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Ratio Stability and Corporate Failure

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THIS STUDY PRESENTS ANOTHER model on corporate failure that uses financial ratios and discriminant analysis as its core. We believe the final word on this methodology has not yet been said.

The essential attribute of our model is its use of the stability of all financial ratios over time, as well as the level of these ratios, as explanatory variables in the derivation of a discriminant function. Our research indicated a substantial degree of instability, measured by (1) the standard deviation of the financial ratios over the past few years, (2) their standard error of estimate, and (3) their coefficient of variation, in the ratios of firms that went bankrupt when compared with those that did not. This instability showed a significant increase over time as the corporation approached failure (Figure 1).

The inclusion of the stability of ratios in the analysis improved considerably the ability of the discriminant function to predict failure. Our model classified firms into failed and non-failed groups with 78 percent accuracy five years prior to failure. This represents a marked improvement over previously reported results.

The next section outlines the milestones of recent corporate failure research. Then the characteristics of our data set are described. Following that we describe our methodology and present our results. Finally, a summary is made of our main conclusions.

Previous Research

Most analytical research done on failing firms uses ratio analysis as its foundation. The descriptive literature, ably summarized by John Argenti [5], identifies the causes of corporate failures to be:

(1) *Internal factors*

I. Bad management manifested through

(a) lack of responsiveness to change in technology

(b) bad communications

(c) misfeasance and fraud

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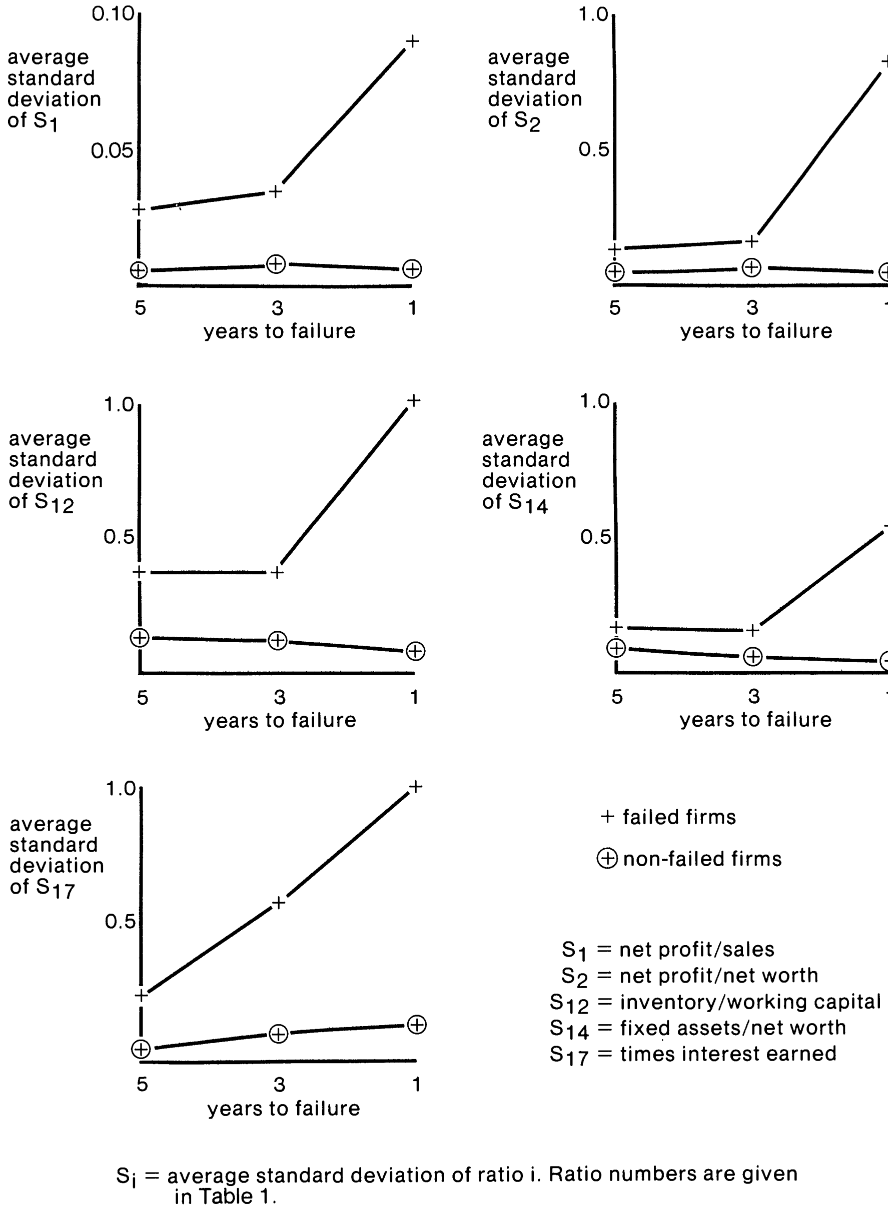

