A Test of Financial Ratios As Predictors Of Turnaround Versus Failure Among Financially Distressed Firms

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Abstract

The objective of this study was to evaluate the usefulness of financial ratios to discriminate among financially distressed firms. The sample consisted of firms identified as distressed during the period 1970 to 1976. Each company was evaluated eight years subsequent to the year of sample entry and assigned to one of three groups according to its financial condition at that point in time. All models tested were biased in their misclassifications of the sample firms. While financial ratios have proved to be meaningful discriminators in prior studies utilizing choice-based sampling designs, these results suggest that they are not so useful in efforts to distinguish between failing firms that effect a turnaround and those that are unsuccessful in their remedial efforts.

Introduction

The use of financial data to predict corporate failure has been a topic of much research interest in accounting and finance since the mid 1960's. The general thrust of these prior efforts is to assess the usefulness of accounting-based variables in distinguishing between failed firms and nonfailed firms, with "failure" most often defined as bankruptcy. The resulting models show success in predicting failure several years before its occurrence.

Bankruptcy prediction models are now widely used in practice. Evidence of such use by auditors, bond analysts, insurance companies, and financial institutions appears throughout the literature. For example, Altman (1983) cites his knowledge of at least 24 commercial banks that rely on failure classification models in their lending decisions and/or security and portfolio analysis. Descriptions of auditors' reliance on the models appear in Mutchler (1984) and Dugan and Zavgren (1988).

Nonetheless, criticisms of the model development process raise questions about the propriety of relying on the models' predictions. One criticism is the utilization of a choice-based sampling technique (i.e., the sample was drawn according to the values of the dependent variable) to identify financial ratios that discriminate among healthy and unhealthy firms. This methodology of over-sampling distressed companies results in estima-tion biases since the firms are selected nonrandomly from separate and distinct populations (Zmijewski, 1984). Deakin (1977) showed that the result is a tendency to over-predict failure, i.e., to predict many companies to fail when, in fact, they do not fail.

More importantly, though, the methodology ignores the possibility that a firm, which exhibits a potential for failure at one point in time, may reverse its negative trend before failure actually occurs. In other words, prior research ignores the "corporate turnaround phenomenon." Deakin (1977) commented on this oversight:

Interpretation of the results of the classifications must be considered in light of the nature of the process a company follows prior to failure....By classifying companies at some time prior to the bankruptcy event, one is then making a classification of failing companies, rather than of companies that have already failed....Indeed, if the failure process is a dynamic process, then a company may be able to enter the failing state, yet avoid entering the final failed state. Because of the possibility of avoidance of the final, identifiable state, identification of erroneous classifications becomes extremely difficult (pp. 80-81).

He illustrated his point by applying a failure classification model to 1780 firms with fiscal year ends in 1971. Two hundred ninety firms were predicted to fail. The

histories of these financially distressed companies were traced for the next 3½ years (through June 30, 1975). Only 18 of the 290 companies actually failed (i.e., underwent bankruptcy, liquidation, or reorganization). The misclassification rate was thus 94 percent. Redefining failure to include loan defaults and omission of preferred dividends improved the misclassification rate somewhat, but it was still rather overwhelming at 80 percent.

Deakin's research clearly demonstrates the tendency of bankruptcy failure models to misclassify nonfailing companies when the sample is more representative of the underlying population of all firms, including healthy as well as distressed companies. However, his conclusions apply only to one potential use of these models, i.e., the routine assessment of the financial health of a population of companies, both failing and nonfailing. Such is not the only known use of bankruptcy prediction models.

For instance, Dugan and Zavgren (1988) describe a very different application of bankruptcy prediction models by auditors in a major public accounting firm:

Auditors in that firm use the model mostly in situations where other sources of audit evidence already indicate the existence of a going concern problem. In such contexts, if the model signals a going concern problem, then its prediction serves to corroborate the other evidence accumulated by the auditor. At the present time, the firm does not apply the model in audits where there is no indication of a going concern problem (p. 50).

The use described here is not merely to assess financial health; the companies in question have already been diagnosed as failing. Rather, the model is being applied *exclusively* to financially troubled companies to assess the likelihood of ultimate failure. Prior research has not addressed the impact of the sampling biases described earlier on the classification accuracy of the prediction models in this particular context. The purpose of this study is therefore to test the ability of ratio-based models to discriminate between financially distressed firms that are able to successfully effect a turnaround and those that are unable to avoid entering the final, failed state.

The next section outlines the progression many firms follow in transitioning from the failing state to the failed state. Subsequent sections provide a brief outline of research in the area of corporate failure prediction and the motivation for this study. Finally, the research method, results, conclusions, and suggestions for future research are presented in the remaining sections.

The Transitional Stages of a Business Failure

Honsberger (1979, p. 30) aptly observed that "bankruptcy does not strike like a bolt of lightning...there are, in fact, many indicators or predictors of its approach." Indeed, bankruptcy is most often preceded by years of financial decay. Fitzpatrick (1934) was one of the earliest writers to describe the transitions that occur as a company progresses toward ultimate failure. He identified five stages leading to business failure: (1) incubation, (2) financial embarrassment, (3) financial insolvency, (4) total insolvency, and (5) confirmed insolvency.

The first stage, incubation, is likely to go unnoticed; it is when the company's financial difficulties are just developing. The second juncture, financial embarrassment, is when management, and possibly others, are likely to note the firm's distressed condition.

An embarrassed firm is one which, because of temporary conditions, is unable to meet its immediate cash needs. The business in this transitional state has assets in excess of its liabilities and still has acceptable earnings power; the problem is that its assets are not adequately liquid to meet maturing obligations. The stage may last for only one day, or it may continue for several months. There are remedies for financial embarrassment, including borrowing sufficient funds to meet the immediate cash needs and/or obtaining short-term extensions from creditors.

