypotheses.

Discriminant Function

The 30 variables in Table 21 were entered as independent variables along with one dependent variable - a dichotomous variable coded 1 if the firm was classified as non-failed and 0 if the firm had failed - into three stepwise multivariate discriminant analyses using SPSS. In testing hypothesis H1, the 216 (108 failed + 108 non-failed) retail and wholesale firms were used; for H2 the 324 (162 failed + 162 non-failed) manufacturing firms were used. All 540 firms (270 failed + 270 non-failed) were used to test H3.

Hypothesis 1

Five accrual variables, including variable 6, net income/total assets, appeared in the original retail/wholesale model; no cash flow variable appeared. Altman (1968) suggested that since MDA is an iterative process a resulting discriminant function may not be optimal. As discussed later, variable 22 (CFFO/total assets) did enter the manufacturing and mixed industry models. Because of this and because variable 22 was a cash flow variable with a high correlation to variable 6 (0.62 - see Appendix B) a revised model was prepared substituting V22 for V6 (NI/TA). When V22 was substituted for V6 in the retail/wholesale model, overall classification accuracy increased from 72.7% to 74.5%. The final model contained one cash flow and four accrual variables. The variables and the resulting discriminant function (model) for the retail/wholesale firms are shown in Table 22.

Table 22

Retail/wholesale Prediction Model

$$Z = -.867 + 1.184X_1 + .559X_2 - 1.290X_3 - 2.643X_4 + 1.347X_5$$

where

Z = Overall index[a]

X_1 = Var11 (WC TRND)

X_2 = Var15 (CA/CL)

X_3 = Var16 (LTD/TA)

X_4 = Var17 (INV/SALES)

X_5 = Var22 (CFFO/TA)

[a]If $Z<0$ then failure is predicted; if $Z>0$ then non-failure is predicted

When applied to the sample, this model achieved a classification accuracy of 74.5% ($p < 0.001$) and jackknife validation accuracy of 73.6% $p < 0.001$). 19.4% of the failed firms were misclassified as non-failed (Type I error) and 31.5% of the non-failed firms were misclassified as failed (Type II error). Table 23 presents a classification matrix summarizing these results.

A z score was calculated for each firm by applying the discriminant function to the 216 firms in the sample. The mean vector of the z scores for failed firms was compared to that of the non-failed firms to test if the mean vectors were equivalent using Hotelling's T^2 test (Rencher, 1995). The resulting Hotelling's T^2 statistic was 80.324 ($p<0.001$) indicating that the model discriminated between failed and non-failed firms. Since the mean vector of the z scores of the failed retail/wholesale firms was significantly different than the mean vector of the z scores of the non-failed retail/wholesale firms, the null hypothesis $H_0 1$ was rejected.

Hypothesis 2

The significant variables identified and the resulting discriminant function (model) for the manufacturing firms are shown in Table 24.

Table 23

Retail/wholesale Model Classification Matrix

		Actual	Group Membership Predicted Failed	Non-failed	Total
Original	Count	Failed	87[a]	21[b]	108
		Non-failed	34[c]	74[a]	108
	percent	Failed	80.6%	19.4%	100.0%
		Non-failed	31.5%	68.5%	100.0%
Cross-Validated[d]	Count	Failed	85[a]	23[b]	108
		Non-failed	34[c]	74[a]	108
	percent	Failed	78.7%	21.3%	100.0%
		Non-failed	31.5%	68.5%	100.0%

[a]Correctly classified. [b]Type I error. [c]Type II error. [d]In cross validation, each firm was classified by the function derived using all firms other than that firm (Lachenbruch, 1967).

Three cash flow variables, 22 (CFFO/total assets), 26 (cash received from the sale of stock, long-term debt, and other financing sources/total cash flow), and 37 (CFFO/net income), appeared in the final model. When applied to the sample, this model achieved a classification accuracy of 76.5% ($p < 0.001$) and jackknife validation accuracy of 75.9% ($p < .001$). The Type I and Type II error rates were 14.2% and 32.7% respectively. Table 25 presents a classification matrix summarizing these results.

A z score was calculated for each firm by applying the discriminant function to the 324 firms in the sample. The mean vector of the z scores for failed firms was compared to that of the non-failed firms to test if the mean vectors were equivalent using Hotelling's T^2 test (Rencher, 1995). The resulting Hotelling's T^2 statistic was 168.668 ($p<0.001$) indicating that the model discriminated between failed and non-failed firms. Since the mean vector of the z scores of the failed manufacturing firms was significantly different than the mean

Table 24

Manufacturing Prediction Model

$$Z = -.567 + 1.284X_1 - .001X_2 + .219X_3 - 1.588X_4 + 1.431X_5 + .001X_6 + .056X_7$$ where

Z = Overall index[a]

X_1 = Var11 (WC TRND)

X_2 = Var12 (Sales/# EMP)

X_3 = Var15 (CA/CL)

X_4 = Var16 (LTD/TA)

X_5 = Var22 (CFFO/TA)

X_6 = Var26 (CR STK+LTD+OFIN/TCF)

V_7 = Var37 (CFFO/NI)

[a]If $Z<0$ then failure is predicted; if $Z>0$ then non-failure is predicted

Table 25

Manufacturing Model Classification Matrix

			Group Membership		
		Actual	Predicted		
			Failed	Non-failed	Total
Original	Count	Failed	139[a]	23[b]	162
		Non-failed	53	109[a]	162
	percent	Failed	85.8[a]	14.2[b]	100.0%
		Non-failed	32.7[c]	67.3[a]	100.0%
Cross-validated[d]	Count	Failed	138[a]	24[b]	162
		Non-failed	54[c]	108[a]	162
	percent	Failed	85.2%	14.8%	100.0%
		Non-failed	33.3%	66.7%	100.0%

[a]Correctly classified. [b]Type I error. [c]Type II error. [d]In cross validation, each firm was classified by the function derived using all firms other than that firm (Lachenbruch, 1967).

vector of the z scores of the non-failed manufacturing firms, the null hypothesis $H_0 2$ was rejected.

Hypothesis 3

The significant variables identified and the resulting discriminant function (model) for the total sample of firms are shown in Table 26. Two cash flow variables, 22 and 26, appeared in the final model. When applied to the sample, this model achieved a classification accuracy of 73.9% ($p < 0.001$) and jackknife validation accuracy of 73.5% ($p < 0.001$). The Type I and Type II error rates were 20.7% and 31.5% respectively. Table 27 presents a classification matrix summarizing these results.

Table 26

Mixed Industry Prediction Model

$$Z = -.904 + 1.311X_1 + .28X_2 - 1.426X_3 + 1.566X_4 + .001X_5$$

where

Z = Overall index[a]

X_1 = Var11 (WC TRND)

X_2 = Var15 (CA/CL)

X_3 = Var16 (LTD/TA)

X_4 = Var22 (CFFO/TA)

X_5 = Var26 (CR STK+LTD+OFIN/TCF)

[a]If $Z<0$ then failure is predicted; if $Z>0$ then non-failure is predicted

A z score was calculated for each firm by applying the discriminant function to the 540 firms in the sample. The mean vector of the z scores for failed firms was compared to that of the non-failed firms to test if the mean vectors were equivalent using Hotelling's T^2 test (Rencher, 1995). The resulting Hotelling's T^2 statistic was 216.826 ($p<0.001$) indicating that the model discriminated between failed and non-failed firms. Since the mean vector of the z scores of the failed retail/wholesale and manufacturing firms was significantly different than the mean vector of the z scores of the non-failed retail/wholesale and manufacturing firms, the null hypothesis H_03 was rejected.

Table 27

Mixed Industry Model Classification Matrix

			Group Membership		
		Actual	Predicted		
			Failed	Non-failed	Total
Original	Count	Failed	214[a]	56[b]	270
		Non-failed	85[c]	185[a]	270
	percent	Failed	79.3%	20.7%	100.0%
		Non-failed	31.5%	68.5%	100.0%
Cross-validated[d]	Count	Failed	213[a]	57[b]	270
		Non-failed	86[c]	184[a]	270
	percent	Failed	78.9%	21.1%	100.0%
		Non-failed	31.9%	68.1%	100.0%

[a]Correctly classified. [b]Type I error. [c]Type II error. [d]In cross validation, each firm was classified by the function derived using all firms other than that firm (Lachenbruch, 1967).