Figure 1. Average Standard Deviation vs. Time Prior to Failure for Selected Ratios, Failed vs. Nonfailed Firms.

(d) insufficient consideration for cost factors (research and development costs in particular)
(e) poor knowledge of financial matters
(f) high leverage position—particularly harmful in an economic downturn

(2) *External factors*

I. Labor Unions: Too high a wage settlement causing the firm to pay its employees in excess of their marginal product.

II. Government Regulations which impede, in some instances, the functioning of the market system distorting in the process its signals to the corporate decision makers.

III. Natural causes: Natural disasters, demographic changes, etc.

The analytical studies on the general macroeconomic causes of corporate failure was begun by Altman [2]. Failure was significantly linked to the prevailing monetary policy (a tight monetary policy increasing the probability of failure), the investor's expectations[1] about economic conditions (the more negative the expectations the more likely failures are to occur), and the state of the economy.

On the micro level, Altman found that the age of the firm has a significant impact on its chance of failure. The significant micro analysis however, came with the usage of discriminant analysis applied to financial ratios in the prediction of corporate failure.

Beaver [6, 7] was among the first to use financial ratios to predict corporate failure. Using a paired sample analysis, with size and industry type used as bases for pairing, Beaver found overwhelming evidence of differences in the ratios of failed and non-failed firms. To test the predictive power of ratios, Beaver used a dichotomous classification technique, and found the cash flow to total debt ratio to be the best predictor of failure five years preceding failure.

Altman [1], improved on Beaver's univariate method of analysis by introducing the multivariate approach, which allows for the simultaneous consideration of several variables in the prediction of failure. The approach is that of multiple discriminant analysis (MDA). The following discriminant function turned in the best performance:

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

where

X_1 = working capital to total assets

X_2 = retained earnings to total assets

X_3 = earnings before interest and taxes to total assets

X_4 = market value of equity to book value of total debt

X_5 = sales to total assets.

These results were later shown by Moyer [*12*] to be less suitable under conditions different from those used by Altman. Using paired sample analysis and step-wise linear MDA on 23 pairs of large manufacturing, retailing, and railroad firms, Moyer found that a model with the first three parameters in Altman's model had explanatory power superior to Altman's. Moyer's results were confirmed by Williams and Picconi[2] using an original sample and a holdout sample.

In his most recent study, Altman [4], with a new data base adjusted to take into account the latest financial reporting standards, used MDA once again with

[1] Expectations are measured by the change in Standard and Poor's index of common stocks.

[2] See R. C. Moyer's reply to Altman [13].

both linear and quadratic structures. The study resulted in new variables explaining corporate failure. These are:

(1) X_1 = Return on Assets. Earnings before interest and taxes to total assets.
(2) X_2 = Stability of earnings. Measured by the "normalized measure of the standard error of estimate around a ten-year trend in X_1."[3]
(3) X_3 = Debt service. Earnings before interest and taxes to total interest payments.
(4) X_4 = Cumulative profitability. Retained earnings to total assets.
(5) X_5 = Liquidity. Current assets to current liabilities.
(6) X_6 = Capitalization. Equity to total capital.
(7) X_7 = Size measured by the firm's total assets.

Altman's latest model predicted better than his earlier model. "The newer Zeta model is far more accurate in bankruptcy classification in years 2–5 with the initial year's accuracy about equal. The older model showed slightly more accurate non-bankruptcy classification in the two years when direct comparison is possible."[4] The classification accuracy of bankrupt firms five years before failure was 69.8 percent using the Zeta analysis and 36 percent using the 1968 model.