The third stage, financial insolvency, occurs if the firm is unable to acquire the necessary funds to meet its obligations. Like financial embarrassment, this condition is also curable. However, the remedial measures are likely to be more long-term in nature, e.g., modification of financial policies, bringing in new management, or issuance of additional stock or long-term debt.

Many financially insolvent firms are successfully restored to a healthy state. Those firms that are unsuccessful in their corrective efforts progress to the fourth transitional stage, total insolvency. According to Fitzpatrick, this is the critical point in the failure:

The fourth stage . . . occurs when the liabilities exceed the physical assets. It is, in a number of instances, the time when the general public and those creditors not yet apprised of the firm's true condition first learn that the company is failing. The business can no longer avoid the confession of failure (p. 338).

At this point, creditors may allow a troubled debt restructuring, or they may take over the business to save the cost of a receivership. The company may also make a final attempt to secure additional funds through financing. If none of the above alternatives proves

acceptable, the business passes to the fifth and final stage, confirmed insolvency.

Confirmed insolvency occurs when legal steps are taken to protect the firm's creditors, i.e., the voluntary or involuntary filing of a bankruptcy petition. Even the bankruptcy filing does not necessarily preclude a turn-around since the firm may still be restored through a reorganization. The majority of businesses that reach this final stage, however, are in fact liquidated.

Prior Research in Corporate Failure Prediction

Research in the area of corporate failure prediction has, for the most part, concentrated on those firms in Fitzpatrick's fourth and fifth stages (with the fifth stage being, by far, the predominant focal point). Beaver's (1966) was the first reported research that tested the usefulness of financial ratios to predict business failure. Many others have since investigated the usefulness of accounting data in that context. The most notable contributions are in the form of methodological refine-ments (e.g., Altman, 1968; Deakin, 1972, 1977; Altman, Haldeman, and Narayanan, 1977; Ohlson, 1980; Casey and Bartczak, 1985; and Gentry et al., 1985) and the determination of other important predictor variables (e.g., Blum, 1974; Altman, Haldeman, and Narayanan, 1977; Casey and Bartczak, 1985; and Gentry et al., 1985). A major weakness of these works is that they all classify the sample firms as either failed or nonfailed. This artificial dichotomization does not explicitly recog-nize that a failing firm may be able to remedy its weakened position before it reaches the final stage of collapse.

The studies by Lau (1987) and Casey et al. (1986) represent major advances toward recognition of the difference between fai<u>ling</u> and fail<u>ed</u> companies and acknowledgement of the turnaround phenomenon. Lau used multinomial logit analysis to construct a five-state financial distress prediction model. The five states were: (1) financial stability; (2) omission of, or reduction in, dividend payments; (3) default on loan principal and/or interest payments; (4) filing for protection under the bankruptcy acts; and (5) bankruptcy and liquidation. Lau identified two samples of 400 firms (350, 20, 15, 10, and 5 firms, respectively, in each of the five states described above). The first sample was used to develop the prediction model, while the second sample was used to test the model. The predictive ability of the model was evaluated for one year, two years, and three years prior to the state determination. Lau's model showed success in determining the probability that a firm would enter each of the five states of financial distress.

While Lau's study recognized a continuum of corpo-rate financial health, it did not allow for the possibility that a distressed firm might successfully effect a turn-

around. The dynamics of the failure process were essentially ignored. Casey et al. (1986) did, however, allow for the reversal of a negative trend. These researchers identified a sample of firms that filed for bankruptcy between 1970 and 1981. The firms were segregated according to whether they had liquidated or successfully reorganized in the period subsequent to the initial filing. The study revealed several significant discriminators between the "liquidations" and "successes." The Casey et al. study nonetheless focused only on bankrupt firms. It therefore does not represent a complete investigation of the turnaround phenomenon as it occurs in the population of distressed firms.