Additional Validation

A split sample validation method suggested by Frank et al. (1965) and used by Altman (1968) and McGurr (1996) was also employed. It involved splitting each group of failed and non-failed firms into analysis and validation subsamples. The analysis subsample was used to generate a new set of discriminating coefficients using the variables from the final model. These were used to predict failure or non-failure in both the analysis and validation subsamples. The procedure was applied to the entire group of 540 firms. The seven replications and their results are summarized in Table 28. Because predictive accuracy

Table 28

Split Sample Validation Results

	Analysis Subsample		Validation Subsample		Predictive Accuracy			
#	Definition	n	Definition	n	Analysis Subsample	X^2 df=5	Validation Subsample	X^2 df=5
1	One-half (random)	270	Remaining one-half	270	75.9%	100.25**	70.7%	77.33**
2	Two-thirds (random)	360	Remaining one-third	180	73.3%	112.65**	75.6%	65.03**
3	Every other firm	270	Remaining one-half	270	78.2%	122.14**	68.9%	58.98**
4	Every 1st & 2nd of 3 beginning with # 1, 2	360	Every 3rd beginning with # 3	180	74.7%	120.40**	70.0%	60.14**
5	Large firms (sales > median)	270	Small Firms (sales < median)	270	73.3%	80.71**	72.6%	124.00**
6	Small Firms (sales < median)	270	Large firms (sales > median)	270	77.4%	124.00**	72.6%	80.71**
7	Firms with financial years prior to Aug 92	273	Firms with financial years after Jul 92	267	75.8%	86.96**	73.8%	86.76**

** $p<.001$

rates were comparable in Tables 23, 25, and 27 separate replications for the 216 retail/wholesale firms and 324 manufacturing firms were not deemed necessary.

Summary of Hypotheses 1-3

The first three research hypotheses posited that cash flow ratios, when included in a multivariate discriminant model and when measured by the means of the z score produced by MDA, can be used to predict failed vs. non-failed firms in the retail/wholesale industry, the manufacturing industry, and in the two industries combined. MDA produced models with classification accuracies of 74.5% (retail/wholesale), 76.5% (manufacturing), and 73.9% (mixed industry). Huberty's (1994) proportional chance criteria suggests a naive model would achieve a 50% classification accuracy rate. All these models achieved classification accuracy rates significantly ($p<.001$) greater than 50%. Hair et al. (1995) suggest that an "acceptable level" of accuracy would be one-fourth greater than that achieved by chance, in this case, 62.5%. All three models exceeded the level suggested by Hair et al. For all three models, the mean vector of the z scores of the failed vs. the non-failed firms was significantly different as measured by the resulting Hotelling's T^2 statistics. Therefore, the null hypotheses, H_01, H_02, and H_03, were rejected and the results support the research hypotheses that cash flow ratios can be used to predict failed vs. non-failed firms in the retail/wholesale industry (H1), the manufacturing industry (H2), and the two industries combined (H3).

Hypotheses 4-6

Research hypotheses 4-6 posited that the retail/wholesale, manufacturing, and mixed-industry failure prediction models developed using cash flow and accrual ratios in H1, H2, and H3 have more ability to predict failed vs. non-failed firms than previously developed retail/wholesale, manufacturing, and mixed industry accrual models which did not utilize cash flow ratios.

Hypothesis 4

To test whether the cash flow and accrual oriented model developed in H1 has more ability to predict failed vs. non-failed firms than an accrual-only model, classification accuracy was compared to McGurr's 1996 failure prediction model. McGurr's model (see Table 10) was developed using only retail firms. Application of McGurr's model to the firms in this sample correctly classified 73.6% of the firms. Classification results from applying McGurr's model to 105 failed and 107 non-failed retail/wholesale firms are presented in Table 29. Data required to replicate McGurr's model were not available for three failed and one non-failed firms, all four of which had been correctly classified by the H1 model.

Table 29

McGurr Model Classification Matrix

		Group Membership		
	Actual	Predicted		
		Failed	Non-failed	Total
Count	Failed	70[a]	35[b]	105
	Non-failed	21[c]	86[a]	107
percent	Failed	66.7%	33.3%	100.0%
	Non-failed	19.6%	80.4%	100.0%

[a]Correctly classified. [b]Type I error. [c]Type II error.

Overall classification accuracy of applying McGurr's 1996 model to data from the current study (73.6%) was similar to that reported earlier with the model developed in H1 (74.5%, see Table 23). The McGurr model had higher Type I error (33.3% vs. 19.4%) but lower Type II error (19.6% vs. 31.5%) rates. McGurr reported a 78% accuracy rate in his original study (1996).

These overall results do not, however, consider whether the same or different firms are classified as failed or non-failed, but only the total number of firms so classified. To compare the accuracy of the cash and accrual oriented prediction model and McGurr's model, McNemar's (1947) test was used. This test examines the firms which are classified differently by the two models. Four different classifications are possible: (1) Both models classify the firm correctly; (2) the H1 model is correct, the McGurr model incorrect; (3) both models classify the firm incorrectly; and (4) the McGurr model is correct, the H1 model incorrect. The results are presented in Table 30.

Table 30

Comparison of Accuracy of H1 (Zordan) vs. McGurr Model

Accuracy of H1	Accuracy of McGurr Model		
(Zordan) Model	Correct	Incorrect	Total
Correct	133	24	157
Incorrect	23	32	55
Total	156	56	212

The two models predicted the same classification for 165 (133+32) of the 212 firms for which data were available. Of the remaining 47 conflicting results, the Zordan model correctly classified one firm more than the McGurr model (24 vs. 23). McNemar's test produces a χ^2 based on only the differences between the two models. In this case, the $\chi^2 < .001$ with 1 degree of freedom (p>.999). This indicates that the cash/accrual model has no more ability to predict failed vs. non-failed retail/ wholesale firms than the McGurr model, which used only accrual oriented ratios. Thus, the null hypothesis $H_0 4$ was not rejected.

Hypothesis 5

To test whether the cash flow and accrual oriented model developed in H2 has more ability to predict failed vs. non-failed firms than an accrual-only model, classification accuracy was compared to Altman's 1968 failure prediction model. Altman's model (see Table 2) was developed using only manufacturing firms. Application of Altman's model to the firms in this sample correctly classified 77.3% of the firms. Classification results from applying Altman's model to 160 failed and 161 non-failed manufacturing firms are presented in Table 31. Data required to replicate Altman's model were not available for two failed and one non-failed firms. Two of these three were correctly classified by the H2 model.

Table 31

Altman Model Classification Matrix

	Group Membership			
	Actual	Predicted		
		Failed	Non-failed	Total
Count	Failed	138[a]	22[b]	160
	Non-failed	51[c]	110[a]	161
percent	Failed	86.3%	13.7%	100.0%
	Non-failed	31.7%	68.3%	100.0%

[a]Correctly classified. [b]Type I error. [c]Type II error.

The overall results of applying Altman's 1968 model to data from the current study were similar to those reported earlier with the model developed in H2 (See Table 25). The Altman and H2 models resulted in 77.3% vs. 76.5% correct classification with 13.7% vs. 14.2% Type I errors and 31.7% vs. 32.7% Type II errors, respectively. Altman reported a 95% accuracy rate in his original study (1968).

These overall results do not, however, consider whether the same or different firms are classified as failed or non-failed, but only the total number of firms so classified. To compare the accuracy of the cash and accrual oriented prediction model and Altman's model, McNemar's (1947) test was used. This test examines the firms which are classified differently by the two models. Four different classifications are possible: (1) Both models classify the firm correctly; (2) the H2 model is correct, the Altman model incorrect; (3) both models classify the firm incorrectly; and (4) the Altman model is correct, the H2 model incorrect. The results are presented in Table 32.

Table 32

Comparison of Accuracy of H2 (Zordan) vs. Altman Model

Accuracy of H2 (Zordan) Model	Accuracy of Altman Model Correct	Incorrect	Total
Correct	212	34	246
Incorrect	36	39	75
Total	248	73	321

The two models predicted the same classification for 251 (212+39) of the 321 firms for which data were available. Of the remaining 70 conflicting results, the Zordan model correctly classified two fewer firms than the Altman model (34 vs. 36). McNemar's test produces a X^2 based on only the differences between the two models. In this case, the X^2 = .014 with 1 degree of freedom (p=.9). This indicates that the cash/accrual model has no more ability to predict failed vs. non-failed manufacturing firms than the Altman model, which did not include any cash flow oriented ratios. Thus, the null hypothesis H_05 was not rejected.

Hypothesis 6

To test whether the cash flow and accrual oriented model developed in H3 has more ability to predict failed vs. non-failed firms than an accrual-only model, classification accuracy was compared to Deakin's 1977 failure prediction model. Deakin's model (see Table 4) was developed using a combination of retail, wholesale, and manufacturing firms. Application of Deakin's model to the firms in this sample correctly classified 75.9% of the firms. Classification results from applying Deakin's model to the 270 failed and 270 non-failed firms are presented in Table 33.

Table 33

Deakin Model Classification Matrix

		Group Membership		
	Actual	Predicted		
		Failed	Non-failed	Total
Count	Failed	214[a]	56[b]	270
	Non-failed	74[c]	196[a]	270
percent	Failed	79.3%	20.7%	100.0%
	Non-failed	27.4%	72.6%	100.0%

[a]Correctly classified. [b]Type I error. [c]Type II error.

The overall results of applying Deakin's 1977 model to data from the current study were similar to those reported earlier with the model developed in H3 (See Table 27). The Deakin and H3 models resulted in 75.9% vs. 73.9% correct classification and 27.4% vs. 31.5% Type II error rates, respectively. Both models had Type I error rates of 20.7%. Deakin reported a 94.4% accuracy rate in his original study (1977).

