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Using Financial Ratios to Predict Insolvency

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The purpose of this study is to explore the feasibility of using financial ratios as an analytical technique to predict financial insolvency. Using discriminant analysis, a credit-risk score was calculated to determine if a lender should accept or reject a prospective borrower. This study reveals that 80% of the cases were correctly predicted by this model.

Introduction

The detection of company operating and financial difficulties is frequently done by financial ratio analysis. Prior to the development of quantitative measures of company performance, agencies were established to supply a qualitative assessment of the credit-worthiness of particular merchants [7]. Several studies of business failure were introduced in the 1930s. A good number of these studies concluded that failing firms exhibit significantly different ratio measurements from those of continuing entities [11, 19]. A study by Hickman [9] concerned ratios of large-asset-size corporations that experienced difficulties in meeting their fixed indebtedness obligations. Beaver [5] analyzed the financial ratios in a the context of predicting bankruptcy. He compared failed firms with a matched sample of firms that had not failed. Beaver concluded that ratio analysis can be useful in the prediction of failure.

The aforementioned studies imply a definite potential for ratios as predictors of insolvency. In general, ratios measuring profitability, liquidity, and capital are the most significant indicators. The order of their importance, however, is not clear since almost every study cited a different ratio as being the most effective indication of impending problems. For instance, a firm with a poor profitability or solvency record may be regarded as a business failure. However, because of its above-average liquidity, the situation may not be considered serious. The potential ambiguity of the relative performance of several firms is clearly evident.

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Statement of Objectives

The objective of this study is to combine several measures into a meaningful predictive model [1–4]. In so doing, the highlights of ratio analysis as an analytical technique will be emphasized. The question becomes, Which ratios are most important in detecting insolvency, What weights should be attached to those selected ratios, and How should the weights be objectively established?

This study adds a unique perspective to internal/operational audits. The question is whether the ratios selected by the bank in this study are the best? More importantly, how can the discriminant analysis be integrated, not only into a loan and loan portfolio evaluation, but also into the internal/operational audit procedures?

Methodology

Multiple discriminant analysis (MDA) has been used extensively in the financial literature. Examples utilizing MDA include Walter [21], who classified firms as to high or low price-to-earnings ratios; Durand [6], who dealt with the risk elements in consumer installment financing; and Myers and Forgy [14], who developed a numerical credit evaluation system for installment loans. These latter studies are particularly relevant to the present study since they deal with credit evaluation systems [8]. However, this study adds a unique perspective on earlier studies, namely, the application of MDA not only to forecasting, but also to internal/operational auditing.

A total of 30 borrowing entities were selected from a regional bank as an experimental sample. Of these companies, ten were classified as insolvent by the bank. The objective of this paper is to look at the financial ratios and determine what type of correlation exists among the 30 companies. We included other financial ratios in addition to those highlighted in the bank's business loan report. This was done to determine which financial ratios were the better predictors. The overall purpose of this study is to formulate and compute a credit risk score that would enable a lender to accept or reject a prospective borrower. An additional group of ten companies were selected as a control group to test the reliability of the model.

Population

The sample was selected from the files of a regional bank. At random, 30 business loan reports were taken from three areas within the bank, three full years prior to the time of this study. The areas were:

1. Commercial Finance.
2. Corporate Banking.
3. Small Business.

Of the 30 companies selected for the experimental sample, ten were considered to be insolvent because of substandard classification, delinquency, or bankruptcy. Of the control group of ten companies, three were insolvent.

The financial highlights in the business loan reports provided the data necessary for calculating the seven variables (ratios) being analyzed in the discriminant model.

These variables were classified into four standard ratio categories including: liquidity, capital, coverage, and profitability. The first three ratios were taken from the bank's business loan reports and were considered by the bank as the most important in making credit decisions. The other four were added to determine which ratios were the better predictors of insolvency and to arrive at a more extensive measurement.

The seven variables used in the discriminant function are:

1. *Net Income/Net Sales*
2. *Earnings before Interest and Taxes (EBIT)/Interest Charges*
3. *Total Liabilities/Tangible Net Worth*
4. *Current Ratio* — Total current assets divided by total current liabilities.
5. *Long-Term Liabilities/Capitalization* — Long-term liabilities divided by the sum of long-term liabilities and net worth.
6. *Net Sales/Tangible Net Worth*
7. *Sales/Working Capital*

Empirical Results

The discriminant model is designed to be used in several ways. First it identifies the most critical financial ratios (variables), for determining the most desirable credit risk. Second, it ranks the critical discriminant variables according to their relative discriminating power. Third, it enables the measurement of borrowers' performance for each of the ratios individually and for all the ratios combined.