Research Motivation

When analyzing a specific company, a decision maker does not have the benefit of hindsight. If the company appears financially healthy, the decision maker may, like the auditors described in Dugan and Zavgren (1988), make no attempt to assess a probability of failure. On the other hand, if the company seems financially trou-bled, that same decision maker is probably quite inter-ested in the likelihood that it will ultimately fail. To make that determination, the decision maker can only use information available at that time, which includes past and current financial information. The decision maker has no knowledge concerning the troubled company's ultimate fate. Furthermore, if the company should ultimately fail, the decision maker has no idea how far from bankruptcy the company is.
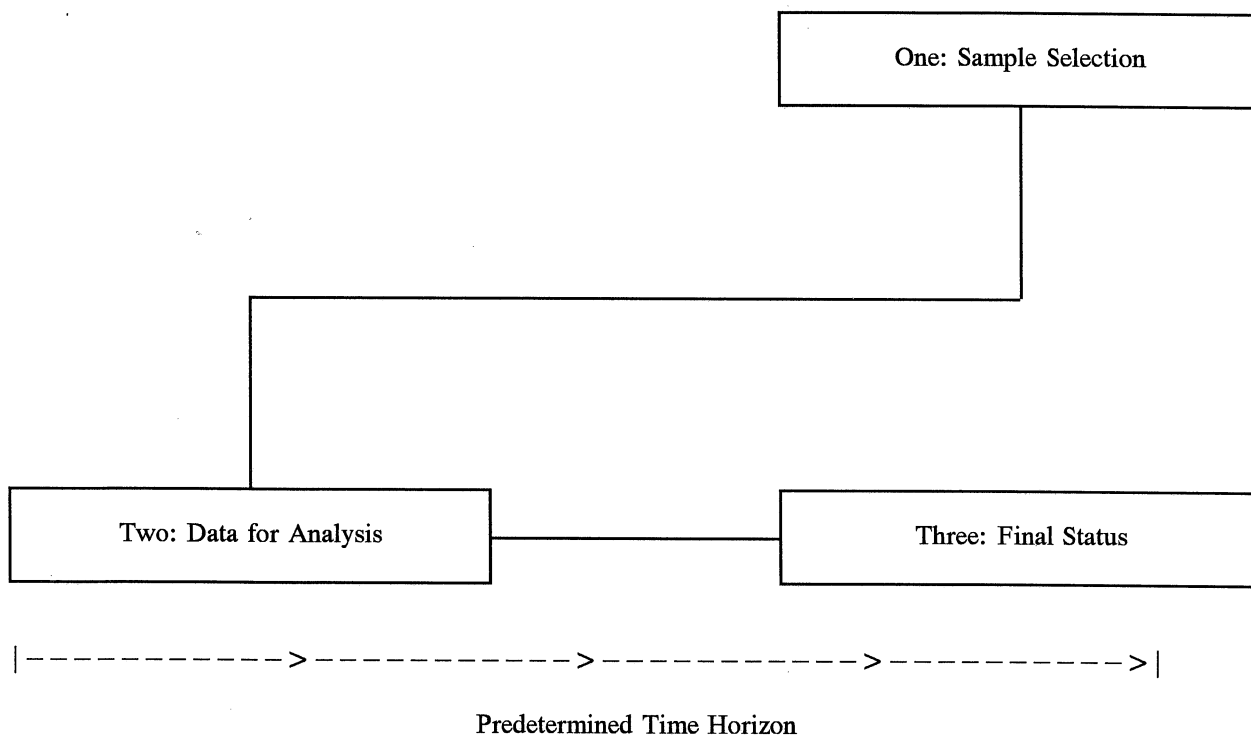
The sampling method used in most prior research is incompatible with such a decision model. In these studies, the criterion for sample entry has typically been the firms' ultimate condition (i.e., failed/nonfailed, or, in the case of Lau (1987), a continuum of financial health). The research objective has been to predict that known resolution of firm status using data from a specific, predetermined period of time prior to the final outcome (e.g., three years preceding bankruptcy, two years preceding bankruptcy, etc.). This method of construct-ing a predictive model is depicted in Figure 1.[1] While the resulting models may prove useful in certain circum-stances, their effectiveness in the specific context de-scribed above remains untested.

This study extends the analysis of financial distress to that particular context. It tests whether financial ratios can discriminate between those troubled companies that are able to cure their financial ills, thereby avoiding bankruptcy, and those that are unsuccessful in their remedial efforts. The sample consists of firms in the earlier phases of financial distress (i.e., Fitzpatrick's (1934) financial embarrassment, financial insolvency, and total insolvency stages). This study is unique in that the sample is not drawn from a priori, separate and distinct populations. Rather, the criterion for sample entry is

that all companies evidence symptoms of financial distress. The firms' eventual status (i.e., success or failure) is *not* known at the time of sample selection. The sample firms are classified as successes or failures based on their financial condition at a later point in time.

distress during the period 1970 to 1976.[2] A firm was considered financially distressed if it met any one of the following three criteria: two or more consecutive operating losses; a current ratio less than 1.0 as of the end of any single fiscal year; or a negative balance in the Retained Earnings account as of the end of any single

Figure 1
Method Used in Prior Studies

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                                            ┌─────────────────────────────┐
                                            │    One: Sample Selection    │
                                            └─────────────────────────────┘

┌─────────────────────────────┐              ┌─────────────────────────────┐
│    Two: Data for Analysis    │              │    Three: Final Status      │
└─────────────────────────────┘              └─────────────────────────────┘

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Predetermined Time Horizon

This methodology is outlined in Figure 2. As the figure shows, the method used herein is more compatible with the auditors' decision model described by Dugan and Zavgren (1988) in two ways: (1) it focuses *only* on distressed firms, and (2) it relies on data coincident with the time of sample selection to forecast the company's ultimate condition.

Research Method

In this study, two different models were used to assess the ability of financial ratios to discriminate between financially distressed firms that successfully accomplish a turnaround and those that are unable to do so. Sampling procedures and model specification are discussed below.

Sample Selection and Classification

The COMPUSTAT tapes were used to select a sample of manufacturing firms that experienced financial

fiscal year. These three measures were chosen primarily because of their general acceptance as key indicators of financial viability (see Mutchler, 1984; Levitan and Knoblett, 1985; and Mutchler, 1985).

The first criterion, called OPLOSS in the study, was chosen as an indicator of weakened short-term earnings power. Firms entering the sample solely due to this criterion could well be in the incubation stage of financial distress (Fitzpatrick, 1934). The second criterion, called CRLESS, was selected to identify firms experiencing liquidity problems (i.e., those in Fitzpatrick's financial embarrassment and financial insolvency stages). A value of 1.0 was selected as a conservative cutoff because it is half of the oft-cited, rule-of-thumb value for the current ratio, which is 2.0.[3] The third criterion, called NEGRET in the study, was chosen as an indicator of impaired long-term earnings power. Companies meeting this criterion were assumed to be in the later stages of business failure.