Again, these overall results do not consider whether the same or different firms are classified as failed or non-failed, but only the total number of firms so classified. McNemar's (1947) test was used to compare the accuracy of the cash and accrual oriented prediction model and Deakin's model by examining the firms which are classified differently by the two models. Four different classifications are possible: (1) Both models classify the firm correctly; (2) the H3 model is correct, the Deakin model incorrect; (3) both models classify the firm incorrectly; and (4) the Deakin model is correct, the H3 model incorrect. The results are presented in Table 34.

Table 34

Comparison of Accuracy of H3 (Zordan) vs. Deakin Model

Accuracy of H3	Accuracy of Deakin Model		
(Zordan) Model	Correct	Incorrect	Total
Correct	346	53	399
Incorrect	64	77	141
Total	410	130	540

The two models predicted the same classification for 423 (346+77) of the 540 firms. Of the remaining 117 conflicting results, the Zordan model correctly classified 53; the Deakin model, 64. McNemar's test produces a X^2 based on only the differences between the two models. In this case, the X^2 = .855 with 1 degree of freedom (p=.355). This indicates that the cash/accrual model developed in H3 has no more ability to predict failed vs. non-failed manufacturing firms than the Deakin model. Thus, the null hypothesis $H_0$6 was not rejected.

Summary of Hypotheses 4-6

A comparison of the differences between correct and incorrect classifications of the models developed in H1, H2, and H3 with the correct and incorrect classifications of prior models (McGurr, Altman, and Deakin) showed no significant differences as measured by McNemar's test. Therefore, the null hypotheses, $H_0$4, $H_0$5, and $H_0$6 could not be rejected. The results fail to support the research hypotheses that cash flow ratios, when included in a multivariate discriminant model and when measured by the percentage of correct predictions of failed vs. non-failed firms by the models containing cash flow and accrual variables, are more accurate than accrual ratios in predicting failed vs. non-failed firms. It appears that failure prediction models containing cash flow and accrual variables developed in this study are not more accurate than models containing only accrual variables. This study did not provide evidence that the SCF contains non-redundant information when used in a bankruptcy prediction model.

Summary

The successful development of discriminating functions for the retail/wholesale industry, the manufacturing industry, and the two industries combined which contain cash flow ratios supports research hypotheses 1-3. Information from the required SCF in the form of ratios and a trend variable were used to develop failure prediction models that predict failed vs. non-failed firms suggesting that the SCF has information content.

Since there were no significant differences between the discriminant functions developed in H1, H2, and H3 and previously developed failure prediction models, research hypotheses 4-6 were not supported. While the SCF appears to have information content (H1-3) this study did not provide evidence that it contains additional non-redundant information beyond that contained in the accrual based financial statements when used in a bankruptcy prediction model.

CHAPTER V

SUMMARY AND CONCLUSIONS

This chapter is composed of four sections. The first section presents a summary of the study and the results obtained. The second section presents conclusions to be drawn. The third section addresses limitations of the study. The final section suggests areas for future research.

Summary and Results

This research study includes a review of the literature regarding ratios, cash flow information, factor-analytic studies, and business failure prediction studies. It was noted that most of the studies used accrual oriented variables. This study adds to the literature by concentrating on post-SFAS No. 95 cash flow ratios. Many of the accrual oriented business failure prediction studies achieved impressive results, at least in the short-term. As cash-based measures of performance gained acceptance in the 1980s, research began to shift towards cash oriented studies, usually focusing on cash flow from operations (CFFO). The results from these cash oriented studies were not as robust as accrual oriented studies and the measurement of cash flow was inconsistent and often criticized. Proxies for cash flow were used since cash flow from operating, investing, and financing activities were not reported before the issuance of SFAS No. 95 in 1987.

Both cash and accrual oriented studies were criticized for their lack of a guiding theory in the selection of predictor variables and the commingling of firms from various industries. The review of the literature led to the formation of six research hypotheses.

Hypotheses 1-3

The first three hypotheses considered whether cash flow ratios can be used to predict failed vs. non-failed firms and were developed as a continuation of the earlier cash oriented studies. Few of the previous cash oriented studies used cash flows as reported in the SCF; those which did use reported cash flows were not industry specific. In order to control for possible industry differences in cash flow ratios, H1 considered the retail/wholesale industry, H2 the manufacturing industry, and H3 the two industries combined. Tests of these three hypotheses involved developing models that predicted failed vs. non-failed firms using cash flow and accrual variables.

Three business failure prediction models containing cash flow and accrual variables were developed in H1, H2, and H3 to predict failed vs. non-failed firms. Overall classification accuracy rates were 74.5% for the retail/wholesale industry model, 76.5% for the manufacturing industry model, and 73.9% for the mixed industry model (see Tables 23, 25, and 27). Since the mean vectors of the z scores of the failed firms used to test H1, H2, and H3 were significantly different than the mean vectors of the z scores of the non-failed firms, the null hypotheses H_o1, H_o2, and H_o3 were rejected. The results support the research hypotheses that cash flow ratios can be used to predict failed vs. non-failed firms in the retail/wholesale industry (H1), the manufacturing industry (H2), and for the two industries combined (H3) suggesting the SCF has information content.

Hypotheses 4-6

Hypotheses 4-6 considered whether the models containing cash flow and accrual variables developed to test the first three hypotheses are better or worse than previously developed models containing only accrual variables. More accurate prediction by the cash/accrual models would indicate the SCF contains additional non-redundant information beyond that contained in the accrual based financial statements.

The percentage of correct predictions of failed and non-failed firms by the models developed in H1, H2, and H3 were compared to the percentage of correct predictions of failed and non-failed firms by previously developed accrual-only models using the firms in this sample. There were no significant differences as measured by McNemar's (1947) test. Therefore, the null hypotheses H_o4, H_o5, and H_o6 could not be rejected. Since the cash/accrual failure prediction models developed in this study were not more accurate than accrual-only models, this study did not provide evidence that the SCF contains non-redundant information when used in a bankruptcy prediction model.

Conclusions

The classification accuracy rate for the mixed industry model (73.9%) was only slightly lower than the retail/wholesale industry model rate (74.5%) and the manufacturing industry model rate (76.5%). This suggests a firm's industry group may have little effect on how that firm is classified when cash flow ratios are included in a prediction model. Contrary to the findings of Platt & Platt (1990, 1991) and McGurr (1996), this may indicate that cash flow patterns and accrual measures do not differ greatly across industries.

Classification results from replicating the older models (Altman, 1968 and Deakin, 1977) were lower than reported in the original studies. The Altman and the cash/accrual model developed in H2 resulted in 77.3% and 76.5% correct classification, respectively, when applied to this study's data from the late 1980's and 1990's. Altman originally reported a 95% accuracy rate. The Deakin and the cash/accrual model developed in H3 resulted in 75.9% and 73.9% correct classification, respectively, when applied to this study's data from the late 1980's and 1990's. Deakin originally reported a 94.4% accuracy rate. These lower accuracy rates may indicate that the Altman and Deakin studies are not generalizable to the current business environment.

Limitations

There are several limitations in the present study related to the population, the data, the industry, and the types of errors identified. First, the population of failed firms was drawn from the Compustat database which includes only firms publicly traded on major stock exchanges. Hence the findings may not be generalizable to non-publicly traded firms.

The study only used independent variables that could be calculated from Compustat data. The use of other variables based on information not available from Compustat may have resulted in the development of discriminant functions with different variables and coefficients with higher classification accuracy.

The study's focus on only two industry groups is a third limitation. This study specifically addressed the retail/wholesale (except restaurants) and manufacturing industries, separately and combined. The findings should not be generalized to the agricultural, mining, construction, transportation, restaurant, financial, or services industries.

Finally, while Type I (misclassifying a failed firm) and Type II (misclassifying a non-failed firm) error rates were identified, the focus was on overall classification accuracy. No attempt was made to quantify the relative costs of the two types of errors since they would be specific to the individual users of the models. All three models (developed in H1, H2, and H3) resulted in higher Type II error rates making them less useful to a user primarily concerned with the costs of Type II errors.

Suggestions for Future Research

Several areas for future research are suggested by the previously mentioned limitations. Non-public firm studies could be based on Small Business Administration or bank lending data. Use of data other than the

Compustat database would allow for the development of other independent variables. Other industry specific models or user specific models that made assumptions regarding the relative cost of Type I and Type II errors could be developed.

Some firms eventually emerge from Chapter 11 bankruptcy; others liquidate under Chapter 7. Research that differentiated between these two groups of failed firms may identify other factors useful in predicting business failure. Consideration of measures of failure other than filing for bankruptcy may also be useful, i.e., loan default or other debt covenant violations, dividend reduction or omission, and going concern or other audit opinion modifications.

Another possibility is the inclusion of other independent predictor variables. For example, other trend variables, variables which consider the variability of cash flows, or dummy variables to represent nonfinancial events such as hostile takeovers or pending lawsuits could be used. Although seldom reported (since most firms use the indirect method of reporting CFFO), the use of other components of CFFO, e.g., cash received from customers, may provide insight into which firms are likely to fail.

