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ON THE ABILITY OF ACCOUNTING RATIOS TO PREDICT FAILURE OF PHILIPPINE BUSINESS FIRMS

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Previous studies indicated that linear multiple discriminant analysis (LMDA) of financial ratios can be used to predict company failure. A discriminant function is derived from a set of financial ratios which, when transformed into Z-scores, characterize firms as failing or nonfailing based on a predetermined cut-off point.

This study sought to develop a prediction model for Philippine firms using LMDA on financial ratios. Twenty-six failing firms in the manufacturing sector were chosen from among the 1,000 top corporations of 1979. For lack of data on bankruptcy, failure was defined as default in loan repayment between 1973 and 1981. A corresponding number of nonfailing firms were chosen from the same industry as the failing counterpart. Fourteen industries were represented.

Some 260 financial statements were examined and over 8,000 ratios were computed for the 52 firms over a 5-year period. The ratios were subjected to various statistical tests to determine which of them should be used in deriving the discriminant function.

Among the thirteen LMDA models developed, the "best" predictor of company failure consisted of four variables. These variables were Cash Flow/Total Liabilities, Net Income/Total Liabilities, Total Liabilities/Total Assets and Sales/Total Assets. It had the highest percentage of correct prediction at Year 1 (83%) and the narrowest range of overlap in Z-scores over the five-year period tested (.26 to − .23).

The uncertainty about a firm's future points to a growing need for more tools with which to anticipate problems, ward them off, or solve them when they arise. This study aims to devise systematic and reliable tools for assessing the firm's future. It is addressed to creditors, stockholders and management.

Nature of Company Failure

For a firm to continue to exist, two things are absolutely necessary, namely: profitability and solvency. When one or both conditions are missing, a firm may be considered a failure. In this study

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company failure is operationalized to mean the inability of a firm to pay its principal and/or interest obligation. The reason for adopting this loose definition was to obtain an early warning of impending bankruptcy and probable liquidation. Company failure in itself is not the focus of interest. In fact, it is desirable that this event be averted. The analyst's concern is primarily to look for danger signals which point to probable failure so that necessary actions may be made to avoid costly mistakes. Financial ratio analysis in itself cannot predict actions that may be undertaken by management to stave off liquidation. But studies have shown that these ratios do differ between failing and healthy firms. When these signals are interpreted correctly and used properly, they may avert financial crisis.

Just as a sick person has symptoms, so does an ailing firm exhibit signs which could give indications of illness. Predicting that a firm would fail, if symptoms of illness are found in it, does not preclude the prevention of failure with the proper administration of remedial actions. It is therefore useful to find characteristics which significantly differentiate between failing and nonfailing firms and to use them as predictive tools. Thus, prediction is used here broadly to mean that a likely event would occur if no preventive measure were undertaken.

Use of Financial Accounting Data In Predicting Financial Difficulties

Accounting data which are encapsulated in the basic financial statements have been used extensively to diagnose the health of a firm. In the process of analyzing financial accounting ratios, one of two probable events may appear: failure or nonfailure. How well do accounting ratios aid in predicting failure of a firm? Which ratio or group of ratios, if there be any, can better predict this future event?

This study aims to investigate empirically the characteristics of failing and nonfailing firms in the Philippines and to develop classification and prediction models with the aid of linear multiple discriminant analysis (LMDA) using accounting ratios as independent variables.

The use of ratio analysis in the interpretation of financial statements dates back to the last half of the 19th century in the United States. More recently, its usefulness in predicting company failure has been proved by Beaver (1966), and Altman (1967), among others. The present study applies multivariate techniques on financial accounting ratios to examine impending failure of Philippine firms.

To the author's knowledge, this is the first study of its kind using data on Philippine business firms.

Prediction and Decision-Making

The "Report of the Committee on Accounting Theory Construction and Verification" of the American Accounting Association (AR, 1971 Supplement) emphasized the need to contextualize prediction models within a decision process. Thus, the prediction model developed in this study forms part of a decision process. The variables used are accounting ratios derived from the firm's financial statements. Ratios are examined simultaneously since the information content of individual ratios is less informative than a group of ratios taken together. The ratios chosen are shown in Table 1. They form the bases of prediction model as viewed in Figure 1.

The leverage variables determine the structure of the firm. They influence the activity variables which indicate the level of operation to be pursued by the firm, an indication of how the firm competes in the marketplace. The activity variables are translated into profitability variables. The profitability variables bear upon the liquidity variables which give information on the firm's ability to meet its financial obligations. The liquidity variables, in turn, influence future activities of the firm. The variables interact with each other not only in sequential fashion but cutting across boundaries.

The prediction model results in the classification of firms into mutually exclusive groups: failure or nonfailure. If the model is acceptable, then it is adopted for use in the decision model.

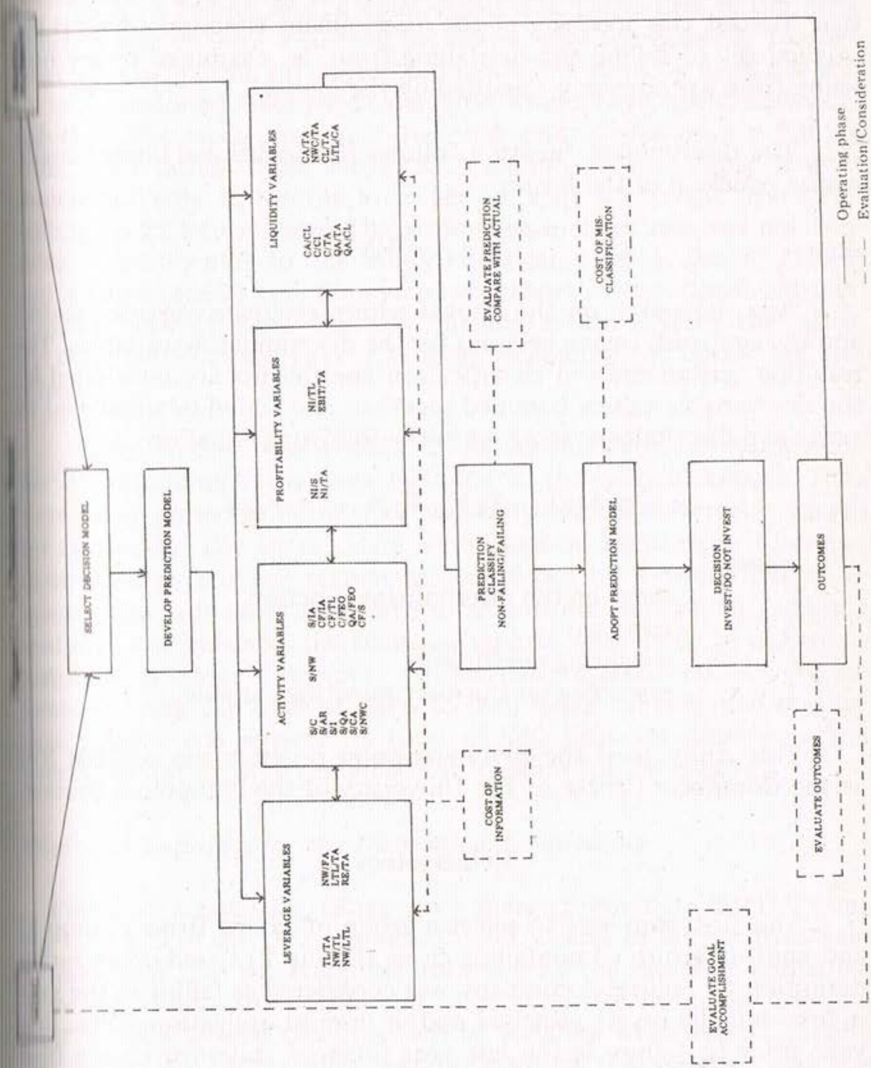
The model can be derived through a mathematical formula, which facilitates the classification of a firm into probable failure or probable nonfailure. The accounting ratios (variables) are subjected to LMDA to develop prediction models. The models compute a Z-score for each firm which is used as a surrogate for the financial "health" of the firm. Firm with Z-scores above 0 are said to be nonfailing whereas those with scores below 0 are considered failing.