While Altman's work, especially his latest, addresses marginally the question of ratio stability, the treatment is far from adequate. It is the stability of every ratio over time that is relevant and not just that of earnings. Wide and increasing downward shifts in the current ratio, for instance, can spell disaster for a firm, particularly one with a high leverage ratio.

The stability model intends to correct this deficiency. Specifically, we intend to introduce various measures of ratio stability. Then, using stepwise discriminant analysis, variables with maximum predictive power will be derived from a pool of variables consisting of 19 ratios and their measures of stability.

Sample and Data Characteristics

Initially we collected data on 68 firms, half of them failed and half of them non-failed. The companies were paired by industry according to their Standard Industrial Classification code listings in Dun and Bradstreets' *Million Dollar Directory*. Data on twelve financial statement items were taken from Moody's *Industrial Manual* for the 8 years prior to failure for failed firms and a corresponding 8-year period for each non-failed firm. This correspondence produced as close a match in time as it was possible to obtain.

Because of inconsistencies in the data, or their unavailability for some of the years, we had to eliminate from our sample eleven pairs of firms. A list of the 46 remaining firms is shown in the appendix. All failures occurred during the 1969–1975 period. The firms are almost equally divided between the retailing and manufacturing sectors.

The balance sheet and income statement data are raw figures with no adjust-

[3] No reference as to functional form used in establishing the trend is made in the study.

[4] Altman (1977), page 40.

ments. The only significant adjustment made by Altman is that of lease capitalization. We have opted to forego such adjustment for the following reasons:

1. Altman's [3] remarks notwithstanding, Elam's [8] conclusions provide sufficient evidence for the non-capitalization of leases. Elam's critical conclusion is that "Evidence gathered by this research clearly does not support the hypothesis that: Addition of capitalized lease data to a firm's financial statements will increase the power of affected financial ratios for predicting firm bankruptcy."

Altman's critique is just that. There is still no proof[5] offered that capitalization of leases does improve the predictive power of a model. And if it does, then a model with a good predictive power of corporate failure would perform even better with lease capitalizations since "...there is evidence that problem firms utilize leasing to a greater extent than non-problem firms, although this relatively greater use may change as the bankruptcy date approaches" [3].

2. The very small information set publicly available on leases restricts the usefulness of any lease capitalization. As is usually the case with any capitalization process, the assumption that future cash flows will match or exceed by a constant growth factor past cash flows, the assumption that the firm remains in the same risk class or that the bankrupt and nonbankrupt firms belong to the same risk class (justifying the constancy of the adjustment to the discount factor used in Altman's Zeta model), and the difficulty in determining the adequate time horizon particularly for the firms that failed, make the capitalization process too imprecise. Attempts by the authors to obtain adequate information on leases on most companies, and to carry out a lease capitalization worthy of the time required, have failed. Hence, the use of the raw data.

From the data we computed, for each company and each year, the 19 ratios listed in Table I. Considerations that governed the process of ratio selection included the following:

(1) data availability that permitted the calculation of ratios across firms and across years;
(2) reasonableness and general acceptability of the ratios in relation to their intended use—the development of a discriminant function; and
(3) the development of a comprehensive set of ratios by types: profitability ratios, activity ratios, liquidity ratios, and indebtedness ratios. These types of ratios have been shown to have considerable merit in financial analysis and in the measurement of financial well being of corporate entities.

We also computed for each company, each ratio, and each of the five years prior to failure, four different measures of ratio stability: (1) the standard deviation of the ratio over three-year periods[6], (2) its standard deviation over four-year periods, (3) its standard error of estimate around a 4-year linear trend, and (4) its coefficient of variation over four-year periods.

[5] What would constitute a proof is running the Zeta model without lease capitalization and observe whether the predictive power of the model decreases significantly.

[6] For example, for the year prior to failure for a failed company the standard deviation was computed from the values of the ratio one, two and three years prior to failure; for the second year prior to failure it was computed from values two, three and four years prior to failure, etc. The same procedure was followed for non-failed companies.