Concluding Remarks

This research has added useful information in the debate over whether financial statements, specifically the statement of cash flows, have information content by considering the ability of cash flow and accrual variables to predict business failure. The present study developed industry specific models including cash flow ratios which were able to predict failed vs. non-failed firms. While these models were not found to be significantly better or worse predictors of failure than prior accrual-only models, the results suggest the SCF has information content and cash flow ratios can be used to predict failed vs. non-failed firms.

APPENDIX A

LIST OF FAILED AND NON-FAILED FIRMS

Appendix A – List of failed and non-failed firms (Sales in $ millions)

SIC	FAILED	FYE	Sales	NON-FAILED	FYE	Sales
2013	RYMER FOODS INC	Oct91	254.935	GOODMARK FOODS	May91	139.408
2024	CHIPWICH INC	Dec91	4.830	TOFUTTI BRANDS	Dec91	4.393
2030	APPLETREE CO	Aug96	28.666	VACU DRY CO	Jun96	26.533
2033	CARIBBEAN SELECT	Dec89	5.807	PRO-FAC COOP	Jun90	72.271
2033	PACKAGING RSRCH	Dec95	17.881	ODWALLA INC	Aug95	35.869
2033	RIVERBEND INTL	Oct90	72.502	AMPAL AMER- ISRL	Dec90	110.401
2040	MANHATTAN BAGL	Dec96	36.945	INTL FRANCHISE	Dec96	22.772
2211	BIBB CO/DEL	Dec93	487.892	CONE MILLS CORP	Dec93	769.230
2250	FARLEY INC	Dec88	1,516.535	FRUIT OF LOOM	Dec88	1,004.700
2250	SHEFFIELD IND	Jun91	29.041	ROCKY MT UNDERG	Dec94	9.511
2253	AILEEN INC	Oct90	59.584	SIGNAL APPAREL	Dec90	76.819
2253	ORGANIK TECH	Jul95	3.806	TECHKNITS INC	Feb95	19.307
2300	ANDOVER TOGS	Nov94	73.767	KLEINERTS INC	Nov94	69.262
2300	BANYAN CORP	May90	65.571	GARAN INC	Sep90	145.337
2300	MARCADE GROUP	Jan92	237.021	UNITOG COMPANY	Jan92	142.834
2320	BAYLY CORP	Oct89	74.555	QUIKSILVER INC	Oct89	70.742
2320	CRYSTAL BRANDS	Dec92	589.022	OXFORD IND	May93	572.869
2320	SALANT CORP	Dec89	469.621	CINTAS CORP	May90	284.536
2320	USA CLASSIC INC	Jun93	79.115	STAGE II APPAREL	Dec94	66.046
2330	BRENNER INTL	Oct90	50.354	BISCAYNE APPAREL	Dec90	48.188
2330	CHEROKEE INC/DE	May92	194.944	HE-RO GROUP LTD	May92	139.836
2330	GITANO GROUP INC	Dec92	826.462	LIZ CLAIBORNE INC	Dec92	2,194.330
2330	GOTHAM APPAREL	Dec93	30.513	DANSKIN INC	Mar94	131.497
2330	LESLIE FAY CO.S	Dec91	836.564	KELLWOOD CO	Apr92	914.926
2330	RUSS TOGS INC	Jan91	217.085	NITCHES INC	Aug90	158.047
2421	WTD INDUSTRIES	Apr90	459.901	POPE & TALBOT INC	Dec89	618.758
2510	CRAFTMATIC IND	Sep94	31.547	RIVER OAKS FURN	Dec94	107.811
2522	GF CORP	Dec88	139.439	TAB PRODUCTS	May89	130.143
2631	GAYLORD CONT	Sep91	723.800	CHESAPEAKE CORP	Dec91	840.500
2673	EQUITABLE BAG CO	Dec93	117.256	UNIFLEX INC	Jan94	25.660
2741	MARTIN LAWRNC	Dec95	19.406	TRO LEARNING INC	Oct95	37.337
2750	MARVEL ENTNMNT	Dec95	829.300	BIG FLOWER PRESS	Jun95	896.595
2750	POWERTEL USA INC	Feb96	1.626	DIMENSIONAL VISN	Jun96	1.084
2790	UNIVERSITY GRAPH	Dec90	3.107	SCHAWK INC -CL A	Dec90	44.996
2821	DOW CORNING	Dec94	2,204.600	ROHM & HAAS CO	Dec94	3,545.000
2821	REXENE CORP	Dec90	502.186	BORDEN CHEM	Dec90	420.631
2834	TELIOS PHARM	Dec93	1.963	NOVEN PHARM	Dec93	3.124
2835	AMERICAN BIO	May90	2.342	NEOGEN CORP	May90	6.022
2835	VIRAL TESTING	Dec93	0.623	CELLULAR PROD	Dec93	2.832
2844	DEP CORP	Jul95	127.689	GUEST SUPPLY INC	Sep95	159.450
2844	FOUNTAIN PHARM	Sep93	0.836	HYDRON TECH	Dec93	0.698
2860	F & C INTL	Jun92	57.874	CAMBREX CORP	Dec92	179.452
2860	INTERSCIENCE COM	Sep96	11.253	FAIRMOUNT CHEM	Dec96	12.552
2860	QUADREX CORP	Dec93	0.850	CELGENE CORP	Dec93	2.002
2870	BIOSYS INC	Dec95	22.999	AMERICAN VANGD	Dec95	55.402
2911	CALUMET IND	Sep89	41.425	WAINOCO OIL CORP	Dec89	36.511
2911	EL PASO REFINERY	Dec91	344.681	HOLLY CORP	Jul91	489.333
2911	HUNTWAY PARTNR	Dec96	99.021	GIANT INDUSTRIES	Dec96	499.184
2990	ENVIROPUR WASTE	Sep95	22.385	QUAKER CHEMICAL	Dec95	227.038
3060	HARVARD INDS INC	Sep89	757.641	CARLISLE COS INC	Dec89	553.678
3080	NVF CO	Dec92	162.725	AMERICAN FILTRN	Dec92	144.655

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SIC	FAILED	FYE	Sales	NON-FAILED	FYE	Sales
3089	APL CORP	Sep92	67.857	SUN COAST INDS	Jun92	61.944
3089	CPC REXCEL INC	Dec91	49.549	HOME PRODUCTS	Dec91	37.013
3089	EMBRACE SYSTEMS	Dec92	2.016	SUMMA IND	Aug92	7.611
3089	ENVIRODYNE IND	Dec91	543.969	RUBBERMAID INC	Dec91	1,667.305
3089	PHOENIX MEDICAL	Dec90	14.934	REUNION IND	Dec90	17.005
3140	JUMPING JACKS SHS	Apr89	36.701	MCRAE INDUSTRIES	Jul89	33.097
3220	NBI INC	Jun90	47.122	SPECTRAN CORP	Dec90	10.572
3241	LONE STAR IND	Dec89	337.547	MEDUSA CORP	Dec89	183.573
3250	ADIENCE INC	Dec91	169.615	GREEN INDUSTRIES	Dec91	170.298
3270	NATIONAL GYPSUM	Dec89	1,364.070	DRAVO CORP	Dec89	279.464
3270	USG CORP	Dec91	1,712.000	AMERON INTL	Nov91	465.136
3281	MARBLEDGE GRP	Feb95	7.684	HYDRAULIC PRESS	Sep94	8.641
3312	CF & I STEEL CORP	Dec89	295.036	KEYSTONE CONS IN	Dec89	297.887
3312	CONSOL STNLESS	Dec96	50.823	UNVL STNLESS/ALL	Dec96	60.258
3317	VALLEY IND	Nov90	78.347	SYNALLOY CORP	Dec90	100.036
3320	OVERMYER CORP	Dec89	35.986	INTERMET CORP	Dec89	397.122
3320	SUDBURY INC	May91	376.182	PRECISION CASTPT	Mar91	538.300
3330	SIMETCO INC	Dec92	32.109	BRUSH WELLMAN	Dec92	265.034
3341	DIVERSIFIED IND	Oct91	198.883	IMCO RECYCLING	Dec91	49.177
3357	CCX INC	Jun93	60.435	AFC CABLE SYS	Dec93	89.890
3420	AMDURA CORP	Dec89	156.715	STARRETT (L.S.) CO	Jun90	201.625
3440	CPT HOLDING CORP	Jun89	63.567	MAXCO INC	Mar89	71.561
3443	NORTH ATLANTIC	Dec95	3.684	MOBILE MINI INC	Dec95	39.905
3452	ALLECO INC	Sep91	19.057	MICHIGAN RIVET	Oct91	28.756
3460	LADISH CO INC	Dec90	304.095	TRIMAS CORP	Dec90	328.470
3490	BARTON IND	Sep89	8.880	GENERAL KINETICS	May89	11.178
3532	BUCYRUS INTL	Dec92	214.535	HARNISCHFEGER	Oct92	1,390.815
3540	AUTODIE CORP	Aug91	76.215	MONARCH MACHN	Dec91	106.057
3540	INTL CNSMR BRNDS	Dec90	16.479	CHICAGO RIVET	Dec90	17.041
3540	WEAN INC/PA	Dec92	42.618	P & F INDUSTRIES	Dec92	48.859
3550	TAPISTRON INTL	Jul95	2.566	THERMWOOD CORP	Jul95	13.828
3555	GEO INTL	Sep92	38.841	LASERMASTER TEC	Jun92	59.857
3559	RAGEN CORP	Sep92	4.878	PRAB INC	Oct92	10.503
3567	CONSUMAT ENVML	Dec94	4.310	BETHLEHEM CORP	May95	14.541
3569	SANBORN INC	Dec92	19.617	PEERLESS MFG CO	Jun92	23.059
3571	ALLIANT COMP	Dec90	72.812	ALPHA MICROSYS	Feb91	52.802
3571	COMMODORE INTL	Jun93	590.800	SILICON GRAPHICS	Jun93	1,091.200
3571	CRAY COMPUTER	Dec93	0.352	TELEPAD CORP	Dec93	1.007
3571	EVEREX SYSTEMS	Jul91	425.067	DATAPOINT CORP	Jul91	265.479
3571	FLOATING POINT	Oct90	46.886	NAI TECHNOLOGIES	Dec90	42.057
3571	KAYPRO CORP	Aug88	72.234	MAXWELL TECH	Jul88	66.104
3571	KENDALL SQUARE	Dec93	18.094	EQUITRAC CP	Feb94	29.122
3571	TSL HOLDINGS INC	Dec91	461.385	STRATUS COMP	Dec91	448.632
3572	MASSTOR SYSTEMS	Dec93	14.514	JTS CORP	Dec93	28.805
3572	MINISCRIBE CORP	Dec88	531.071	QUANTUM CORP	Mar89	208.017
3572	REXON INC	Sep94	204.752	SYQUEST TECH	Sep94	221.001
3572	STREAMLOGIC	Dec95	211.264	HMT TECHNOLOGY	Mar96	194.401
3575	GENISCO TECH	Sep93	12.651	DOTRONIX INC	Jun93	17.323
3575	MEMOREX TELEX	Mar93	1,326.372	NETWORK C DEV	Dec92	120.345
3575	MONITERM CORP	Dec90	26.214	IIS INTELLIGENT	Dec90	36.192
3576	ALLOY COMPUTER	Dec91	15.295	AMATI COMMUNIC	Jul91	15.630
3576	CODENOLL TECH	Dec93	6.611	PROXIM INC	Dec93	8.078