Linear Multiple Discriminant Analysis

Linear multiple discriminant analysis is a statistical tool used in analyzing multiple measurements using numerous variables considered in combination. It assigns objects (firms) into groups on the basis of a set of characteristics (financial ratios). For a more detailed discussion of LMDA the reader is referred to Cooley and Lohnes

Table 1 -- List of Ratios

		Symbol
Liquidity		
X_1	Current assets/Current liabilities	CA/CL
X_2	Cash/Current liabilities	C/CL
X_3	Cash/Total assets	C/TA
X_4	Quick assets/Current liabilities	QA/CL
X_5	Quick assets/Total assets	QA/TA
X_6	Current assets/Total assets	CA/TA
X_7	Net working capital/Total assets	NWC/TA
X_8	Current liabilities/Total assets	CL/TA
X_9	Long-term liabilities/Current assets	LTL/CA
Profitability		
X_{10}	Net income/Sales	NI/S
X_{11}	Net income/Total assets	NI/TA
X_{12}	Net income/Total liabilities	NI/TL
X_{13}	Earnings before interest and taxes/ Total assets	EBIT/TA
Leverage		
X_{14}	Total liabilities/Total assets	TL/TA
X_{15}	Net worth/Total liabilities	NW/TL
X_{16}	Net worth/Long-term liabilities	NW/LTL
X_{17}	Net worth/Fixed assets	NW/FA
X_{18}	Long-term liabilities/Total assets	LTL/TA
X_{19}	Retained earnings/Total assets	RE/TA
Activity		
X_{20}	Sales/Cash	S/C
X_{21}	Sales/Account receivable	S/AR
X_{22}	Sales/Inventory	S/I
X_{23}	Sales/Quick assets	S/QA
X_{24}	Sales/Current assets	S/CA
X_{25}	Sales/Net working capital	S/NWC
X_{26}	Sales/Total assets	S/TA
X_{27}	Cash flow/Sales	CF/S
X_{28}	Cash flow/Total assets	CF/TA
X_{29}	Cash flow/Total liabilities	CF/TL
X_{30}	Cash/Fund expenditure for operations	C/FEO
X_{31}	Quick assets/Fund exp. for operations	QA/FEO
X_{32}	Sales/Net worth	S/NW


SELECT DECISION MODEL
DEVELOP PREDICTION MODEL
LEVERAGE VARIABLES
TL/TA NW/TL NW/LTL
NW/FA LTL/TA RE/TA
ACTIVITY VARIABLES
S/C S/AR S/I S/QA S/CA S/NWC
S/NW
S/TA CF/TA CF/TL C/FEO QA/FEO CF/S
PROFITABILITY VARIABLES
NI/S NI/TA
NI/TL EBIT/TA
LIQUIDITY VARIABLES
CA/CL C/CI C/TA QA/TA QA/CL
CA/TA NWC/TA CL/TA LTL/CA
COST OF INFORMATION
EVALUATE PREDICTION COMPARE WITH ACTUAL
COST OF MIS-CLASSIFICATION
PREDICTION CLASSIFY NON-FAILING/FAILING
ADOPT PREDICTION MODEL
DECISION INVEST/DO NOT INVEST
OUTCOMES
EVALUATE OUTCOMES
EVALUATE GOAL ACCOMPLISHMENT
Operating phase
Evaluation/Consideration

(1962). It is used used here to classify firms into the failing and the nonfailing group. If variables can be found which can accurately discriminate membership between a group of failing and a group of nonfailing firms, then those same variables can be used to identify firms with as yet unknown membership but with known characteristics. To test the accuracy of the discriminant function (model) the original set of failing and nonfailing firms is examined to see how many firms are correctly classified by the model.

The discriminant function follows the traditional linear classification equation of the form:

$$Z = A + VX$$

It is derived from the pooled within groups covariance matrix and the centroids (mean vectors) for the discriminating variables. The resulting unstandardized classification coefficients are multiplied by the raw variable values, summed together, and added to a constant to arrive at a discriminant score, as in the following equation:

$$Z = A + V_{i1}\ X_1 V_{i2} X_2 + \ldots + V_{in} X_n$$

where:

Z	:	score on the discriminant function
A	:	constant
V	:	weighting coefficient
X	:	raw score on the discriminating variable.

This study used the SPSS computer program run on IBM 370 at the Computer Center of the University of the Philippines System.

Methodology

The first step was to select a group of failing firms (Group 1) and another group of nonfailing firms (Group 2) based on an earlier definition of failure. A company was considered as failing in the year it first defaults on its principal and/or interest obligation. Thus, first year prior to failure is the last year financial statements were filed immediately before the year of default. These firms were identified through inquiries from different financial institutions because this information was not available at the Securities and Exchange Commission (SEC). They belonged to the manufacturing sector which defaulted on their loans during the period 1973-1981 and whose financial statements for the last five years prior to default were available. These firms were featured among the *SEC — Business Day's Top*

1000 Corporations of 1979 except for two firms. These two, however, also made it to the listing sometime during the period under study but were overrun by firms with higher sales.

To each failing firm, a counterpart nonfailing firm in the same industry was chosen. Fourteen industries were represented. The original plan of pairing off failing and nonfailing firms by asset size had to be abandoned because the sample would have been drastically reduced. The mean asset size one year prior to failure was ₱308.6 million for failing firms and ₱221.1 million for nonfailing firms as shown in Table 2; for the same period, asset size ranged from ₱22 million to ₱1,845 million. This difference in asset size was not considered detrimental to the study. Horrigan (1965), Beaver (1966) and Altman (1967) have discovered that there was no significant relationship between asset size and financial ratios. Besides, the ratios, by their very nature, have a built-in mechanism of correcting size effects.

Based on the above criteria, 26 failing and a corresponding number of nonfailing firms were included in the original sample. Data were taken from the companies' audited financial statements except for two firms. The latter's data were based on credit reports because their audited financial statements could not be located. The statements were adjusted according to a uniform format to facilitate analysis. For instance, the financial reports were made to adhere to historical costing. Therefore, revaluations of fixed assets were adjusted to bring the value of assets to their historical costs and revaluation surplus was ignored. A total of 260 financial statements and over 8,000 ratios were examined for 52 firms for five years.

Choice of Variables for the Discriminant Functions

Financial accounting ratios were then subjected to LMDA using the IBM 370 of the UP Computer Center. Ratios of failing firms were entered first into the computer followed by the ratios of nonfailing firms. To choose the optimal set of variables for the linear discriminant models, several combinations of variables were tested. Initially the whole set of variables was included in the function but this proved to be unwieldy. The variables had to be subjected to statistical tests to determine which of them should be included in the function. One test for inclusion of variables was the t-test, a test for equality of means. If the two-tailed probability for the null-hypothesis is less than the present significance level alpha, α , then the null-hypothesis of equality of means would be rejected. It means that the variables come from different populations. They can therefore be

Table 2 – Comparative Asset Size of Failing and Nonfailing Firms by Industry, One Year Before Failure