Table I

Ratios Used in the Analysis

Profitability Measures	
1.	Net Profit/Sales
2.	Net Profit/Net Worth
3.	Net Profit/Net Working Capital
4.	Net Profit/Fixed Assets
5.	Net Profit/Total Assets
Activity and Turnover Measures	
6.	Sales/Net Worth
7.	Sales/Net Working Capital
8.	Sales/Inventory
9.	Cost of Sales/Inventory
Liquidity Measures	
10.	Current Ratio
11.	Acid Test Ratio
12.	Inventory/Net Working Capital
13.	Current Debt/Inventory
Indebtedness Measures	
14.	Fixed Assets/Net Worth
15.	Current Debt/Net Worth
16.	Total Debt/Net Worth
17.	Times Interest Earned
18.	Funded Debt/Net Working Capital
19.	Total Debt/Total Assets

These measures of ratio stability showed remarkable differences between failed and non-failed firms. One of the most striking examples is perhaps that of the standard deviation of the profit/net worth ratio on the year prior to failure, measured over the past 4 years. For the twenty-three non-failed firms the standard deviation has values in the range 0 to 0.06, with a relatively uniform spread over that range. For the failed firms, on the other hand, only four of the twenty-three values are 0.06 or less, whereas twelve of the values—that is those of more than half of the failed firms—exceed 0.50.

Methodology and Results

Our purpose was to have a measure of the improvement in predictive ability achieved by incorporating our measures of stability to discriminant analysis predictive models that are based upon ratios only.

We first developed "best" linear discriminant functions for one, three and five years prior to failure using the ratios alone.[7] Table II summarizes these results. It should be noted that Wilks' lambda values and the percent correct classification of the sample itself indicate a good degree of separation between groups for year 1, a considerable decline in discriminant power for year 3, and a drastic decline for year 5.

We then developed similar best discriminant functions, this time using as

[7] We will refer to data from n years prior to failure as "year n" data. It should be understood that for non-failed companies "year n" means "n years prior to failure of the paired failed company."

Table II

Linear Discriminant Analysis Results

	Years Prior to Failure	Variables in the Model	Percent Correct Classification: Failed	Non-failed	Total	Wilks' λ
Ratios Alone	1	R1 R2 R3 R5 R6 R7 R12 R16 R18	89	100	94.4	0.235
	3	R6 R7 R10 R17 R19	81	78	79.7	0.557
	5	R1 R5 R19	66	75	70.3	0.758
Ratios and Standard Deviations	1	R4 R12 R15 R19 S15 S19	91	100	95.7	0.200
	3	R10 R14 R17 R19 S5 S18	87	91	89.1	0.395
	5	R1 R5 R14 R18 R19 S12 S14	78	87	82.6	0.542
Variables from Year 5; Ratios and Std. Deviations	1	R1 R5 R14 R18 R19 S12 S14	83	100	91.2	0.390
	2	R1 R5 R14 R18 S19 S12 S14	83	87	84.8	0.562
	3	R1 R5 R14 R18 R19 S12 S14	78	87	82.6	0.493
	4	R1 R5 R14 R18 R19 S12 S14	83	96	89.1	0.493

Ri is the *i*th. ratio and *Si* the standard deviation of the *i*th. ratio, where the ratio numbers are given in Table I.

discriminating variables both the ratios and their standard deviations over the past 4 years. These results are also shown in Table II. In both cases we used the WILKS method with the DISCRIMINANT procedure of SPSS.

The following points are noteworthy:

1. For year 1, introducing the standard deviations we obtained a discriminant function that classified correctly a higher percent of the sample and produced a better value of Wilks' Λ using fewer variables than with ratios alone. The differences between with and without standard deviations, however, do not seem very significant. This is perhaps to be expected, since one year prior to failure most models classify quite accurately.
2. For year 3, the improvements observed when one introduces the standard deviations are much more marked. The best discriminant function with the standard deviations contains one more variable than the best without them, but it has a 10 percent improvement in classification accuracy and a much better value of Wilks' lambda.
3. For years 5, only 3 of the 19 ratios are meaningful in discriminating between groups when ratios alone are used, and the resulting discriminant function has a poor degree (70%) of classification accuracy. When the standard deviations are introduced, on the other hand, 5 ratios and 2 standard deviations enter the model and produce a classification accuracy of almost 83%.
4. When the best variables of year 5 (5 ratios and 2 standard deviations) are used to develop discriminant functions for years 1 through 4, the resulting functions classify correctly 91.3% of the sample in year 1, 84.8% in year 2, 82.6% in year 3 and 89.1% in year 4 (Table II, rows 7–10).