Figure 2
Method Used in This Study

Unknown Time Horizon
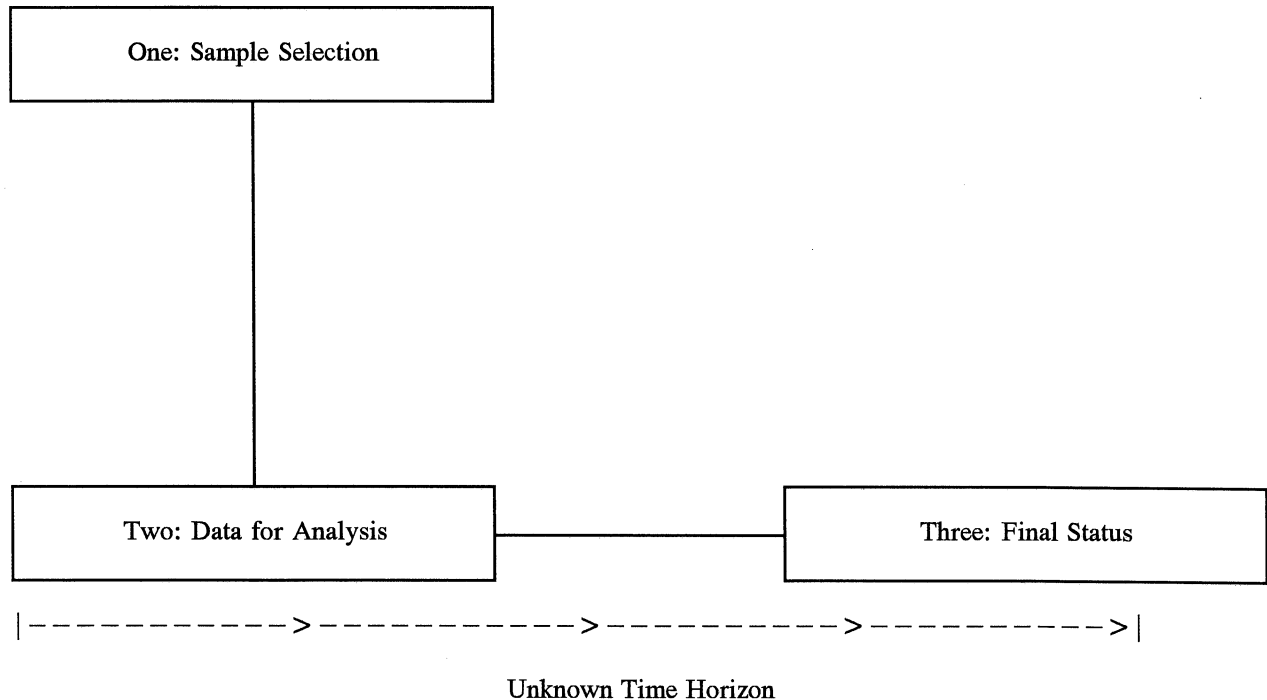
Bibeault (1982) suggests that the average turnaround cycle is approximately seven to eight years. Accordingly, each firm's financial condition was evaluated eight years after the time it was pinpointed for inclusion in the study. Based on that evaluation, each company was assigned a value for the categorical dependent variable, STATUS. If a company filed for bankruptcy or liquidated at any time during the eight-year period, it was classified as a business failure and assigned a value of "1" for STATUS. If, after eight years, the company was still in financial distress, according to the three criteria listed above, it was classified as a survivor with unknown ability for continued success and assigned a value of "2" for STATUS. Finally, if a company was no longer financially distressed, based on the same three criteria, it was classified as a turnaround firm and assigned a value of "3" for STATUS.

Any company that merged with another corporation during the eight-year period was not considered a candidate for the sample. Any company deleted from the COMPUSTAT tapes for a reason other than bankruptcy or liquidation was also ignored in the sample selection process. In addition, companies that had missing values for certain key data items were eliminated from the sample.

Model Specification

The first analysis in this study tested a previously-developed model's ability to discriminate among the sample of financially distressed companies. The model chosen was Altman's (1968) Z-score. Altman et al. (1977) have since developed a more refined model (known as the ZETA model) with reported classification accuracy far better than that of the original model. However, because the rights to the ZETA model are separately owned, the coefficients on the variables in the model are not disclosed in the literature. Altman's Z-score, for which the coefficients on the variables are in fact readily available, thus has retained a high degree of popularity.

The second analysis involved model construction. The motivation for this analysis was not to identify significant predictor variables in the context being studied, but rather to test the general propriety of using ratio-based failure prediction models in that context. The selection of independent variables for the model was motivated by the work of Pinches et al. (1975). Their research identified seven ratio-based factors that explained more than 90 percent of the variation in the sample companies' ratio data. The initial model constructed in this

study consisted of one ratio from each of the seven factors. Several variants of this model were also analyzed, and one variant was tested on a temporal holdout sample.

Altman's (1968) Z-score. Altman evaluated a sample of 33 bankrupt firms and 33 nonbankrupt firms using multiple discriminant analysis. The firms were matched on the basis of industry and size. Twenty-two ratios were initially selected for the study. The final discriminant function consisted of five ratios; it has become known as the Z-score model:[4]

$$Z = 1.2x_1 + 1.4x_2 + 3.3x_3 + 0.6x_4 + 1.0x_5,$$

where
Z = Overall Classification Index,
x_1 = Working capital/Total assets,
x_2 = Retained earnings/Total assets,
x_3 = Earnings before interest and taxes/Total assets,
x_4 = Market value of equity/Book value of total debt,
x_5 = Sales/Total assets.

A Z-score less than 1.81 is associated with a high probability of failure, while a Z-score greater than 2.99 is indicative of a financially healthy firm. Altman called the region between 1.81 and 2.99, inclusive, the "zone of ignorance"; it is the region over which misclassifications are likely. To test the ability of the model to correctly classify firms dichotomously, as either failed or non-failed, Altman used a cutoff of 2.675 for the Z-score. The dichotomous classification model was quite accurate for up to two years preceding failure.

Pinches et al. (1975) factor analysis. Observing the growing reliance on financial ratios for predictive studies, Pinches et al. sought to identify key groups of financial ratios and to determine the relationships among the financial ratios in those groups. An oblique factor analysis of 48 selected ratios for 221 firms yielded seven major factors. Together, these seven factors explained over 90 percent of the common variation in the ratio data.

The seven factors were labeled Return on Investment, Capital Turnover, Inventory Turnover, Financial Leverage, Receivables Turnover, Short Term Liquidity, and Cash Position. Pinches et al. (1975, p. 304) suggested that:

By selecting one ratio from each classification, researchers and analysts can identify a set of financial ratios which essentially are independent of each other...but which represent the seven different empirical aspects of a firm's operations.