Industry Classification	Failing Firms I.D. Number	Assets (₱ '000)	Year of Failure	Nonfailing Firms I.D. Number	Assets (₱ '000)
Coconut Products	1.01.02.01	180,906	1981	1.01.02.27	192,254
Sugar Milling	1.01.12.02	88,184	1980	1.01.12.28	153.277
	1.01.12.03	283,178	1980	1.01.12.29	372,479
TEXTILES					
Spinning, Weaving, Finishing	1.02.02.04	642,058	1980	1.02.02.30	104,467
	1.02.02.05	91,146	1980	1.02.02.31	90,970
	1.02.02.06	84,239	1980	1.02.02.32	109,040
	1.02.02.07	93,186	1980	1.02.02.33	110,901
	1.02.02.08	84,782	1980	1.02.02.34	142,245
	1.02.02.09	84,179	1979	1.02.02.35	162,232
	1.02.02.10	305,651	1980	1.02.02.36	304,753
	1.02.02.11	441,937	1980	1.02.02.37	262,626
	1.02.02.12	66,249	1980	1.02.02.38	168,574
Wearing Apparel	1.02.03.13	201,137	1980	1.02.03.39	36,561
	1.02.03.14	64,384	1980	1.02.03.40	68,934

Table 2 (Continued)

Industry Classification	Failing Firms I.D. Number	Assets (₱ 000)	Year of Failure	Nonfailing Firms I.D. Number	Assets (₱ '000)
Rope, Twine, Net & Carpet Mfg.	1.02.04.15	61,570	1980	1.02.04.41	47,641
Man-made fibers	1.02.05.16	759,763	1980	1.02.05.42	22,172
	1.02.05.17	204,391	1980	1.02.05.43	128,148
Vegetable & Animal Oils/Fats	1.04.03.18	292,674	1980	1.04.03.44	245,239
Pulp & Paper	1.07.02.19	161,183	1980	1.07.02.45	123,175
Plastics & Plastic Prod.	1.09.01.20	117,862	1980	1.09.01.46	88,994
Iron and Steel	1.10.01.21	363,064	1978	1.10.01.47	101,373
	1.10.01.22	1,200,500	1980	1.10.01.48	1,844,872
Cigar & Cigarettes	1.12.01.23	411,846	1980	1.12.01.49	481,807
Motor Vehicles	1.14.03.24	1,601,441	1980	1.14.03.50	211,438
Electrical Appliances	1.15.01.25	38,070	1980	1.15.01.51	146,353
Pulp & Paper	1.07.01.26	100,368	1980	1.07.01.52	27,881
	Mean:	308,613		Mean:	221,092

used to discriminate between the two groups. Setting the $\alpha = .10$, the significant variables came out as shown in Table 3.

Table 3 — Significant Variables in the T-test

Variables	Symbol	T-Value	Probability
CF/TA	X_{28}	−3.47	.002
CF/TL	X_{29}	−3.85	.001
NI/TA	X_{11}	−2.97	.006
NI/TL	X_{12}	−3.19	.003
LTL/CA	X_{9}	2.31	.028
TL/TA	X_{14}	2.08	.046
NI/TL	X_{12}	−2.27	.031
NW/FA	X_{17}	−2.31	.028
S/TA	X_{26}	−2.03	.050
LTL/TA	X_{18}	2.14	.041

Result of the Discriminant Analysis

From the preceding selection methods, 13 models were developed and subjected to statistical tests. Only three were found good enough predictors. They were identified here as Alternative Models 1, 2 and 3 respectively, and are the only models discussed here. Their prediction results are explained. Validation tests for Model 1 are presented, and its classificatory effectiveness is compared with chance models. Bayesian adjustments and cost of misclassifications are considered before choosing the "best" model.

Before discussing the results, perhaps it might be necessary to elaborate on some of the statistical terms used and their importance. In the process of deriving a discriminant function, the following statistical measures are also computed: eigenvalue, canonical correlation, Wilks' lambda (λ), chi-square (x^2) and its significance level and the F-value. The eigenvalue measures the relative importance of the discriminant function. It measures the total variance existing in the descriminating variables. Therefore, the higher the eigenvalue, the more significant the function. The canonical correlation is a measure of association between the single discriminant function and the set of (g—l) dummy variables which define the g group memberships. It tells us how closely the function and the "group variable" are related, which is another measure of the function's ability to discriminate among groups. The eigenvalue and its related canonical correlation denote the relative ability of the function to separate groups. The higher the value, the greater the ability of the function to separate the groups, i.e., the more significant the function is. Wilks' lambda is an inverse measure of the discriminating power in the original variables which has not yet been removed by the discriminant function. Lambda can be transformed into a chi-square statistic for a test of significance. The corresponding significance level of the Wilks' lambda and chi-square values indicate the probability of the model occurring due to chance (Nie, 1975).

Model 1

This model used data of Year 2 prior to failure in deriving the discriminant function. The variables used here were *CF/TL*, *NI/TL*, *TL/TA*, and *S/TA*. One of the 13 models tested showed the ratios *CF/TL* and *NI/TL* to be significant discriminators. Would the model be improved with the inclusion of other variables also found to be good discriminators? To test this, another model was developed using the two variables above with the addition to *TL/TA* and *S/TA* ratios. The last two ranked first and second, respectively, in three of the five years when ten ratios were subjected to STEPWISE discriminant analysis in another model (Table 4).

Table 4 — Summary Results of Alternative 1

	Year Prior to Failure From Which Discriminant Function Was Derived				
Variables	1	2	3	4	5
X_9 *(CF/TA)*					2
X_{11} *(NI/TA)*		4			
X_{12} *(NI/TL)*	3				
X_{14} *(TL/TA)*		1	1		1
X_{15} *(NW/TL)*					
X_{17} *(NW/FA)*					
X_{18} *(LTL/TA)*					
X_{26} *(S/TA)*	2	2		2	
X_{28} *(CF/TA)*		3		1	
X_{29} *(CF/TL)*	1				

Stepwise discriminant analysis with four maximum steps. The numbers under each column refer to the sequential appearance of the variable in the function.

This model performed well on data of Year 1 prior to failure although it did not do as well on data of Year 2 as seen in Table 5. Despite an overall predictive power of only 75 per cent on Year 2 data, it proved to be statistically significant with predictive accuracy of 79 per cent and 71 per cent for the failing and the nonfailing firms, respectively. The discriminant function of Model 1 is:

$$Z = 3.12958 X_{29} - 3,25829 X_{12} - 0.83000 X_{14} + 0.15390 X_{\text{[illegible]}} + 0.32453$$

Model 2

This model used the same variables as Model 1 but used data of Year 1 to derive the discriminant function. Its overall disciminatory ability was 79 per cent, with failing firms being classified more accurately than nonfailing firms. The model is shown in Table 6.

Model 3

The variables used in this model were *CF/TA*, *CF/TL*, *NI/TA* and *NI/TL* using data of Year 4 prior to failure. They were the ratios which exhibited the highest t-values. This model yielded a high prediction accuracy for failing firms (92%) but its overall effectiveness was low (79%) due to a high misclassification error for nonfailing firms. The statistical tests showed that the model was relatively significant. The performance of this alternative model is shown in Table 7.

Validation Techniques

The classification results of the above models were not enough grounds for determining the "best" model. There is an inherent bias in the choise of sample and of alternatives, hence it is necessary to validate the results.

Two validation procedures were used. One tested the model over time. The other was to test the model on an entirely new group of sample firms, the holdout sample.

When Model 3 was tested on data of Years 1, 2, 3 and 5 it gave very high prediction accuracy for failing firms but misclassified a large number of nonfailing firms. The overall accuracy ranged from 71 per cent in Year 1 down to 69 per cent in Year 2, 64 per cent in Year 3 and zooming up to 74 per cent in Year 5. Failing firms were correctly classified 91 per cent of the time in Years 1 and 5. Its prediction accuracy, however, declined in Years 2 and 3.