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SIC	FAILED	FYE	Sales	NON-FAILED	FYE	Sales
3576	WEITEK CORP	Dec95	17.600	PERFORMANCE TEC	Dec95	17.891
3577	COMMUN INTEL	Dec93	2.595	VOICE CONTROL	Dec93	2.446
3577	EECO INC	Dec88	60.863	CALCOMP TECH	May89	43.677
3577	FINGERMATRIX INC	May92	0.258	DI AN CONTROLS	Dec91	0.284
3577	SCRIPTEL HOLDING	Dec96	0.512	VIDEOLAN TECH	Dec96	0.328
3577	SYMBOLICS INC	Jun92	26.461	DATAMETRICS	Oct92	22.358
3578	CELEREX CORP	Dec93	1.013	ELECTRONIC RET	Dec93	1.122
3579	SMITH CORONA	Jun94	278.636	GENERAL BINDING	Dec94	420.449
3613	STATORDYNE CORP	Jun94	0.405	TECHNOLOGY RES	Mar96	17.379
3621	MRL INC	Jan96	4.737	UNIQUE MOBILITY	Oct95	4.714
3640	CHRONAR CORP	Dec89	18.591	ASTRONICS CORP	Dec89	22.145
3640	DYNASTY CLASSICS	Dec92	84.928	JUNO LIGHTING INC	Nov92	96.633
3651	CRAIG CONSUMER	Dec96	80.632	UNIVERSAL ELECTR	Dec96	98.589
3651	EMERSON RADIO	Dec92	815.286	ZENITH ELECTR	Dec92	1,269.500
3651	HOME THEATER PR	Jun94	36.449	KOSS CORP	Jun94	36.670
3661	FIRST PACIFIC NET	Mar96	4.999	INTELIDATA TECH	Dec95	4.186
3661	TIE/COMMUNICATN	Dec89	223.118	TELLABS INC	Dec89	181.280
3663	AT&E CORP	Dec90	0.474	SONAR RADIO CORP	Jun91	0.503
3663	CHYRON CORP	Jun89	44.157	DATRON SYSTEMS	Mar90	45.205
3663	REPCO INC	Dec90	8.179	DESTRON FEARING	Feb91	8.297
3670	MICROWAVE LAB	Apr93	7.043	FEDERATED PURCH	Oct92	6.794
3670	SFE TECHNOLOGIES	Oct90	25.658	AMERICAN TECH	Jun90	21.546
3672	COMPTRONIX CORP	Dec95	92.211	BENCHMARK ELEC	Dec95	97.353
3672	METROPOLITAN	Feb89	27.394	CIRCUIT SYSTEMS	Apr89	22.134
3674	SILICONIX INC	Dec88	128.526	BURR-BROWN CORP	Dec88	176.673
3674	SOLITRON DEVICES	Feb91	30.035	SUPERTEX INC	Mar91	24.207
3679	INSILCO CORP	Dec89	762.235	APPLIED MAGNETIC	Sep89	314.105
3679	MICRON PRODUCTS	Jun90	3.907	CONOLOG CORP	Jul90	3.473
3679	VOICE POWERED	Dec96	10.813	VARI-L COMPANY	Dec96	12.211
3690	DIGITRAN SYSTEMS	Apr96	3.441	ION LASER TECH	Mar96	4.247
3690	LASER PHOTONICS	Dec92	10.238	ENERGY CONVERSN	Jun92	14.916
3690	UNITECH IND	Oct94	10.332	ESHED ROBOTEC	Dec94	13.606
3695	OPUS COMPUTER	Sep89	11.396	CERTRON CORP	Oct89	32.016
3714	EAGLE-PICHER IND	Nov89	729.915	STANDARD PROD	Jun89	558.861
3714	VOPLEX CORP	Dec90	56.546	DEFIANCE INC	Jun90	60.126
3715	FRUEHAUF TRAILER	Dec95	421.039	DORSEY TRAILERS	Dec95	227.944
3716	MALLARD COACH	Oct91	104.127	THOR INDUSTRIES	Jul91	140.853
3730	AMERICAN SHIP BD	Sep92	91.488	AVONDALE IND	Dec92	592.011
3730	TACOMA BOATBLD	Dec90	56.121	RPC INC	Dec90	112.202
3751	RDM SPORTS GRP	Dec96	366.683	CANNONDALE	Jun96	145.976
3790	COBRA INDUSTRIES	Dec94	250.505	ARCTIC CAT INC	Mar95	367.144
3790	SCAT HOVERCRAFT	Dec89	3.794	KIT MFG	Oct89	69.367
3812	CINCINNATI MICRO	Dec95	79.199	EDO CORP	Dec95	91.113
3812	TRACOR INC	Dec89	701.866	FIGGIE INTERNATL	Dec89	1,313.484
3827	OPTO MECHANIK	Jun93	37.199	GALILEO CORP	Sep93	34.307
3842	AMERICAN WHT CR	Dec95	87.351	STERIS CORP	Mar96	91.192
3842	BIOPLASTY INC	Jul92	6.754	POSSIS MEDICAL	Jul92	10.261
3844	IRT CORP	Mar93	18.695	AMERICAN SCI ENG	Mar93	18.949
3845	CLINI-THERM CORP	Jun89	1.583	CDX CORP	Jun89	1.332
3861	ANACOMP INC	Sep95	591.189	AVID TECHNOLOGY	Dec95	406.650
3861	COLOROCS CORP	Dec90	42.685	ARC INTERNATL	Dec90	83.850
3861	KEYSTONE CAMRA	Dec89	40.467	AFP IMAGING CORP	Jun90	48.292