Empirical Discriminant Model: Distinguishing between Solvent and Insolvent Borrowers

Table 1 shows all the ratios in the initial analysis. In addition, Table 1 describes the strength of the discriminant model by showing Wilks' Λ and the F ratio and its respective level for each of the discriminant variables. In Table 1 the lender's perspective is emphasized. Accordingly, an insolvent borrower is classified as a "work-out situation." Problem loans require much time and effort from lenders, and it is very difficult to turn a bad loan around. Moreover, in attempting to turn a bad loan around the lender may advance more funds, further increasing its risk exposure. This model can anticipate these situations and thereby reduce the number of problem loans [12].

The nonstandardized coefficients of the discriminant function are reported in Table 2, along with the discriminant ratios of the borrowers. To obtain a discriminant score for the function, multiply the coefficient by the respective ratio value and sum the products plus the constant. The ratio value is computed from the business loan reports of the selected borrowers.

The products of the discriminant coefficients (d_j) and their respective standardized financial ratios ($z_{i,j}$) provide the analyst with a single-ratio discriminant score (SRDS) for each loan. These SRDSs show the contribution of each ratio to a single-borrower discriminant score, as well as to the loan portfolio discriminant score. Therefore, each SRDS is useful in and of itself. Accordingly, an analyst can rank the SRDS for a single borrower to determine the weaknesses and the strengths for

Table 1. Wilks' Λ (*U* Statistic) and Univariate *F* Ratio with 1 and 28 Degrees of Freedom

Features[a]	Wilks' Λ	F	Significance
1. Net Income/Net Sales	0.83	0.53+1	0.02
2. Ebit/Int. Charges	0.96	0.11+1	0.29
3. Total/Liab./Tang NW	0.87	0.39+1	0.05
4. Current Ratio	0.99	0.59−1	0.80
5. Long Term Liab./Cap.	0.99	0.72−1	0.79
6. Sales/Net Worth	0.90	0.28+1	0.10
7. Sales/Work Cap.	0.86	0.43+1	0.04

Canonical Discriminant Functions

Function	Eigenvalue	Percent of Variance	Cumulative Percent	Canonical Correlation
7[b]	0.90	100.00	100.00	0.68
Function	**Wilks' Λ**	**χ-Square**	**D.F.**	**Significance**
0	0.525	15.77	7	0.02

[a]Prior probability for each group is 0.50; the features here are based on the above financial information obtained from the selected borrowers.
[b]Marks the 1 canonical discriminant-function coefficients.

each borrower. This evaluation can be applied in a similar way to an entire loan portfolio. However, when the total portfolio SRDS is used, the analyst should note that single-borrower SRDSs offset each other.

Table 2 shows the coefficient results using three ratios. The purpose of Table 2

Table 2. Nonstandardized Canonical Discriminant-Function Coefficients Using the Experimental Sample

Financial Ratios	Three-Ratio Model Coefficients
Net Income/Net Sales[a]	0.63+0
Ebit/Int. Charges[a]	−0.31−1
Total Liab./Tang. N.W.[a]	0.40+0
(Constant)	−0.12+1

[a]Most significant factor loadings.

Table 2a. Varimax Rotated Factor Matrix of Financial Ratios for Three-Ratio Model Design Analysis

Financial Ratios	Factor 1 Net Income Net Sales	Factor 2 Ebit./Int. Charges	Factor 3 Total Liab/ Tang. N.W.
Net Income/Net Sales	0.92[a]	0.28	0.01
Ebit/Int. Charges	0.25	0.93[a]	0.12
Total Liab./Tang. N.W.	0.33	0.29	0.95[a]
Current Ratio	0.12	0.13	0.13
Long Term Liab./Cap.	0.01	0.26	0.04
Sales/Net Worth	0.47	0.21	0.15
Sales/Work Cap.	0.42	0.29	0.36

[a]Most significant factor loadings.

Table 3. Standardized Canonical Discriminant Function Coefficients

Rank Order	Financial Ratios	Coefficients
1	Net Income/Net Sales	-1.73
2	Ebit/Int. Charges	0.81
3	Total Liab./Tang. N.W.	-0.72

is to compute the discriminant score on both groups of ratios and to determine which group provides a more accurate prediction and classification [12].

In addition, Table 2a shows the varimax factor analysis which reduces the number of ratios from seven to three without significant information loss.

The standardized model is most advantageous when this discriminant analysis is completely computerized. However, when the computations are done manually, a nonstandardized model would be more convenient since it relieves the analyst from computing Z scores, mean scores, and standard deviations. Therefore, a nonstandardized model was developed.