Table 5 — Validation Results of the Discriminant Model: Model 1

$$Z = 3.12958X_{29} - 3.25829X_{12} - 0.83000X_{14} + 0.15390X_{26} + 0.32453$$

Year Before Failure	Total Number of Valid Cases		Firms Correctly Classified				Firms Misclassified				Overall % Correct Classification
			Failing		Nonfailing		Failing		Nonfailing		
	F	NF	No.	%	No.	%	No.	%	No.	%	
1	23	25	20	87.0	20	80.0	3	13.0	5	20.0	83.3
2	24	24	19	79.2	17	70.8	5	20.8	7	29.2	75.0
3	23	23	19	82.6	17	73.9	4	17.4	6	26.1	78.3
4	24	23	19	79.2	16	69.6	5	20.8	7	30.4	74.5
5	23	23	15	65.2	17	73.9	8	34.8	6	26.9	69.6

Eigenvalue : 0.60
Cancor : 0.61
Wilks' λ : 0.62
Centroids
Failing : −0.19
Nonfailing : 0.19

X^2 : 20.77
df : 4
sig. : 0.000

Table 6 — Validation Results of the Discriminant Model: Model 2

$$Z = 5.49820X_{29} - 3.60089X_{12} - 0.34335X_{14} + 0.22287X_{26} - 0.23766$$

Year Before Failure	Total Number of Valid Cases		Firms Correctly Classified				Firms Misclassified				Overall % Correct Classification
			Failing		Nonfailing		Failing		Nonfailing		
	F	NF	No.	%	No.	%	No.	%	No.	%	
1	23	25	19	82.6	19	76.0	4	17.4	6	24.0	79.2
2	24	24	20	83.3	17	70.8	4	16.7	7	29.2	77.1
3	23	22	20	87.0	15	68.2	3	13.0	7	31.8	77.8
4	24	23	21	87.5	15	65.2	3	12.5	8	34.8	76.6
5	23	18	18	78.3	12	66.7	5	21.7	6	33.3	73.2

Eigenvalue : 0.80
Cancor : 0.67
Wilks' λ : 0.55
Centroids
Failing : −0.27
Nonfailing : 0.25

X^2 : 25.94
df : 4
sig. : 0.000

Table 7 — Validation Results of the Discriminant Model: Model 3

$$Z = 3.38785X_{28} + 1.07602X_{29} + 1.56510X_{11} - 1.33413X_{12} - 0.27694$$

Year Before Failure	Total Number of Valid Cases		Firms Correctly Classified				Firms Misclassified				Overall % Correct Classification
			Failing		Nonfailing		Failing		Nonfailing		
	F	NF	No.	%	No.	%	No.	%	No.	%	
1	23	25	21	91.3	13	52.0	2	8.7	8	32.0	70.8
2	24	24	20	83.3	13	54.2	4	16.7	9	37.5	68.8
3	23	22	18	78.3	11	50.0	5	21.7	11	50.0	64.4
4	24	24	22	91.7	16	66.7	2	8.3	8	33.3	79.2
5	23	23	21	91.3	13	56.5	2	8.7	10	43.5	73.9

Eigenvalue : 0.56
Cancor : 0.60
Wilks' λ : 0.64
Centroids
Failing : −0.20
Nonfailing : 0.19

X^2 : 20.26
df : 4
sig. : 0.000

Model 2 yielded a relatively high prediction accuracy for failing firms, more than for nonfailing firms. Prediction accuracy for failing firms was highest for Year 4 at 88 per cent but was down to 83 per cent in Year 2, up to 87 per cent in Year 3 and down again to 78 per cent in Year 5. The gradual decline in overall accuracy from 79 per cent in Year 1 to 73 per cent in Year 5 is consistent with the argument that accuracy decreases the farther away the observations are from the year of failure. Table 6 shows the results of this discriminant model.

When Model 1 was tested on data of all years, its overall prediction accuracy was high at 83 per cent in Year 1 but went down to 75 per cent in Year 2, then up again to 78 per cent in Year 3 and gradually deteriorated in the fourth and fifth years prior to failure. Failing firms were classified more accurately than nonfailing firms, ranging from 87 per cent in Year 1 to 65 per cent in Year 5.

One significant observation about this model was its narrow range of overlap of misclassified firms. A look at Figure 2 shows this range of overlap. Notice the narrow band of overlap manifested consistently during the whole five years under study. The highest misclassification in Z-score ranged from .23 in Year 5 and −.26 in Year 4. This had an overriding influence in the choice of the model.

The other validation test for Model 1 used a holdout sample. Financial statements of failing and nonfailing firms for the years 1979 to 1982 were compiled, their relevant ratios calculated, and their Z-scores computed. This time the companies were not confined to manufacturing firms only. The validation test showed very encouraging results. The overall classificatory accuracy on the secondary sample was 80 per cent, compared with 75 per cent on the original sample. Again, the percentage of correct classification was higher for failing firms than for nonfailing firms. The model classified correctly 85 per cent of the failing firms which compared favorably with the 79 per cent in the original sample. Also, the model outdid its performance on the original sample by classifying 74 per cent of the nonfailing firms correctly, compared with the 70 per cent on the original sample. Table 8 summarizes the result of the validation test on the secondary sample.

Based on the preceding tests, Model 1 was chosen as the "best" model. Its overall prediction accuracy was the highest among all the valid models at Year 1. Its test statistics showed stability and its discriminating power was significant. Moreover, its range of overlap was the least among the different models examined. This is useful in defining a cut-off score for failing firms.