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SIC	FAILED	FYE	Sales	NON-FAILED	FYE	Sales
3861	STYLES ON VIDEO	Dec96	2.614	DYCAM INC	Dec96	2.455
3911	HARLYN PRODUCTS	Jun96	25.915	IWI HOLDING LTD	Dec96	30.840
3911	TOWN & COUNTRY	Feb97	209.153	OROAMERICA INC	Jan97	177.065
3944	HAPPINESS EXPRS	Mar95	60.022	EQUITY MKTING	Dec94	61.776
3949	SLED DOGS CO	Jun96	0.877	TEARDROP GOLF	Dec96	0.847
3949	SLM INTL INC	Dec94	180.806	JOHNSON WORLD	Sep94	284.343
3960	UNITED MERCHANT	Jun90	350.272	VICTORIA CREAT	Jun90	52.983
5013	REDDI BRAKE SUP	Jun96	62.725	OAKHURST CO INC	Feb96	47.339
5040	SAVIN CORP	Dec91	312.279	VWR SCIENTIFIC	Dec91	440.983
5045	IRG TECHNOLOGIES	Sep94	146.572	AURORA ELECT	Sep94	120.386
5045	KLH COMPUTERS	Jan91	240.584	TECH DATA CORP	Jan91	441.777
5047	HEALTHCO INTL	Dec90	463.487	VALLEN CORP	May91	151.398
5065	ASTREX INC	Mar90	17.443	UNIVERSAL SEC	Mar90	21.612
5065	DOUGLAS COM INT	Dec88	5.874	FARMSTEAD TELE	Dec88	4.850
5065	MIDWEST COMM	Jun90	190.484	RICHARDSON ELEC	May90	160.101
5070	IRONSTONE GROUP	Dec89	246.786	WATSCO INC	Dec89	94.318
5080	AERO SYSTEMS INC	Feb92	22.656	VENTURIAN CORP	Dec91	24.973
5090	BEN FRANKLIN	Mar95	354.788	SCHNITZER STEEL	Aug94	261.697
5090	PRINS RECYCLING	Dec95	76.692	SCORE BOARD INC	Jan96	74.953
5090	TRI-R SYSTEMS	Jul90	7.796	SECURITY CAP	Sep90	2.109
5099	ALLIANCE ENTMT	Dec96	691.099	HANDLEMAN CO	Apr96	1,132.607
5122	MODEL IMPERIAL	Dec94	160.505	ALLOU HEALTH-BY	Mar95	237.542
5190	CRITICAL IND	Dec91	17.879	AG SERVICES OF A	Feb92	35.534
5190	WNS INC	Dec90	25.477	PAGES INC/OH	Feb91	24.289
5200	ERNST HOME CTR	Oct95	572.157	GENERAL HOST	Jan96	593.270
5200	STANDARD BRANDS	Jan90	314.023	SUNBELT NURSERY	Aug89	154.198
5211	COLOR TILE INC	Dec94	673.528	BMC WEST CORP	Dec94	547.109
5211	GENERAL BUILDING	Nov91	44.726	STROBER ORG	Dec91	90.150
5211	GROSSMANS INC	Dec95	669.899	WICKES INC	Dec95	972.612
5211	NATIONAL LUMBER	Jan89	152.025	MICHIGAN GEN'L	Dec88	311.817
5211	PAY'N PAK STORES	Feb91	498.364	WOLOHAN LUMBER	Dec90	295.570
5211	PAYLESS CASHWAY	Nov96	2,642.829	HECHINGER CO	Jan97	2,199.067
5211	ROBERTSON COS	Dec89	18.892	RIVERSIDE GROUP	Dec89	95.059
5311	ALLIED STORES	Jan89	3,063.176	MEYER (FRED) INC	Jan89	2,073.544
5311	BROADWAY STRS	Jul90	2,982.819	MERCANTILE STRS	Jan91	2,393.776
5311	MACY (R H) & CO	Jul91	6,960.726	MAY DPT STORES	Jan90	9,602.000
5311	MONTGOMRY WRD	Dec96	6,620.000	DILLARDS INC	Jan97	6,412.058
5331	50 OFF STORES INC	Jan96	175.023	TUESDAY MORNING	Dec95	210.265
5331	ALL FOR A DOLLAR	Dec93	69.021	UNIVERSAL INTL	Dec93	53.447
5331	AMES DEPT STORES	Jan90	4,793.125	PRICE CO	Aug89	5,011.589
5331	BRADLEES INC	Jan94	1,880.511	SHOPKO STORES	Feb94	1,738.746
5331	BRENDLES INC	Jan92	300.198	VALUE CITY DEPT	Jul92	674.692
5331	CALDOR CORP	Jan95	2,748.634	HOMEBASE INC	Jan95	3,650.281
5331	DOLLAR TIME GRP	Mar94	20.199	VALLEY FAIR CORP	Jan94	69.877
5331	F&M DISTRIBUTORS	Jan94	721.847	PAMIDA HOLDINGS	Jan94	656.910
5331	HILLS STORES CO	Jan90	2,075.603	COSTCO WHOLESL	Aug89	2,999.656
5331	JAMESWAY CORP	Jan92	855.098	CONSOLIDATED ST	Jan92	771.497
5331	MCCRORY CORP	Jan91	1,518.450	VENTURE STORES	Jan91	1,420.672
5331	ODDS-N-ENDS INC	Jan93	25.671	SOLO SERVE CORP	Jan93	154.386
5331	RETAILING CORP	Mar90	108.462	PEEBLES INC	Jan91	143.969
5331	ROSES STORES INC	Jan93	1,362.243	FAMILY DOLLAR	Aug92	1,158.704
5331	SPROUSE-REITZ	Jan91	223.890	DOLLAR GENERAL	Jan91	653.151

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SIC	FAILED	FYE	Sales	NON-FAILED	FYE	Sales
5331	STUARTS	Jan90	140.002	ZIONS CO-OP	Jan90	194.480
5331	VALUE MERCHNTS	Jan93	363.496	FREDS INC	Jan93	316.494
5331	WAREHOUSE CLUB	Sep93	222.089	MACFRUGALS BRG	Jan94	627.063
5399	BELL (W.) & CO INC	Jan90	110.558	CROWLEY MILNER	Jan90	113.623
5399	BEST PRODUCTS	Jan90	2,094.570	SERVICE MDS	Dec89	3,307.110
5399	LURIA (L.) & SON	Jan97	121.566	LIQUIDATION WRLD	Sep96	52.646
5411	APPLETREE MRKTS	Dec90	838.042	HOMELAND HLDG	Dec90	767.804
5411	KASH N KARRY	Jul93	1,086.125	RISER FOODS INC	Jun93	1,108.178
5411	LLOYD'S SHOP CNT	Dec90	94.895	WESTERN BEEF INC	Dec90	202.232
5411	MEGAFOODS STRS	Dec93	409.222	BUTTREY FOOD	Jan94	428.746
5412	CIRCLE K CORP	Apr89	3,494.891	GIANT FOOD INC	Feb89	2,987.154
5412	NATIONAL CONV	Jun90	1,062.183	DAIRY MART CONV	Jan91	570.769
5412	SOUTHLAND CORP	Dec89	7,993.144	WINN-DIXIE STRS	Jun90	9,744.492
5412	SUNSHINE-JR STRS	Dec91	217.711	UNI-MARTS INC	Sep91	256.514
5500	ACTION AUTO STRS	Jun89	90.350	TRAVEL PORTS-AM	Apr90	104.179
5531	AUTOMOTIVE IND	Sep88	55.877	TYLER CORP/DE	Dec88	664.645
5600	C & R CLOTHIERS	Jan92	106.486	FREDERICKS OF HD	Aug91	114.134
5600	CASUAL MALE	Jan89	95.243	S & K FAMOUS BRD	Jan89	52.437
5600	EDISON BROTHERS	Jan95	1,476.400	MENS WEARHOUSE	Jan95	317.127
5600	TODAYS MAN INC	Jan95	216.893	CLAIRES STORES	Jan95	301.435
5621	BRAUNS FASHIONS	Feb96	97.296	MOTHERS WORK	Sep95	106.005
5621	CASCADE INTL	Jun90	52.444	CACHE INC	Dec90	43.396
5621	CLOTHESTIME INC	Jan95	340.801	LOEHMANNS INC	Jan95	392.606
5621	CONSTON CORP	Feb90	169.209	ONE PRICE CLOTHG	Dec89	88.754
5621	GANTOS INC	Jan93	273.872	DEB SHOPS INC	Jan93	229.459
5621	KENWIN SHOPS INC	Dec93	24.367	VSI HOLDINGS INC	Jan94	19.489
5621	PAUL HARRIS STRS	Jan90	235.978	DRESS BARN INC	Jul90	283.592
5621	PETRIE STORES LIQ	Jan94	1,480.071	CHARMING SHOP	Jan94	1,254.122
5651	JACOBS (JAY) INC	Feb93	159.250	BUCKLE INC	Jan93	112.898
5651	LAMONTS APPAREL	Oct93	251.015	DESIGNS INC	Jan94	240.925
5651	MERRY-GO-ROUND	Jan93	877.499	BURLINGTON COAT	Jun92	997.698
5661	DIVERSIFIED RET	Mar89	13.473	WIENER ENT	Jan89	88.112
5700	HOME CENTERS INC	Jan90	78.222	THREE D	Jul90	41.634
5700	KITCHEN BAZAAR	Jan92	14.685	ALLIANCE NW IND	Dec91	1.611
5712	FURNISHINGS 2000	Jun89	117.811	BOMBAY CO INC	Jun89	109.165
5712	LEVITZ FURNITURE	Mar97	979.655	HEILIG-MEYERS CO	Feb97	1,593.119
5731	CAMPO ELECTRS	Aug96	294.967	REX STORES CORP	Jan97	427.378
5731	FRETTER INC	Jan95	858.849	SUN TV & APPLNCE	Feb95	751.883
5731	HARVEY GROUP	Jan95	22.814	AUDIO KING CORP	Jun94	45.826
5731	HIGHLAND SUPERS	Jan92	575.201	INTERTAN INC	Jun92	690.451
5731	NEWMARK & LEWIS	Jan91	293.835	GOOD GUYS INC	Sep90	293.967
5731	WALL - WALL SND	Feb89	152.059	LUSKIN'S INC	Jan89	122.000
5734	ELEK-TEK INC	Dec96	333.498	EGGHEAD INC/WA	Mar97	360.715
5734	NEOSTAR RETAIL	Jan96	513.548	COMPUSA INC	Jun95	2,813.064
5735	PEACHES ENTMNT	Mar95	31.961	SPEC'S MUSIC INC	Jul95	79.603
5735	WHEREHOUSE ENT	Jan95	499.625	TRANS WORLD ENT	Jan95	536.840
5940	GAYLORD CO	Dec96	13.304	HIBBETT SPRT GDS	Jan97	86.401
5940	HOUSE OF FABRICS	Jan94	546.664	FABRI-CENTERS-AM	Jan94	582.071
5940	SPORTS HEROES	Dec94	2.073	LAS VEGAS DISC	Dec94	8.967
5940	SPORTSTOWN	Jan94	166.556	SHARPER IMAGE	Jan94	147.441
5940	STARLOG FRAN	Jun95	3.511	PARTY CITY CORP	Dec96	48.528
5940	ZAMS INC	Dec93	10.111	VILLAGE GREEN BK	Jan94	9.104