Accordingly, this was the approach taken in constructing

the prediction equations in this study. The independent variables for the initial version of the model were, with one exception, the highest loading ratios on each of the seven identified factors. The exception was with regard to the representative measure for Short Term Liquidity. The current ratio loaded highest on that factor. However, since CRLESS would be added to the model in one of the later variations, the quick ratio, which was the second highest loading ratio, was used instead.

The seven ratios, measured at the time each company entered the sample, were: INCCAP = Income/Total capital, representing the Return on Investment factor; SALESPLT = Sales/Net plant, representing the Capital Turnover factor; INVTRN = Inventory/Sales, representing the Inventory Turnover factor; TLCAP = Total liabilities/Total capital, representing the Financial Leverage factor; RECTRN = Receivables/Inventory, representing the Receivables Turnover factor; QKRATIO = Quick assets/Current liabilities, representing the Short Term Liquidity Factor; CASHTA = Cash/Total assets, representing the Cash Position factor.

McKelvey and Zavoina's (1975) probit model, which was developed specifically for the analysis of data with ordinal level dependent variables, was chosen for development of the prediction equation.[5] The overall significance of the model can be assessed by a statistic equal to minus two times the log likelihood function, which is distributed as χ^2 with degrees of freedom equal to the number of independent variables. The fit of the probit model can be assessed by the estimated R^2. This statistic has much the same interpretation as the coefficient of determination used in classical regression analysis. It represents the percentage of the variability in the dependent variable that is explained by the probit model if the ordinal level dependent variable could have been measured on its underlying interval level scale.

Research Results

Because the data demands for the two models were different, and because of missing data for some items, the number of firms used for the two analyses varied. For purposes of constructing the model based on Pinches et al. (1975), 204 firms were identified. These 204 firms constituted the base sample. Because nine of the 204 companies in the base sample had missing values for the market value of common equity, Altman's Z-score model was tested on 195 companies.

Each of the 204 firms' financial condition was evaluated eight years subsequent to the year of entry into the sample. Based on that evaluation, 46 companies were classified as business failures (STATUS 1), while 123 firms were classified as turnarounds (STATUS 3). Thirty-five of the 204 sample firms were in existence after eight years, but still met at least one of the three

entry criteria. These 35 companies were classified as survivors with unknown ability for survival (STATUS 2).[6]

Characteristics of the base sample are presented in Tables 1 through 4. Table 1 indicates the number of firms (grouped by STATUS) that entered the sample each year during the period 1970 to 1976. Table 2 presents the number of firms entering the sample for every possible combination of entry criteria. Table 3 shows the company ages at the time of sample entry.[7] Finally, Table 4 reports how far the STATUS 1 firms were from bankruptcy or liquidation at the time of sample entry.

Tests of the Z-score

Two versions of the Z-score model were investigated. The first variation included the area termed by Altman as the "zone of ignorance," i.e., the range of Z-scores between 1.81 and 2.99, inclusive. In this study, the "zone of ignorance" was viewed as equivalent to a STATUS 2 categorization.

The classification results using Altman's three-way grouping system are presented in Table 5. The Z-score correctly determined STATUS for only 31 percent of the firms; this is markedly lower than the accuracy that could be obtained by naively classifying all firms as healthy. Table 5 indicates that this model demonstrated a bias toward classifying healthy firms as failures (over 50 percent of the firms were predicted to fail, when in reality less than 25 percent failed within eight years).

The second version of the Z-score model utilized the values suggested by Altman for a dichotomous categorization of firms as either bankrupt or healthy. The results of this analysis are reported in Table 6. When the STATUS 2 firms were ignored, the predictive accuracy of the Z-score improved somewhat to approximately 43 percent. Still, though, the bias was toward forecasting failure, with a Type II error rate (i.e., classifying a healthy firm as a failure) of approximately 73 percent.

Tests of the Probit Model

Four different probit models were constructed using the seven ratios, described earlier, from the Pinches et al. (1975) factor analysis. The first variation incorporated only the seven ratios. The expected signs for the coefficients on the independent variables and the resulting probit model are reported in Table 7. Table 8 shows the classification accuracy of the probit model.

Table 1
Number of Firms Entering the Sample Each Year

	STATUS[a]				
Year	1	2	3	Total	Percent
1970	21	17	40	78	38%
1971	7	3	15	25	12%
1972	2	1	18	21	10%
1973	3	3	4	10	5%
1974	7	3	8	18	9%
1975	5	7	26	38	19%
1976	1	1	12	14	7%
Total	46	35	123	204	100%

[a]1 = Business failure
2 = Survivor with unknown ability for continued success
3 = Turnaround

Table 2
Reason for Entry into the Sample

Reason for Entry[b]	STATUS[a]			Total	Percent
	1	2	3		
OPLOSS	14	13	63	90	44%
CRLESS	3	1	6	10	5%
NEGRET	11	10	30	51	25%
OPLOSS & CRLESS	0	0	0	0	0%
OPLOSS & NEGRET	9	8	18	35	17%
CRLESS & NEGRET	6	1	3	10	5%
OPLOSS, CRLESS, NEGRET	3	2	3	8	4%
Total	46	35	123	204	100%

[a]1 = Business failure
2 = Survivor with unknown ability for continued success   3 = Turnaround
[b]OPLOSS = Two or more consecutive operating losses
CRLESS = Current ratio less than 1.0
NEGRET = Negative balance in Retained Earnings

Table 3
Company Ages at Time of Entry (n = 203)

Age at Entry	STATUS[a]			Total	Percent
	1	2	3		
0 to 5 years	6	2	16	24	12%
6 to 10 years	10	5	25	40	20%
11 to 15 years	5	10	7	22	11%
16 to 20 years	8	4	18	30	15%
21 to 25 years	2	1	14	17	8%
> 25 years	15	13	42	70	34%
Total	46	35	122	203	100%