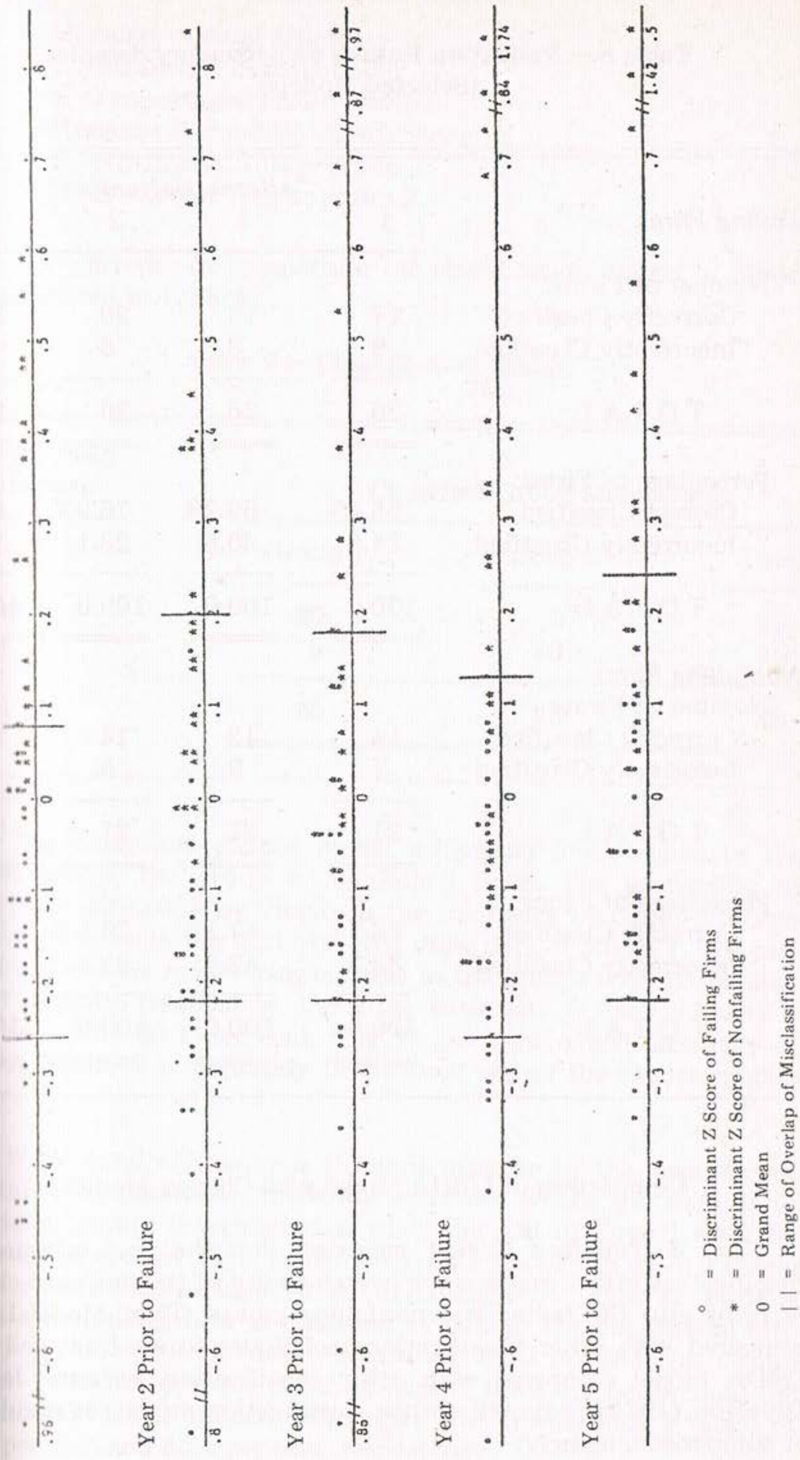

Year 2 Prior to Failure
Year 3 Prior to Failure
Year 4 Prior to Failure
Year 5 Prior to Failure
° = Discriminant Z Score of Failing Firms
* = Discriminant Z Score of Nonfailing Firms
0 = Grand Mean
| | = Range of Overlap of Misclassification

Table 8 — Validation Results on Secondary Samples (Selected Models)

	AlternativeNumber			
Failing Firms	4	3	2	1
Number of Firms:				
Correctly Classified	17	18	20	22
Incorrectly Classified	9	8	6	4
TOTAL	26	26	26	26
Percentage of Firms:				
Correct Classified	65.4%	69.2%	76.9%	84.6%
Incorrectly Classified	34.6	30.8	23.1	15.4
TOTAL	100.0	100.0	100.0	100.0
Nonfailing Firms				
Number of Firms:				
Correctly Classified	14	12	14	17
Incorrectly Classified	7	9	5	6
TOTAL	21	21	21	23
Percentage of Firms:				
Correctly Classified	66.7%	57.1%	76.2%	73.9%
Incorrectly Classified	33.3	42.8	23.8	26.1
TOTAL	100.0	100.0	100.0	100.0

Comparison of LMDA Model with Chance Models

Joy & Tollefson (1975) suggested that the best measure of classificatory effectiveness is the overall ability of the model to classify firms into the failing and nonfailing groups. Thus, Model 1 was compared with other classification techniques to see how well this LMDA model compared with other classification systems. Joy & Tollefson (1975) proposed chance classification models as standards of comparison, namely:

- o Measures of total efficiency
    1. Maximum chance model
    2. Proportional chance model
- o Measures of conditional efficiency
    1. Northwest cells or group 1
    2. Southeast cells or group 2

For purposes of comparison the classification matrix of Model 1 is presented in Table 9.

Table 9 — Classification Matrix

Actual Group Membership	Classified Group Membership		
	Group 1	Group 2	Total
Group 1	20	3	23
Group 2	5	20	25
Total	25	23	48

The maximum chance model assigns all observations to the largest group, the group of nonfailing firms. The probability of correct classification by chance is the frequency of Group 2 occurrence which would be 52.1 per cent using data of Model 1. The proportional chance model assigns firms to the groups with probability equal to group frequencies. Using the same data as used in Model 1, this would be 50.1 per cent. The 75 per cent overall accuracy of LMDA Model 1 is definitely better than any of the chance models above.

While total efficiency is the best measure of the discriminant function's effectiveness, there are instances where the analysis of individual groups is warranted as when the cost of Type 1 error far exceeds the cost of Type II error. Type I error occurs when a failing firm is erroneously classified as nonfailing while Type II error is when a nonfailing firm is classified as failing. The conditional efficiency measures using Model 1 data are 80.0 per cent for Group 1 and 86.9 per cent for Group 2. Again, these are better than the conditional chance models which give the corresponding values of 47.9 per cent and 52.1 per cent, respectively.

Bayesian Adjustment

The preceding analysis assumes that the sample group frequencies are equal to the prior probabilities. In the failure-nonfailure prediction study, this condition may not hold as the number of firms that fail in the real world is usually smaller than those which remain healthy. If the sample group frequencies are very different from the *a priori* probabilities of group membership, then predictive inferences based upon such classification may be misleading.

It is difficult to determine the prior probability of the firms which fail in the Philippines as elsewhere. But for the sake of argument, we will assume a 5 per cent failure rate.

Using the prior .05 for failing firms and .95 for nonfailing firms, Model 1 was run again in the computer. The resulting classification accuracy for the nonfailing group improved to 100 per cent whereas the classification accuracy of the failing group deteriorated to 8 per cent, or a 54 per cent classification efficiency. There is a trade-off in considering prior probabilities with a bias to the nonfailing group classification. This trade-off is to be compared with the cost of Type 1 error. Is it better to have a lower Type II error at the expense of a Type I error? Since it is assumed that the Type I error is more costly, i.e., it is more expensive to misclassify a failing firm than to misclassify a nonfailing firm, the trade-off is not considered satisfactory. The cost of misclassification has to be accounted for. As suggested by Joy & Tollefson (1975), it is possible to approximate misclassification costs even when the cost of misclassification is not actually known, by using the Bayesian approach. Following their formula, the comparative costs of the different models using data of Model 1 were computed.

$$C(LMDA) = (.05)\,(.13)C_{12} + (.95)\,(.20)C_{21}$$
$$C(PROP) = (.05)\,(.95)C_{12} + (0.05)\,(0.95)C_{21}$$
$$C(MAX) = .05C_{12}$$

where:

prior probability of being classified as failing = .05
prior probability of being classified as nonfailing = .95
Type I error = .13
Type II error = .20
C_{12} = cost of Type I error
C_{21} = cost of Type II error
$C(LMDA)$ = cost of LMDA model
$C(PROP)$ = cost of proportional chance model
$C(MAX)$ = cost of maximum chance model

Solving the equation, it can be seen that the LMDA model is less costly than the the proportional chance model if and only if $C_{12} > 3.47C_{21}$, that is the cost of misclassifying a failing firm is more than about 3.5 times the cost of misclassifying a nonfailing firm. The LMDA model is better than the *C(MAX)* model if and only if $C_{12} > 4.37C_{21}$, that is, the cost of misclassifying a failing firm is more than about 4.4 times the cost of misclassifying a nonfailing firm. It seems safe to assume that the cost of granting a loan to a failing firm is more than four times the cost of granting a loan to a nonfailing firm, considering the overhead costs involved plus the trouble and the time lost in going after bankrupt borrowers. It is therefore concluded that using the LMDA is superior to the use of the chance models.

Use of Alternative Models

It was suggested earlier that in case of uncertainty, the two other models can also be used. Model 3 may be used as a supplementary test if the cost of Type 1 error is to be minimized since it best predicted the failing firms. Model 2 also promises to be a useful model. If the different models classify a firm consistently either as failing or nonfailing, then one can rely more on the result of the test.

Potential Bias

A study like this one is bound to have biases. First of all, a sampling bias existed in the choice of the original sample. The process of selection of firms relied heavily on financial institutions to pinpoint the failing firms. Once identified, one can be sure they are properly classified. This is not so for nonfailing firms. There was no guarantee that the sample firms chosen as nonfailing were in fact so. It may be that, among the financial institutions surveyed, a firm had no bad account but may have overdue accounts in other financial institutions not interviewed for it is not uncommon for firms to borrow from one financial intermediary to pay off loans in other institutions. There was, however, no way of getting around this constraint as there was no master list of firms with overdue accounts. This seems to be implied by the result of the study where some firms in the nonfailing list were consistently misclassified as failing. The observation is particularly true with firms in the textile industry. As listed in Table 10, most of these textile firms in the nonfailing list were misclassified by one or more models, a possible indication that the sample firms were misclassified in the first place and that the models were in fact effective in correctly classifying the firms. If this were so, then the models are even more efficient than they appear.