Appendix A – List of failed and non-failed firms (Sales in $ millions)

SIC	FAILED	FYE	Sales	NON-FAILED	FYE	Sales
5944	BARRYS JEWELERS	May91	158.425	JAN BELL MKTG	Dec90	177.246
5944	CIRO INC	Dec92	45.890	LITTLE SWITZERLD	May93	63.396
5944	ZALE CORP	Mar91	1,386.169	SIGNET GROUP PLC	Jan91	2,188.857
5945	AMBERS STORES	Jan95	65.694	RAG SHOPS INC	Aug94	89.529
5945	CHILD WORLD	Jan91	829.419	OFFICE DEPOT INC	Dec90	625.764
5945	LIONEL CORP	Jan90	428.848	MICHAELS STORES	Jan90	289.754
5945	OLD AMERICA STRS	Jan97	135.775	NOODLE KIDOODLE	Jan97	59.410
5961	GANDER MOUNTN	Jun95	297.784	NATIONAL MEDIA	Mar96	292.607
5961	SPORTING LIFE INC	Jul90	14.188	SPORTSMANS GD	Dec90	20.606
5990	SILK GREENHOUSE	Jan90	99.343	DUTY FREE INTL	Jan90	87.417
5990	STERLING OPTICAL	Jun91	77.810	COSMETIC CENTER	Sep91	87.628

APPENDIX B

VARIABLE CORRELATION MATRIX

Appendix B - Variable Correlation Matrix

- - Correlation Coefficients - -

	V01	V02	V03	V04	V05	V06
V01	1.0000					
V02	.8203**	1.0000				
V03	.8272**	.9071**	1.0000			
V04	.0999*	-.0507	-.0308	1.0000		
V05	.0431	.1202**	.1374**	-.1811**	1.0000	
V06	.8203**	.8666**	.9603**	-.0185	.1408**	1.0000
V07	.2767**	.0736	.0602	.0904*	.2058**	.0815
V08	.1758**	-.0578	-.0857*	.3991**	-.2638**	-.0635
V09	.2521**	.0478	.0549	.8170**	-.1442**	.0676
V10	-.1053*	.0578	.0812	-.1766**	.7413**	.0824
V11	.2317**	.1007*	.2146**	.1470**	-.0109	.2108**
V12	.0242	.0565	.0767	-.0491	.2137**	.0930*
V13	.0026	.0800	.1574**	-.0308	.1111**	.1339**
V14	.0225	.0142	.0152	-.0191	-.0208	.0184
V15	.3195**	.0970*	.1151**	.7218**	-.2140**	.1225**
V16	-.0183	-.0124	.0051	-.1667**	-.0241	.0002
V17	.0798	-.1139**	-.1715**	.2139**	-.3038**	-.1260**
V18	-.0528	-.0133	.0102	-.0170	-.0991*	.0171
V19	.2234**	.0341	.0403	.7533**	-.2828**	.0516
V20	-.0009	-.0033	-.0038	.0076	-.0318	.0077
V21	.0920*	.0460	.0656	-.0209	.2734**	.0622
V22	.4080**	.6154**	.6769**	-.1713**	.2767**	.6205**
V23	.0087	.0072	.0087	-.0104	-.0022	.0044
V24	.0028	.0952*	.0873*	-.0432	.1135**	.0726
V25	-.0616	-.0283	-.0408	-.0187	.0130	-.0417
V26	.0070	.0079	.0219	-.0064	.0590	.0223
V27	.0352	.0370	.0421	-.0036	-.1088*	.0372
V28	-.2724**	-.3097**	-.2844**	.0615	-.1104*	-.3876**
V29	-.0742	-.0670	-.0438	-.0366	-.0396	-.0453
V30	-.0880*	-.0947*	-.1171**	-.1787**	.0122	-.1050*
V31	-.0015	-.0030	-.0134	.0127	-.1086*	-.0096
V32	.1615**	-.0044	-.0161	.7857**	-.2649**	.0002
V33	.2088**	.0522	.0624	.8198**	-.1913**	.0741
V34	.8662**	.9282**	.9825**	-.0183	.1135**	.9409**
V35	.0474	.2019**	.3319**	-.4476**	.2208**	.2827**
V36	-.0299	.1629**	.2455**	-.5401**	.2484**	.2040**
V37	.0331	.0147	.0197	-.0088	-.0036	.0178
V38	-.0213	-.0184	-.0161	-.0030	.0095	-.0223
V39	-.4608**	-.6133**	-.6564**	.2070**	-.2556**	-.6734**
V40	.0350	.0224	.0212	.0036	.0459	.0226
V41	.8141**	.9184**	.9803**	-.0519	.1569**	.9307**
V42	.8192**	.9216**	.9847**	-.0469	.1502**	.9340**
V43	-.0048	-.0998*	-.1047*	.1583**	-.4644**	-.0973*
V44	-.1460**	-.1334**	-.1698**	.1747**	.1104*	-.1541**
V45	-.0362	.1609**	.2390**	-.5555**	.2506**	.1983**
V46	.0435	.1192**	.1263**	-.0076	.0664	.1036*

* - Signif. LE .05   ** - Signif. LE .01   (2-tailed)

Appendix B - Variable Correlation Matrix

- - Correlation Coefficients - -

	V07	V08	V09	V10	V11	V12
V07	1.0000					
V08	.3146**	1.0000				
V09	.3620**	.5657**	1.0000			
V10	-.3767**	-.3322**	-.2744**	1.0000		
V11	.0961*	.1657**	.2228**	-.0649	1.0000	
V12	.1092*	-.0427	-.0102	.1499**	.0032	1.0000
V13	.0289	-.1535**	-.0364	.0938*	.0584	.0549
V14	.0372	-.0255	-.0253	-.0334	.1045*	-.0500
V15	.2725**	.5472**	.8813**	-.2996**	.2974**	-.0472
V16	-.3519**	-.2451**	-.3304**	.2002**	.0320	-.0933*
V17	.2664**	.1431**	.1808**	-.3724**	-.0334	-.1837**
V18	-.0436	.0248	-.0323	-.0665	-.0477	.1226**
V19	.1919**	.6578**	.8562**	-.3057**	.2103**	-.0052
V20	-.0200	.0180	.0119	-.0089	.0403	.0139
V21	.3885**	-.0417	.0805	.0116	.0505	.5130**
V22	-.0636	-.2348**	-.0986*	.2283**	.1094*	.0738
V23	.0155	-.0018	-.0168	-.0084	-.0448	-.0137
V24	.0317	-.0454	-.0200	.0933*	.0635	.0431
V25	.0402	-.0490	.0133	-.0144	-.0513	-.0201
V26	.0100	-.0071	-.0071	.0467	-.0077	-.0115
V27	-.0231	-.0370	-.0153	-.0681	-.0818	-.0050
V28	-.1135**	.0279	.0085	-.0552	.0752	-.0581
V29	-.0226	-.0281	-.0678	-.0345	-.0616	-.0019
V30	-.1020*	-.1367**	-.2581**	.0425	-.1580**	-.0486
V31	-.0329	-.0015	-.0021	-.0998*	-.0249	-.0041
V32	.1494**	.7096**	.8292**	-.2581**	.1550**	-.0666
V33	.1220**	.4539**	.9103**	-.2068**	.1834**	-.0349
V34	.0710	-.0495	.0535	.0557	.1646**	.0554
V35	-.0494	-.3491**	-.3938**	.1745**	.1425**	.0961*
V36	-.0977*	-.3832**	-.5083**	.2121**	.0441	.0562
V37	.0202	.0529	-.0061	-.0186	.0781	-.0137
V38	-.0135	-.0270	-.0052	.0267	.0301	.0248
V39	.0341	.3267**	.1594**	-.1994**	.0363	-.0902*
V40	.0414	.0181	.0134	.0311	-.0234	-.0342
V41	.0508	-.0985*	.0233	.0970*	.1832**	.0867*
V42	.0618	-.0946*	.0319	.0862*	.1875**	.0936*
V43	.0929*	.1273**	.1678**	-.4643**	-.0507	.0162
V44	.4539**	.2221**	.3202**	-.1590**	-.1602**	.1066*
V45	-.1022*	-.3932**	-.5240**	.2157**	.0346	.0461
V46	.0303	.0156	.0505	.0346	.0807	.0507