[a]1 = Business failure
2 = Survivor with unknown ability for continued success
3 = Turnaround

Table 4
Approximate Time Lapse[a] Between Entry and Failure

Time Lapse (T)	Number of Firms	Percent
0 months ≤ T ≤ 6 months	2	4%
7 months ≤ T ≤ 1 year	2	4%
1 year ≤ T ≤ 2 years	7	15%
2 years ≤ T ≤ 3 years	11	24%
3 years ≤ T ≤ 4 years	7	15%
4 years ≤ T ≤ 5 years	5	11%
T > 5 years	12	27%[b]
Total	46	100%

[a]The approximate time lapse was calculated by comparing the date each company petitioned for bankruptcy, as reported in the Wall Street Journal Index, to the date of sample entry (i.e., the fiscal year end).
[b]Rounded up to total 100%.

Table 5
Classification Results for Z-score with
Zone of Ignorance (n = 195)

STATUS[b]	Z-score Classification[a]			Total
	Bankrupt	Zone of Ignorance	Healthy	
1	29	10	7	46
2	17	12	3	32
3	52	45	20	117
Total	98	67	30	195

[a]Z < 1.81 = Bankrupt
1.81 ≤ Z ≤ 2.99 = Zone of ignorance
Z > 2.99 = Healthy
[b]1 = Business failure
2 = Survivor with unknown ability for continued success
3 = Turnaround

Table 6
Classification Results for Z-score without
Zone of Ignorance (n = 195)

STATUS[b]	Z-score Classification[a]		Total
	Bankrupt	Healthy	
1	38	8	46
2	27	5	32
3	85	32	117
Total	150	45	195

[a]Z ≤ 2.675 = Bankrupt
Z > 2.675 = Healthy
[b]1 = Business failure
2 = Survivor with unknown ability for continued success   3 = Turnaround

Two of the variables were significant at the one percent level, and both had signs in the expected directions. The signs on the four remaining variables (for which specific directions were anticipated) were not as expected.[8] The overall model was significant at the 0.01 level; nonetheless, the predictive accuracy for this initial model is only slightly greater than that which could be obtained by classifying all firms as turnarounds. Further, while the Z-score models demonstrated a bias toward categorizing all firms as failures, this model did just the opposite in inaccurately assigning over 78 percent of the STATUS 1 companies.

Because there is some evidence that the magnitude of financial ratios of manufacturing firms shifts over time (Pinches et al., 1973), some predictive ability may have been lost by examining company-specific ratios gathered at different points in time (1970 to 1976, depending on the time of sample entry for each observation). To compensate for this possibility, the original probit model was revised to include industry-normalized versions of the seven ratios. These new variables were calculated by dividing each company-specific ratio in the year of sample entry by the average value of that same ratio for all firms in the industry for that same year.[9] Utilizing industry-normalized, rather than company-specific, ratios actually caused a decline in R^2 (to 0.16); the overall classification accuracy was just over 62 percent.[10]

In a further attempt to construct an improved model, six control variables were added to the two previously tested versions: AGE = a value between 0 and 5 depending on the company's age at the time of entry into the sample;[11] OPLOSS = 1 if income from opera-

tions was negative for two consecutive years at entry, and 0 otherwise; CRLESS = 1 if the current ratio was less than 1.0 in the year of entry, and 0 otherwise; NEGRET = 1 if the balance in Retained Earnings was negative at the time of sample entry, and 0 otherwise; YRENT = a value between 0 and 6 depending on the year (1970 to 1976) that the company entered the sample; LOGTAGNP = Log(Total assets/GNP price-level index) at time of entry.

Company age was added to the model because of the a priori belief that older firms are more capable of survival than younger firms. OPLOSS, CRLESS, and NEGRET were added as indicators of the reason(s) for entry into the sample. YRENT was added since the independent variables for any two firms might very well be from different years. Finally, LOGTAGNP was added as a measure of company size. Again, since the age of one of the 204 companies in the base sample was not found, the sample size for these last two probit analyses was 203.

Incorporating additional independent variables into both the company-specific and industry-normalized versions of Model Two did not result in greatly improved classification. The 13-variable, company-specific version yielded an R^2 of 0.29. It correctly classified 66.5 percent of the sample firms. The industry-normalized version had an R^2 of 0.21 and overall accuracy of 63.6 percent. Both models were statistically significant at the 0.01 level. Interestingly, AGE was negative and insignificant in both analyses.

An examination of the company ages at the time of

Table 7
Probit Results for Initial Model (n = 204)

Variables	Expected Sign	Maximum Likelihood Estimate (MLE)	MLE/Standard Error
Constant	NA	1.58	5.11
INCCAP	+	-0.75	-1.89
SALESPLT	+	-0.01	-0.80
INVTRN	-	-1.33	-2.75†††
TLCAP	-	-0.57	-2.85†††
RECTRN	+	-0.11	-0.95
QKRATIO	+	-0.01	-0.26
CASHTA	+/-	1.74	1.26

Probit R^2	0.27
Model χ^2 (7 df)	25.42†††
Percent Correctly Predicted	63.24

†††$p < 0.01$

Table 8
Classification Results for Initial Probit Model (n = 204)

STATUS[a]	Probit Model Classification[a]			
	1	2	3	Total
1	10	0	36	46
2	6	0	29	35
3	4	0	119	123
Total	20	0	184	204

[a]1 = Business failure
2 = Survivor with unknown ability for continued success
3 = Turnaround

entry documents the reasonableness of the probit results for this variable, however. As shown in Table 3, 70 of the 203 companies were over 25 years old at the time of sample entry. Of the 46 failed firms, 15 were over 25 years old, whereas only 42 of the turnaround firms were in that same age category. Clearly, for this particular sample, age was not a discriminator among the three classes of firms. This is evidenced by the lack of any observable pattern in the age distribution across those classes.