Table 10 — Summary Results of Misclassification

Company I.D. Number	Alternative Number																			
	4					3					2					1				
Failing Firms	I	II	III	IV	V	I	II	III	IV	V	I	II	III	IV	V	I	II	III	IV	V
1.01.02.01																				
1.01.12.02				x	x				x	x					x					
1.01.12.03		x					x													
1.02.02.04																				
1.02.02.05																			x	
1.02.02.06	x		x	x	x	x		x			x			x	x	x			x	x
1.02.02.07																				
1.02.02.08																				
1.02.02.09	x	x	x	x			x	x			x	x	x			x	x	x		x
1.02.02.10																				
1.02.02.11																				
1.02.02.12			x					x					x	x	x			x	x	x
1.02.03.13																	x			x
1.02.03.14		x					x					x					x			x
1.02.04.15											x									x

Company I.D.	Alternative Number																			
Number	4					3					2					1				
Failing Firms	I	II	III	IV	V	I	II	III	IV	V	I	II	III	IV	V	I	II	III	IV	V
1.02.05.16	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
1.02.05.17																				
1.04.03.18																				
1.07.02.19												x					x	x	x	x
1.09.01.20			x					x												
1.10.01.21																				
1.10.01.22															x					x
1.12.01.23																				
1.14.03.24																				
1.15.01.25																				
1.07.01.26																x				
Nonfailing Firms																				
1.01.02.27																				
1.01.12.28																				
1.01.12.29																				
1.02.02.30					x					x					x					x
1.02.02.31																				
1.02.02.32		x	x	x	x	x	x	x		x		x	x	x						
1.02.02.33	x		x			x		x			x		x			x		x		

Table 10 (Continued)

Company I.D. Number	Alternative Number																			
	4					3					2					1				
Nonfailing Firms	I	II	III	IV	V	I	II	III	IV	V	I	II	III	IV	V	I	II	III	IV	V
1.02.02.34	x				x	x				x	x				x	x	x			x
1.02.02.35		x	x	x			x	x	x	x		x	x	x			x	x	x	
1.02.02.36			x	x	x			x	x	x			x	x	x			x	x	x
1.02.02.37	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
1.02.02.38				x	x	x	x		x	x				x	x				x	
1.02.03.39				x	x			x	x	x										
1.02.03.40			x	x				x	x					x			x		x	x
1.02.04.41							x													
1.02.05.42						x														
1.02.05.43	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
1.04.03.44	x	x				x	x	x		x		x	x	x				x	x	
1.07.02.45		x	x	x		x	x	x				x	x	x				x	x	
1.09.01.46																				
1.10.01.47	x					x	x	x			x									
1.10.01.48																				
1.12.01.49																				
1.14.03.50	x	x				x	x				x	x				x	x			
1.15.01.51																				
1.07.01.52	x	x				x	x					x								

The second kind of bias was the search bias. This is inherent in any empirical study and enters in the choice of variables in the process of reducing the size of the original set of variables. While a subset of variables is effective on the original sample, there is no absolute certainty that it would be just as powerful for the population in general. The above deficiencies would lead to an upward bias — rejecting the hypothesis of equality of group means more often than is actually the case.

Analysis of Ratio Trends

To get an insight into the behavior of the discriminant functions, it may be useful at this point to examine the trend of some related ratios used in the discriminant analysis. This may help explain the performance of the discriminant models.

An examination of selected ratios of both failing and nonfailing firms revealed a general deterioration during the five years under study. This could be due to the then prevailing business environment characterized by economic uncertainty due to the change in the political system coupled with oil price increases which adversely affected the total economy causing dislocation in many firms, both the healthy and the not-so-healthy. The healthy firms may have survived the economic shocks but these difficulties were nevertheless reflected in their financial statements as shown in the ratio trends.

Figure 3 shows that the total resources of failing firms exceeded that of nonfailing firms. But in failing firms these resources were mostly funded by borrowings. Furthermore, the failing firms were less efficient in resource utilization than their nonfailing counterpart. The nonfailing firms were able to generate more sales per peso of asset invested. Furthermore, the profitability ratios *(NI/S)* of the nonfailing firms were higher than those of the failing firms. This put the latter at a disadvantage vis-a-vis the nonfailing firms. The above situation is highlighted in Figure 4.

One possible explanation for the above situation is the following: In 1975, the firms were expanding as a response to the numerous incentives offered by the government. Some erstwhile healthy firms rushed into the expansion program financed by borrowings. Unfortunately, since sales did not keep pace with expansion of assets they were saddled with obligations they could not service for lack of funds. The problem was compounded where firms had foreign loans because the value of the peso vis-a-vis the dollar kept depreciating. Those firms which were highly leveraged had nothing to

Figure 3 — Trend of Means of Total Assets, Total Liabilities, Total sales and Net Income

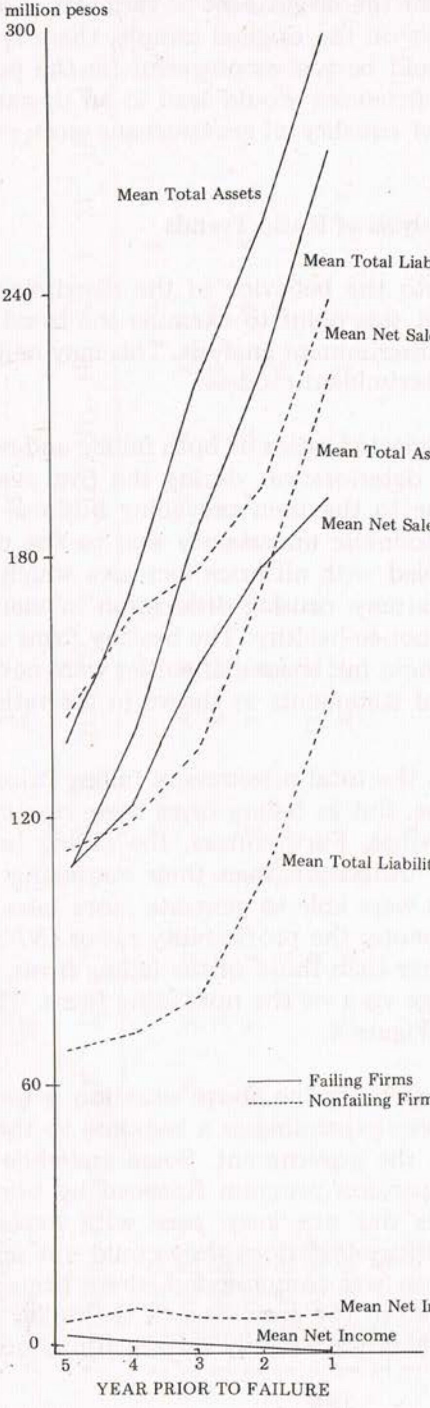
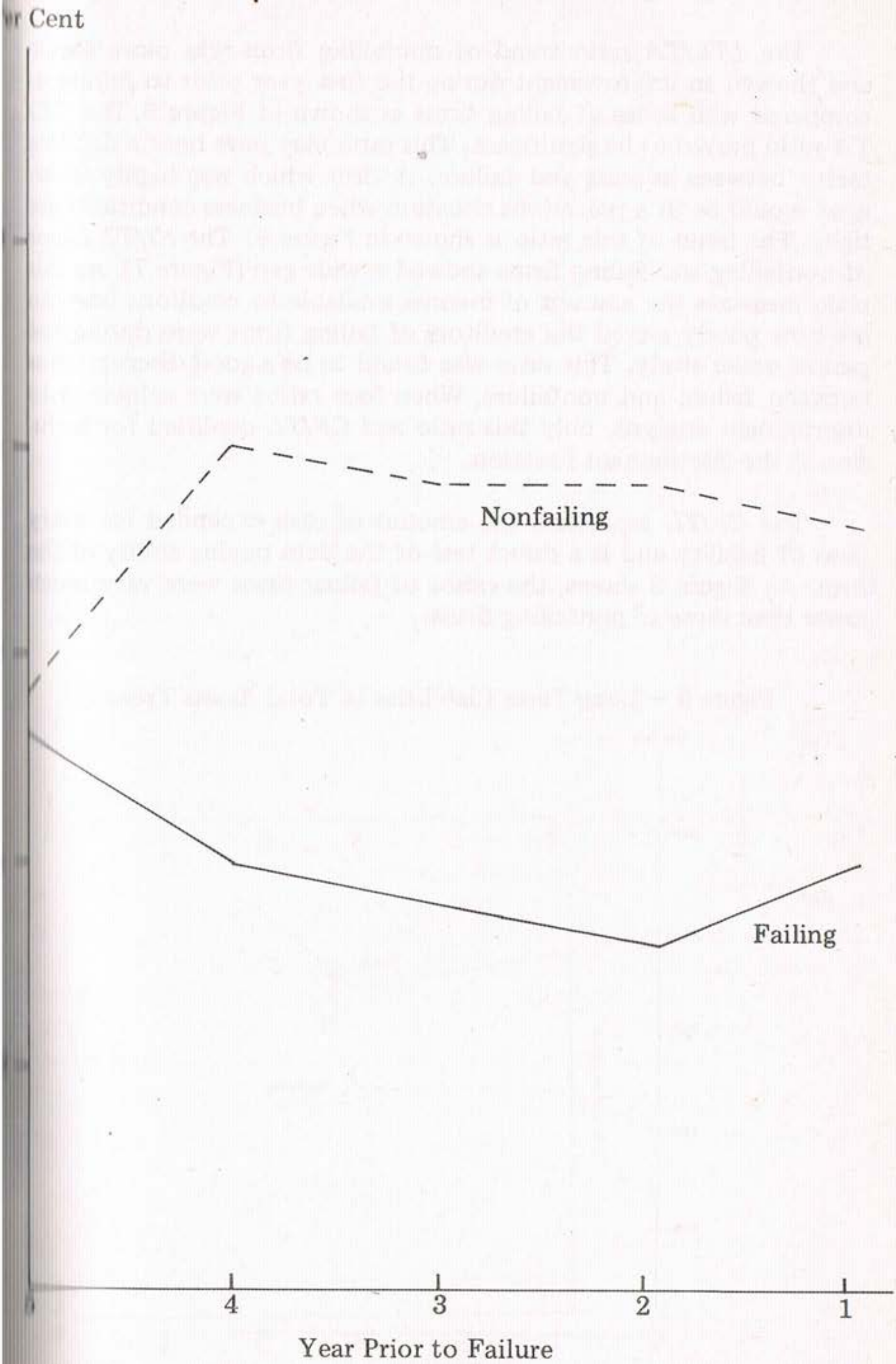