Both the standardized and nonstandardized models require the computation of the SRDS. However, the nonstandardized model requires adding a constant value (C) to the SRDS ($a_j x_{i,j}$) to arrive at the single-borrower discriminant score (D_i). This formula was applied to all 30 companies to derive their respective discriminant scores.

Table 3 shows the standardized canonical discriminant function which is a derivative of the nonstandardized discriminant function (Table 2). The standardized discriminant-function coefficients are of great analytical importance in and of themselves. When the sign is ignored, each coefficient represents the relative contribution of its associated ratio to the discriminant function. The sign denotes whether the variable is making a positive or negative contribution to the discriminant insolvency score.

Table 3 can be used to rank the discriminating ratios according to their discriminating power. Accordingly, the higher the standardized discriminant coefficient's absolute value, the stronger its discriminating power. Therefore, because the Net Income/Net Sales ratio has the largest absolute standardized discriminant coefficient (1.73), it has the most predictive discriminating power. The negative signs have no meaning in and of themselves. They are used only collectively to compute the discriminant score.

The standardized discriminant-function coefficients (Table 3) are used to compute the discriminant score for each prospective borrower. The discriminant score is computed by multiplying each discriminating variable by its corresponding coefficients and adding together these products.

The rank orders in Table 3 confirm that the ratios used in the bank's business loan reports were actually the better predictors of financial insolvency because of their significantly higher absolute values. Accordingly, this discriminant analysis can also be used for internal/operational auditing of the effectiveness of loan approval procedures [10].

Table 4 provides the results of the model using the three ratios selected by the factor analysis. This table reveals that the discriminant model is rather powerful

Table 4. Borrowers Classification by Discriminant Model (three ratios) Using a Control Sursample

		Predicted Group Memberships	
Actual Group	No. of Cases	1	2
Group 1	7	6 (85.7%)	1 (14.3%)
Group 2	3	1 (33.3%)	2 (66.7%)
Percent of "Grouped" Cases Correctly Classified:			80%

Borrowers Classification by Discriminant Model (three ratios) Using the Experimental Sample

		Predicted Group Memberships	
Actual Group	No. of Cases	1	2
Group 1	20	17 (85%)	3 (15%)
Group 2	10	1 (10%)	9 (90%)
Percent of "Grouped" Cases Correctly Classified:			86.6%

in predicting correctly the classification of prospective borrowers in the control sample since 80% of the cases were correctly classified. The desirable or solvent prospective borrowers represented by Group 1 have a correct classification of 85.7% compared with the same prediction record of 33.3% for the undesirable or insolvent prospective borrowers.

Summary, Conclusions, and Implications

The discriminant function was tested indicating that 80% of the cases were correctly classified. The discriminant scores vary from borrower to borrower and need to be empirically evaluated for each individual case. Therefore, the discriminant scores were computed for each borrower determining the level of insolvency for each respective company.

In conclusion, this paper seeks to assess the analytical quality of ratio analysis. In an effort to precisely assess its potential, a set of financial ratios was combined using discriminant analysis to predict financial insolvency within a three-year period. The theory is that ratios, if analyzed within this type of framework, will take on greater statistical significance than the common technique of unweighted ratio comparisons.

The implications of this study can be presented in three main areas of interest to banks and financial institutions:

1. Evaluating a single prospective or current borrower to determine whether or not to accept his loan request. In the case of current borrowers, it can provide assistance in quantifying improvements or deficiencies by comparing scores periodically.
2. Evaluating an entire loan portfolio to determine its degree of risk. For in-

stance, a multibranch banking firm can use this model as a monitoring instrument to reevaluate existing portfolios. Thus, loans that appear to be undesirable can be sold.

3. Evaluating the portfolio manager in terms of his loan portfolio. It can compare his performance to that of others by showing the levels of risk in a given period of time. This analysis can be repeated at different times, comparing the individual's performance from one period to the other. In addition, the model can be used to evaluate the methods and ratio selections used by the various financial institutions.

This evaluation should be integrated into internal/operational auditing procedures to assure that the most efficient and effective financial ratios are being used in evaluating individual prospective borrowers and current borrowers, as well as entire portfolios. Moreover, this repeated evaluation is particularly applicable in a volatile economy since the relative predictive power of financial ratios may change with changes in the economy. Likewise, the predictive power of ratios may also depend on variables related to service, industry, or geography. Accordingly, it may be advisable to repeat this analysis periodically and update the model for those factors.

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