* - Signif. LE .05   ** - Signif. LE .01   (2-tailed)

Appendix B - Variable Correlation Matrix

-- Correlation Coefficients --

	V13	V14	V15	V16	V17	V18
V13	1.0000					
V14	.0038	1.0000				
V15	-.0220	-.0095	1.0000			
V16	.0030	.0818	-.1266**	1.0000		
V17	-.0925*	.0761	.1506**	-.0570	1.0000	
V18	.0361	-.0425	-.0693	-.0452	-.2351**	1.0000
V19	-.0549	-.0396	.9311**	-.1706**	.0696	.0546
V20	-.0008	.0043	.0135	-.0481	-.0055	.0224
V21	.0342	-.0089	.0020	-.1725**	-.0341	.0960*
V22	.2009**	-.0520	-.0196	.0700	-.4244**	.0311
V23	.0026	-.0054	-.0046	.0880*	-.0210	.0172
V24	.3674**	-.0118	-.0094	.0270	-.1202**	-.0003
V25	.0064	.0123	.0093	-.0563	.0012	.0545
V26	.0003	-.0091	-.0017	-.0191	-.0476	.2067**
V27	-.0091	-.0041	-.0136	.0197	.0043	.1299**
V28	.0142	.0049	-.0049	.0455	.0541	-.0597
V29	.0012	.0532	-.0883*	.0761	-.0395	.0051
V30	-.1036*	-.0171	-.2451**	.0510	-.0274	.0130
V31	-.0010	.0017	.0411	-.0176	.0197	.0354
V32	-.0822	-.0233	.8735**	-.1762**	.1266**	-.0337
V33	-.0653	-.0320	.8125**	-.2846**	.1215**	-.0211
V34	.1041*	.0144	.1004*	-.0249	-.1174**	.0029
V35	.2529**	.0148	-.2919**	.0743	-.4132**	.0459
V36	.2538**	-.0054	-.4044**	.0959*	-.4386**	.0350
V37	.0051	.0185	.0451	.0368	.0000	-.0333
V38	.0098	.0205	.0018	.0332	.0093	-.0940*
V39	-.1359**	.0359	.1120**	-.0869*	.2653**	-.0493
V40	-.0019	-.0076	.0188	-.0008	-.0020	.0724
V41	.1400**	.0107	.0762	.0093	-.1897**	.0218
V42	.1499**	.0137	.0862*	.0074	-.1807**	.0179
V43	-.3142**	-.0608	.1197**	-.1195**	.1335**	.3148**
V44	-.0395	-.0706	-.0309	-.8110**	.1132**	.0591
V45	.2508**	-.0034	-.4191**	.1006*	-.4359**	.0326
V46	.0179	-.0288	.0536	-.0258	-.1379**	-.0029

* - Signif. LE .05   ** - Signif. LE .01   (2-tailed)

Appendix B - Variable Correlation Matrix

- - Correlation Coefficients - -

	V19	V20	V21	V22	V23	V24
V19	1.0000					
V20	.0210	1.0000				
V21	-.0166	.0076	1.0000			
V22	-.0902*	.0048	.0041	1.0000		
V23	.0037	-.0030	-.0051	.0098	1.0000	
V24	-.0213	-.0022	-.0095	.2330**	.0044	1.0000
V25	-.0247	.0034	-.0181	-.0263	-.0067	.0005
V26	.0142	.0018	-.0006	.0424	-.0064	.0047
V27	-.0012	.0092	-.0202	.0027	.0356	-.0045
V28	.0132	.0037	-.0409	-.1963**	-.0044	-.0505
V29	-.0509	.0015	-.0335	-.0479	.0097	.0007
V30	-.2246**	-.0085	-.0763	-.0531	.0076	-.0009
V31	.0476	.0012	.0008	-.0205	.0017	-.0242
V32	.9520**	.0104	-.0520	-.1506**	-.0074	-.0410
V33	.7985**	.0147	-.0012	-.0539	-.0194	-.0386
V34	.0405	-.0008	.0458	.6159**	.0046	.0589
V35	-.3833**	-.0014	.0593	.5730**	.0051	.2272**
V36	-.4721**	-.0004	.0237	.6413**	.0063	.2457**
V37	.0191	.0017	-.0202	.0330	-.0029	-.0225
V38	-.0097	.0066	.0010	.0223	-.0025	-.0015
V39	.1645**	.0053	-.0267	-.7655**	-.0110	-.1702**
V40	.0115	-.0052	.0000	-.0045	-.0024	-.0014
V41	.0091	-.0017	.0630	.7081**	.0069	.0965*
V42	.0165	-.0038	.0743	.7036**	.0077	.0984*
V43	.2496**	.0365	-.0192	-.2345**	.0292	-.1806**
V44	.0492	.0174	.2465**	-.2003**	-.0537	-.0187
V45	-.4863**	-.0009	.0216	.6377**	.0068	.2442**
V46	.0271	.0002	.0064	.2320**	.0005	.4458**

	V25	V26	V27	V28	V29	V30
V25	1.0000					
V26	.0475	1.0000				
V27	.1147**	.3317**	1.0000			
V28	-.0037	-.0143	-.0136	1.0000		
V29	-.0081	-.0201	.0424	-.0291	1.0000	
V30	.0003	.0066	.0220	.0090	.2749**	1.0000
V31	.0001	.0105	.0364	.0009	-.0057	-.0113
V32	-.0335	-.0060	-.0113	.0278	-.0494	-.2179**
V33	-.0021	-.0057	-.0089	.0097	-.0685	-.1936**
V34	-.0373	.0192	.0537	-.2893**	-.0468	-.0875*
V35	-.0101	.0137	-.0155	-.0665	-.0066	.1981**
V36	.0316	.0181	-.0126	-.0789	.0038	.1808**
V37	-.0075	-.0819	-.0068	.0246	-.0655	-.0210
V38	-.0554	-.2533**	-.1294**	.0087	-.0056	.0128
V39	.0326	-.0331	-.0317	.3065**	-.2025**	-.2469**
V40	.0425	.4278**	.1107*	-.0073	.0682	.0230
V41	-.0469	.0192	.0483	-.2763**	-.0440	-.1100*
V42	-.0460	.0203	.0465	-.2718**	-.0456	-.1148**
V43	.0054	-.0091	.0673	.0012	.0683	-.0167
V44	.0466	-.0135	-.0218	-.0235	.0083	-.0686
V45	.0333	.0192	-.0084	-.0812	.0032	.1846**
V46	-.0046	.0043	-.0094	-.0263	-.0367	-.0745

* - Signif. LE .05 ** - Signif. LE .01 (2-tailed)

Appendix B - Variable Correlation Matrix

- - Correlation Coefficients - -

	V31	V32	V33	V34	V35	V36
V31	1.0000					
V32	.0332	1.0000				
V33	.0114	.7805**	1.0000			
V34	-.0072	-.0035	.0619	1.0000		
V35	-.0090	-.4683**	-.3775**	.2487**	1.0000	
V36	-.0147	-.5365**	-.4734**	.1759**	.9321**	1.0000
V37	-.0078	.0313	-.0089	.0151	.0127	.0170
V38	-.0136	-.0042	-.0070	-.0154	-.0066	.0053
V39	.0364	.2220**	.1104*	-.6335**	-.4148**	-.4623**
V40	-.0075	.0090	.0077	.0196	.0062	-.0043
V41	-.0103	-.0431	.0332	.9775**	.3382**	.2734**
V42	-.0103	-.0369	.0388	.9787**	.3374**	.2694**
V43	.0644	.1362**	.1391**	-.0770	-.2849**	-.3081**
V44	-.0387	.0938*	.2349**	-.1372**	-.1651**	-.1669**
V45	-.0146	-.5474**	-.4869**	.1710**	.9206**	.9970**
V46	-.0225	.0087	.0414	.0916*	.1791**	.1809**

* - Signif. LE .05 ** - Signif. LE .01 (2-tailed)

	V37	V38	V39	V40	V41	V42
V37	1.0000					
V38	.0068	1.0000				
V39	.0274	-.0254	1.0000			
V40	-.0184	-.6361**	-.0245	1.0000		
V41	.0169	-.0122	-.6733**	.0210	1.0000	
V42	.0179	-.0170	-.6675**	.0231	.9985**	1.0000
V43	-.0416	-.0575	.1035*	-.1232**	-.1142**	-.1093*
V44	-.0917*	-.0191	.1610**	-.0088	-.1540**	-.1547**
V45	.0177	.0053	-.4630**	-.0094	.2671**	.2630**
V46	.0018	-.0177	-.1372**	.0048	.1326**	.1316**

	V43	V44	V45	V46
V43	1.0000			
V44	.1344**	1.0000		
V45	-.3083**	-.1698**	1.0000	
V46	-.0983*	.0129	.1763**	1.0000

* - Signif. LE .05 ** - Signif. LE .01 (2-tailed)

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IMAGE EVALUATION TEST TARGET (QA-3)

150mm

6"

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