Figure 4 — Net Income to Sales Trend

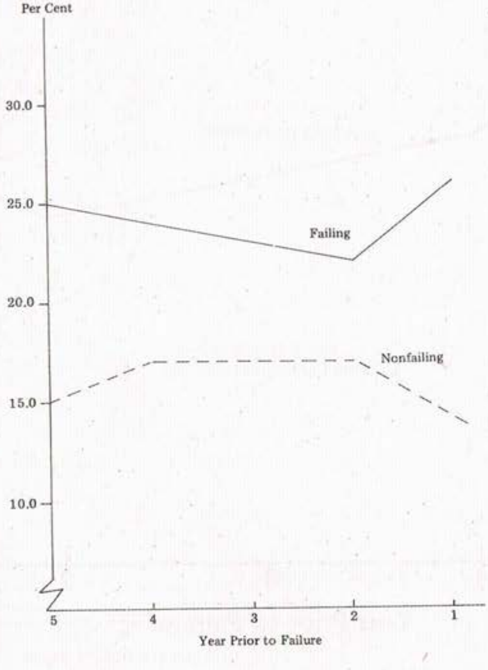


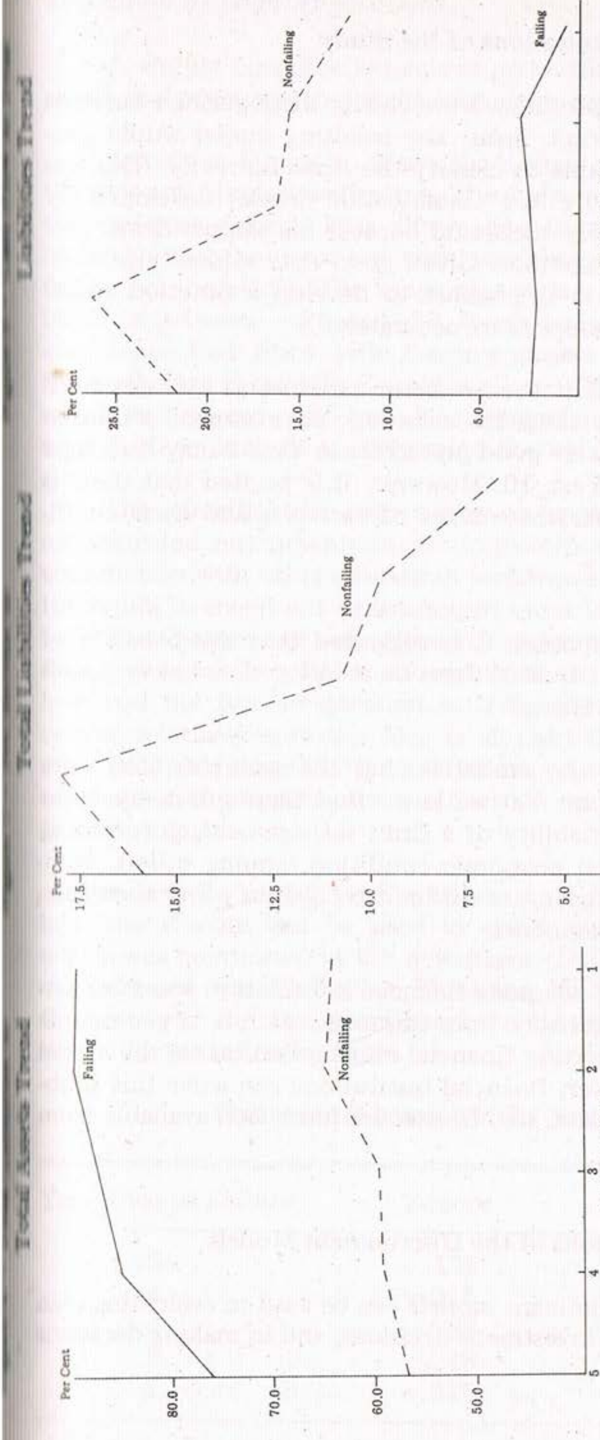
fall back on and were more adversely affected by this event than those with high capital base. This could have led to the default.

The *LTL/TA* ratio trend of nonfailing firms was more stable and showed an improvement during the first year prior to failure as compared with those of failing firms as shown in Figure 5. The *TL/TA* ratio proved to be significant. This ratio may have been a decisive factor between success and failure. A firm which was highly leveraged would be in a precarious situation when business conditions are tight. The trend of this ratio is shown in Figure 6. The *NI/TL* ratios of nonfailing and failing firms showed a wide gap (Figure 7). As this ratio measures the amount of income available to creditors, one can see how poorly served the creditors of failing firms were during the period under study. This ratio was found to be a good discriminator between failure and nonfailure. When four ratios were subjected to discriminant analysis, only this ratio and *CF/TL* qualified for inclusion in the discriminant function.

The *CF/TL* represents the amount of cash expended for every peso of liability and is a direct test of the debt paying ability of the firm. As Figure 8 shows, the ratios of failing firms were very much lower than those of nonfailing firms.