Supplemental Analyses

Before conducting any tests on a holdout sample and drawing conclusions about the ability of financial ratios to discriminate among financially distressed firms, several other analyses were performed on various subsets of the data. These included:

1. An analysis excluding the 35 STATUS 2 firms. The companies in this "in-between" category were eliminated because of the possibility that they might be obscuring the results.
2. An analysis excluding the 78 firms that entered the sample in 1970. These companies were dropped because they are potentially very different from the remaining 126 firms in that they could have been distressed (according to the three criteria used in this study) for an extended period of time prior to entering the sample.
3. An analysis without the 63 STATUS 3 firms that entered the sample only because of having two or more consecutive operating losses. These companies were removed from the sample because continued operating losses over the short-run are not, in and of themselves, indicative of a failing firm.
4. An analysis without the 24 firms that were less than six years old at the time of entry into the sample. These companies were excluded because very young firms may be more likely to experience characteristics of distress than firms which have been in existence for a longer time.
5. An analysis without the STATUS 1 firms that were deleted from the active COMPUSTAT files because of liquidation as opposed to bankruptcy. These companies were dropped from the sample since the characteristics of firms liquidating for the benefit of shareholders may differ from those of firms filing for bankruptcy. Nine of the 46 STATUS 1 companies fell into this category.

In each case, all variations of both the Z-score and probit models, which were described in the preceding sub-sections, were tested. Additionally, the analyses described in items (2) through (5) above were performed both with and without the STATUS 2 firms. The results of these supplemental analyses were very similar to those of the initial tests of the Z-score and probit models. All variations of the Z-score model were biased toward predicting failure (high Type II error rates). With only one exception, the various versions of the probit model were biased toward classifying the sample firms as turnarounds (high Type I error rates).

The exception to the general biases was provided by a 13-variable model with company-specific ratios. In this model, the STATUS 3 firms that qualified for the sample only because of consecutive losses (63 companies) and all the STATUS 2 companies (35 firms) were deleted. The sample size was thus 105. The probit R^2 for this model was 56.39 percent. It was statistically significant beyond the 0.01 level. Table 9 presents the classification results. The overall classification accuracy of about 75 percent is a notable improvement over the 56 percent accuracy rate that could be obtained by naively classifying all companies as turnarounds. Further, the Type I error rate (28 percent) was much lower than the corresponding error rates associated with the various trials discussed previously. At the same time, however, this particular variation showed a greater Type II error rate (22 percent) than that seen in all other versions of the probit model.

Because of this model's relative success (compared to the other models evaluated in this study) in correctly classifying the firms in the original sample, its predictive accuracy was tested using a temporal holdout sample. The holdout sample consisted of the firms on the COMPUSTAT annual and research tapes that:

1. Met any one of the sample entry criteria as of the end of fiscal year 1977, 1978, or 1979. (Any STATUS 3 firm that entered only because of having experienced two consecutive years of operating losses was subsequently dropped from the sample.)
2. Had complete data availability for the model variables.
3. Did not merge with another corporation during the eight years subsequent to identification as distressed.
4. Were not dropped from the COMPUSTAT active files for a reason other than bankruptcy or liquidation.
5. Were not members of the original sample.

Seventy-six companies were identified for the holdout sample. Five were STATUS 1, 34 were STATUS 2, and the remaining 37 were STATUS 3 companies.

The classification results of this version of the probit model for the holdout sample are presented in Table 10. Because the model being tested was constructed without STATUS 2 companies, the model's assignment of the 34 STATUS 2 companies in the holdout sample is omitted. The model's overall predictive accuracy for the holdout sample was approximately 79 percent. This is somewhat

less than the 88 percent accuracy that could be obtained using the naive scheme of forecasting all companies to survive. The model was unsurprisingly most successful in its classification of the STATUS 3 firms, as evidenced by the over 86 percent accuracy rate. The model's bias toward predicting failed firms to endure for at least eight years is apparent from the 80 percent misclassification rate for the five STATUS 1 firms.

Of the 34 STATUS 2 companies in the holdout sample, only one was identified on the COMPUSTAT research tapes; the remaining firms were found on the active tapes. If these STATUS 2 firms were to be re-classified as either STATUS 1 or STATUS 3 depending on their actual, ultimate conditions (as opposed to their conditions eight years subsequent to entry), the overall predictive accuracy for this probit variation would be slightly greater than 80 percent. This likewise compares unfavorably to the 92 percent accuracy obtainable by merely predicting all companies to succeed. In this scenario, two-thirds of the failed firms would be erroneously predicted to succeed. The misclassification rate for the turnarounds would be about 16 percent.

Table 9
Classification Results for Revised Probit Model ($n = 105$)

STATUS[a]	Model Classification[a]		Total
	1	3	
1	33	13	46
3	13	46	59
Total	46	59	105

[a]1 = Business failure
3 = Turnaround

Table 10
Predictive Accuracy of Revised Probit Model
for Holdout Sample (n = 42)

STATUS[a]	Model Classification[a]		Total
	1	3	
1	1	4	5
3	5	32	37
Total	6	36	42

[a]1 = Business failure
3 = Turnaround

Summary and Conclusion

Existing research in the area of corporate failure prediction has ignored the corporate turnaround phenomenon, i.e., the notion that a distressed firm, once distressed, does not necessarily fail. Further, most past research efforts have used the sample companies' ultimate outcomes as the basis for entry into the sample; this methodology results in a biased sample for studying failure. Both shortcomings have been recognized repeatedly (e.g., Beaver, 1966; Deakin, 1977; Ball and Foster, 1982; Zmijewski, 1984), but have not heretofore been addressed together in a single empirical study.