In regard to our results when we used the other three measures of stability, it should be pointed out that 1) standard deviations over a period of three years produced results very similar to those with standard deviations over four years; 2) standard errors of estimate around 4-year linear trends, when used as a measure of stability, produced results slightly inferior to those with standard deviations and 3) our results using the coefficients of variation as a measure of stability were decidely inferior to those we obtained with the standard deviations.

The percent correct classifications of Table II are all upward-biased estimators of the true classification rates. To have a feeling for the magnitude of these biases we validated the results of the best discriminant function of year 5 with standard deviations, as well as the results of these best discriminant variables when applied to years 3 and 1, by the leaving-one-out validation method. This validation procedure was originally proposed by Lachenbruch [9], who describes it as follows:

> "Compute the discriminant function for each of the possible samples of size $n_1 + n_2 - 1$ obtained by omitting one observation from the original sample and record for each of these functions whether the omitted observation is misclassified. If m_1 and m_2 are the numbers of observations misclassified, we may estimate P_1 and P_2 by m_1/n_1 and m_2/n_2. The error estimates obtained will be unbiased for the probabilities of misclassification for a discriminant function based on $n_1 - 1$ and n_2 observations and n_1 and $n_2 - 1$ observations respectively."

This procedure is widely accepted as the best validation method unless the sample is very large, in which case the classical holdout method is often used. It not only is unbiased, it is also of the holdout type, since observations are left out from the computation of the function by which they are classified.

The validated correct percent classifications for years 1, 3, and 5 were 87%, 85% and 78% respectively. In each of the three years the difference between the apparent error rates and the validated results was very small. Moreover, two of the misclassifications in the year 5 validation for companies that were correctly classified originally were by a minute margin (the absolute values of the corresponding Z-scores were less than 0.01 units in a scale where the group centroids were about 1.40 units apart).

Concluding Remarks

The strength of the preceding analysis lies not only in the superior predictive power of the model, but in the improvement in the conceptual framework of models for predicting corporate bankruptcy.

The standard deviation of ratios over time appears to be the strongest measure of ratio stability, which is the essence and the promise of the analysis.

Our best discriminant function, which included the ratios of net profits to sales, net profits to total assets, fixed assets to net worth, funded debt to net working capital, total debt to total assets, and the standard deviations of inventory to net working capital, and of fixed assets to net worth, account for essentially the same types of ratios—profitability, leverage, and liquidity—that most previous analyses have shown to be relevant in predicting corporate failure.

The profitability ratios offer a reasonable measure of management effectiveness; the leverage ratios and the stability of the fixed asset to net worth ratio represent historical reasons for corporate failure, reasons that are directly related to the excessive or unwise use of leverage. The stability of the liquidity ratio constitutes a necessary measure of corporate solvency.

Some further experimentation with the stability concept is, we feel, warranted. The authors are presently exploring new horizons.

Appendix

List of Companies in the Sample

Failed firms	*Non-failed firms*
American Beef Packers	Airco
Arlans Dept. Stores	Arnet Inc.
Beck Industries	Assoc. Dry Goods
Bishop Industries, Inc.	Caldor
Bohack Stores	Chesebrough-Ponds, Inc.
Botany Industries, Inc.	Cubic Corporation
Bowmar Instruments	Digital Equipment
Daylin	General Dynamics
Esgro Corp.	Hewlett Packard
M. H. Fishman	Hughes and Hatcher, Inc.
Grant (W.T.) Co.	Iowa Beef Prod. Pckrs.
Gray Mfg.	Jamesway

Hartfield Zody's
Hoe, R.
Interstate Dept. Stores
Kenton Corp.
Lockheed Aircraft
Mangel Stores
Mohawk Data Sciences
National Bellas Hess
National Video Corp.
Potter Instruments
Roberts Co.
Kroger
Leesona Corp.
S. W. Mays
National Shoes
Neisner Bros. Inc.
Outlet Co.
Pay N'Save
Varian Associates
Walgreen
Wood Industries, Inc.
Zayre

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