Figure 5 — Long-Term Liabilities to Total Assets Trend




Total Assets Trend
Per Cent
80.0
70.0
60.0
50.0
Failing
Nonfailing
5
4
3
2
1
Year Prior to Failure
Total Liabilities Trend
Per Cent
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
-2.5
Nonfailing
Failing
5
4
3
2
1
Year Prior to Failure
Liabilities Trend
Per Cent
25.0
20.0
15.0
10.0
5.0
Nonfailing
Failing
Year Prior to Failure

Limitations of the Study

If the original sample firms were clearly distinguished between bankrupt and nonbankrupt firms, the resulting model would probably have been better able to classify the firms correctly. This was probably the reason why the classification model developed by Altman (1967) was highly successful because his sample firms were very distinct from one another. Given good data which give well-defined characteristics, it is possible to develop a function which could classify the two groups more accurately.

One limitation is that the predictor variables as well as coefficients change over time since the economic environment is nonstationary. Variables which are good predictors in Year 1 may no longer be good predictors in Year 10. However, it is posited that there is a relevant range of time where a set of variables and their coefficients can be used.

To make the model more responsive to the needs of individual users, like finance companies, it is suggested that the behavior of some selected variables of client firms be monitored and new models developed as conditions change.

One drawback of the model is that the variables used were purely financial in nature. Yet we know that there are many other factors affecting the variability of a firm: management, government policies, and the general economic condition, among others. Nonfinancial variables, however, are difficult to quantify and therefore, difficult to input into the model.

Finally, the lack of adequate financial information was a big setback. Results would probably have improved with a larger sample size. The difficulty in getting financial information makes the model more expensive. However, financial institutions can solve this problem by using in-house data, i.e., financial information available from their clients.

Applications of the Discriminant Models

The multiple discriminant models can be used in evaluating loan applications, in making investment decisions, and in making decisions internal to the firm.

Evaluation of Loan Applications

A simple classification rule is presented here which could help credit analysts assess the credit worthiness of a firm.

A look at Figure 2 shows the degree of overlap in *Z*-scores, or the amount of misclassification. The degree of overlap is narrow over the five-year period. This allows one to estimate cut-off *Z*-scores beyond which one can say with confidence that the firm is either failing or nonfailing. The range of overlap for the five years combined is between −.26 and .23. It can be said with some degree of confidence that firms with *Z*-scores greater than .23 are nonfailing firms whereas firms with *Z*-scores below −.26 are failing firms. Those which lie between −.26 and .23 inclusive, are in the "gray area" and need further analysis to determine the eventual status of the firm.

This classification rule is easy to apply and does not require sophisticated instruments in its implementation. It can be used in conjunction with other evaluation techniques.

The *Z*-score not only gives information on whether the firm is failing or nonfailing, but it also gives one an insight into how good or how bad the firm in question is. If the *Z*-score is high, the analyst can be relatively sure the firm is all right financially. But if the *Z*-score is low or negative, the analyst may have to go into other types of credit evaluation to make a decision on whether to recommend granting a loan.

It may be useful to cite an example from the sample data of how the *Z*-score can be used in credit evaluation. One company which was mentioned in the newspaper (*Daily Express*, 3.12.81:10) as distressed was Philippine Blooming Mills (PBM). A look at its *Z*-scores over the five years bears out its deteriorating condition as shown by the following table.

Philippine Blooming Mills: Selected Data

Year Prior to Failure	*Z*-score	*CA/CL*	*TL/TA*
5	.175	1.33	.55
4	−.015	1.18	.68
3	−.137	1.10	.76
2	−.248	1.07	.81
1	−.315	1.00	.84

The Z-scores clearly indicated that financial problems were piling up for PBM. If only the current ratio one year prior to failure were considered, one would still find the company viable, although a closer look at the TL/TA ratio points to a very high leverage. The TL/TA ratio shows how debt/asset profile increased from 55 per cent to 84 per cent one year prior to failure. During these five years under study, its net income/sales ratio was consistently positive although rather low. Its earnings before interest and taxes fluctuated between 7 per cent five years prior to failure and 9 per cent one year prior to failure. Yet in general, the company was in serious financial trouble. If one looked only at univariate ratios, one could say that the firm was not doing too badly, when in fact it was in a dangerous situation.

It must be emphasized, however, that the discriminant models should not be used as the only basis for granting loans. There are other important factors to consider which are not captured by the model, such as management capability, securities offered on the loan and term of the loan, among others. The discriminant Z-score can be used only as a guide in minimizing the cost of investigation of loan applicants. Less effort should be spent on firms with very high and very low Z-scores. Only those belonging to the "gray area" would call for a more thorough investigation. This method is especially helpful in evaluating short-term loans where normal credit and evaluation process is costly relative to the size of the loan. The discriminant model provides a relatively cheap and handy tool in credit evaluation.

Inherent in the discriminant analysis is the chance of misclassification. It is assumed here that granting a loan to a firm which eventually fails is more expensive for the lending institution than denying a loan to a firm which can meet its obligation. The cost associated with a Type I error is the loss of interest and/or principal on the loan less whatever is recovered in the form of collaterals.

Misclassifying a failed firm also involves opportunity costs of lost income represented by that income which could have earned on alternative investments. Another cost is the loss of a prospective customer.

On the other hand, the cost of the Type II error is represented by the interest income on the loan not granted. This is true if no alternative investment is found. If there is, then the loss is the differential between that interest on the loan not granted and the interest on the loan which was actually granted. Also, there is a loss of customer if a creditworthy customer is turned down.

In the final analysis it is better to commit a Type II error than commit a Type I error because of the repercussions involved. And this implies that, in case of doubt, it is beneficial to use other models suggested here, especially Model 3 as it has the ability to predict more accurately the percentage of failing firms and tends to minimize the Type I error.

Investment Evaluation

In these times of uncertainty it is important to make correct investment decisions in order to minimize losses. The investor group may find an efficient predictor of financial difficulties a valuable means for screening out undesirable investments which could be used with other evaluation techniques. Conversely, the investee group may also have recourse to the discriminant model *Z*-score in bargaining for the right price. Both groups would have a sound basis for making a decision.

Another potential use to the present investor of a failing firm is to be able to determine when to unload one's investment. It was shown that as failure approached, the *Z*-score deteriorated. A keen investor would use these *Z*-scores to help him unload on time, i.e., to sell his investment at a reasonable price. Altman (1967) found out that the price of bankrupt firms declined as the firms approached bankruptcy. If an investor is able to monitor his investment portfolio with the aid of *Z*-scores, he may find the effort rewarding.

Internal Management Use

The discriminant model can also be used for internal management purposes. It could help management assess its problems early enough and do something about it. The *Z*-score could indicate danger signals to the officers of the firm and they could work out solutions to avert the impending financial crisis. This may come in the form of additional capitalization, additional borrowing, mergers or consolidations.

If the problem is additional capitalization, this can be forecasted early enough and the necessary solution undertaken. If the problem can be solved by additional borrowing, then planning such borrowing in advance would result in cheaper loans and favorable terms. If the solution calls for reorganization, then the best possible way of doing this can be implemented with the minimum loss to the present investors. If merger is to be undertaken, present stockholders and creditors may be in a better bargaining position if merger negotiations are done early enough instead of doing it when the firm is up for liquidation. More losses can be averted if the ailing firm is salvaged on time.

Some benefits which accrue to the timely rescue of a distressed firm include the preservation of assets, the avoidance of loss of jobs in the distressed firm (which is very important in periods of high unemployment) and "face-saving" for executives and major stockholders of the distressed company. Moreover, the loss to present stockholders and creditors is minimized if the firm is salvaged on time.

Conclusion and Recommendation

In summary, it may be said that there are indeed real advantages in using the discriminant model in predicting company failure or nonfailure and the cost of developing such a model is commensurate with the benefits derived from using it.

Since the importance of having tools with which to assess a firm's future is found very useful it is hoped that more research on this area be undertaken.

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