The sampling design employed in this study allowed for the explicit recognition of the turnaround phenomenon. The objective was to test the ability of financial ratios to discriminate among financially distressed firms that are able to remedy their weakened condition and those that are unsuccessful in their remedial efforts. The results suggest that financial ratios are of questionable value in this context.

In this research, the eventual status of the sample firms was not known at the time of selection. The criterion for analysis was, more realistically, that there be a basis to believe the sample companies might eventually fail. The values for the dependent variable were determined after the fact, rather than before the fact. This method represents a direct departure from the choice-based sampling design so common in the failure prediction research genre.

None of the various models tested yielded classification results notably better than those achievable by naively classifying all firms as turnarounds. All versions of the Z-score model were consistently biased toward classifying distressed firms as failures (i.e., they demonstrated a high Type II error rate). While such a bias represents only an opportunity loss for potential creditors and investors, it is much more serious from the viewpoint of the companies involved and their existing creditors and shareholders. This bias could result in a going concern qualification, thereby inhibiting the ability of managers to obtain external financing in a time of dire need and ultimately force the ailing company into bankruptcy, possibly resulting in significant losses for existing creditors and shareholders. The various probit models, on the other hand, were consistently biased toward classifying all ailing firms as turnarounds (i.e., they demonstrated high Type I error rates). From the viewpoint of potential investors and creditors, this is a most costly error because these individuals are led to invest in firms that will experience failure.

Suggestions for Future Research

How decision makers actually apply previously-developed failure prediction models is not completely known. A relevant question is whether the models are routinely applied without regard to the companies' apparent health (or lack of it). Certainly, one would suspect that a decision maker is less likely to assess a probability of failure for a clearly healthy firm than for a firm that is obviously experiencing characteristics of distress. If this is indeed the case, the merits of existing failure prediction models (which have focused on discriminating among firms a priori known to be from separate and distinct populations) must be seriously re-evaluated in light of the results reported herein.

Creditors', investors', and auditors' needs to assess the probability of failure are very real. Inaccurate assessments can have great costs (in the form of actual losses, as well as opportunity losses) for all parties involved, including the companies being scrutinized. It is not apparent, however, whether the application of existing financial ratio-based models can minimize those costs, especially in light of the present research. In fact, if the present research results are generalizable, there is additional reason to suspect great biases in the way existing models will classify ailing firms. Accordingly, these results suggest a need for further scrutiny of the nature of financial distress and a need to identify variables that are relevant to the determination of which distressed firms will survive and which will ultimately fail.   ❧

✳✳✳Endnotes✳✳✳

1. Figure 1 is representative of the approach used in all cited studies except Casey et al. (1986). The methodology used therein is more like that shown in Figure 2 in that the sample companies were chosen on the basis of having filed for bankruptcy. Their ultimate status of liquidation or reorganization was not known at the time of selection.
2. The COMPUSTAT files used to generate the sample were the annual industrial, the annual over-the-counter, the industrial research, and the over-the-counter research files.
3. The cutoff of 1.0 has been used in at least one other study (Levitan and Knoblett, 1985). Interestingly, all of Beaver's (1966) sample firms, bankrupt and nonbankrupt alike, had current ratios greater than 2.0.
4. The coefficients in this model are not the same as those reported in Altman (1968). The model shown here is taken from Altman (1977). It differs from the original in that the coefficients on the first four variables are multiplied by 100. The original model assumed that all ratios were expressed as absolutes (e.g., if the ratio, Working Capital/Total Assets, were 42 percent, it would be entered as 42.0). The revised model conforms to the typical mathematical expression of 42 percent as 0.42.

5. In this study, STATUS was considered to be ordinal in nature, i.e. STATUS 3 is better than STATUS 2, which is in turn better than STATUS 1. The hierarchical relationship might be questioned for STATUS 2 firms given that their ultimate resolution is not clear. However, in this analysis, it was assumed that a firm that could survive eight years (even if it was clearly distressed after those eight years) was healthier than one that was unable to survive for that long.

6. Most of the "questionable survivors" were identified from the COMPUSTAT annual industrial and over-the-counter tapes. However, three of the STATUS 2 firms were found on the research tapes. Given knowledge of the tapes on which the companies were found, all the STATUS 2 firms could have been classified as either failures or turnarounds. This was not the approach taken, however. For consistency, the STATUS 2 firms were classified using the same strict, eight-year guidelines that were established for the STATUS 1 and 3 companies. This was done without regard to their ultimate condition beyond the eight-year turnaround horizon utilized in this study. Furthermore, five of the 123 STATUS 3 firms were located on the research files. Again, because these companies no longer met any of the three criteria for sample entry after eight years, they were classified as turnarounds rather than failures.

7. Each company's age at entry was calculated as the difference between the year of entry into the sample and the date the business was originally established, as reported in *Moody's Industrial Manual* or *Moody's OTC Manual*. One company's age was not reported in these sources; that company was a STATUS 3 firm that was identified on the research files, i.e., the company is no longer in existence.

8. The presence of multicollinearity may partially explain why the signs on the coefficients were not as expected.

9. In calculating the industry average for the ratios, an industry was defined by its two-digit SIC code. For each industry, the average was based on all firms (with reported values for the ratio in question) appearing on the four COMPUSTAT tapes from which the sample was drawn.

10. Basing the industry-normalized ratios on SIC codes assumes that the SIC system produces groups of firms that are sufficiently homogeneous to account for industry-specific factors. The observed decline in explanatory power and classification accuracy may be due to an inability of the SIC coding system to appropriately group firms.

11. Each firm was assigned a value between zero and five for AGE as follows:

    AGE   = 0 if company age is 0 to 5 years
                = 1 if company age is 6 to 10 years
                = 2 if company age is 11 to 15 years
                = 3 if company age is 16 to 20 years
                = 4 if company age is 21 to 25 years
                = 5 if company age is over 25 years

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