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ABSTRACT: The risk classification of commercial bank loans is performed by loan officers, bank controllers, auditors, and bank examiners. Despite the importance of this classification decision, little empirical research has been performed to explain this subjective evaluation procedure. In this paper, a simple linear model is developed which reproduces most of the lending officer's classification decisions. Two variables, a debt-to-total-assets ratio and a funds-flow-to-fixed-commitments ratio, provided most of the explanatory power, but a sales trend variable was also significant. For some of the loans for which the model and the actual classification differed, the model's classification was found to be an advance indicator of a subsequent reclassification by the lending officer. The simple three-variable linear model provided much better predictions of loan risk classification than did two popular bankruptcy prediction models.

INTRODUCTION

ASSESSMENT of default risk on loans made to corporations is a common practice in commercial banking. Estimates of default risk facilitate the internal evaluation and review of lending operations and help to determine loan loss reserves for financial reporting. Other uses include the external review of a loan portfolio by bank examiners and the assessment of the internal control system by auditors of the bank. Indeed, many applications of loan risk estimates exist despite the fact that loan risk is not directly measurable.

In order to describe the default risk on a commercial loan, a large bank utilizes a a five-category classification scheme.[1] Each loan is assigned to one of five mutually exclusive categories:

I CURRENT—normal acceptable banking risk

IA ESPECIALLY MENTIONED—evidence of weakness in the borrower's financial condition or an unrealistic repayment schedule

II SUBSTANDARD—severely adverse trends or developments of a financial, managerial, eco-

[1] The categories used by this bank are patterned after the classification system used by the Comptroller of the Currency. The *Comptroller's Handbook of Examination Procedure* (1973) lists 3 "classified" loan categories. They are Substandard, Doubtful, and Loss. Another category, Other Loans Especially Mentioned, lists loans that "constitute undue or unwarranted credit risks but not to a point justifying classifying." Loans that are not listed in any of the categories are referred to as current. While the category names used by the Comptroller of the Currency are the same as those used by this bank, the bank does not claim that its classification scheme is identical to the one used by the Comptroller of the Currency. For this reason, we cannot claim that our estimated model will be generalizable across all banks.

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nomic, or political nature which require prompt corrective action

III DOUBTFUL—full repayment of the loan appears to be questionable. Some eventual loss (as yet undetermined) seems likely. Interest is not accrued.

IV LOSS—loan is regarded as uncollectible

At present, the classification of a loan is a subjective decision made independently by loan officers, auditors, and bank examiners. Although there is no prescribed evaluation procedure, classification decisions incorporate insights gained from analyzing financial ratios and trends and from subjective evidence concerning the company's management, industry, market position, and future prospects.

The objective of our study is to develop a simple linear model which can replicate the judgment used in classifying loan risk. An explicit classification model can be useful in a number of ways. First, it provides a rough check on the consistency of the loan officer's classification process by focusing attention on those loans for which the model and the expert judgment disagree. Naturally, the model cannot capture many of the subjective and nonquantifiable aspects of the loan classification decision. For these cases for which the model predicts a classification different from the actual classification, it should be relatively easy to verify whether the discrepancy is due to these subjective factors or to a failure to recognize some fundamental change in a company's financial condition as revealed by the model. Second, the model may be useful in predicting changes in the classification status of a loan. By observing the changes in the model score for a loan over time, the deteriorating or improving financial condition of a company may be observed before it would otherwise be noticed by the loan officer or other reviewer. In addition, having a simple model that can be applied inexpensively enables a bank to screen through a large population of potential loan candidates to identify those companies for which a new loan would not be adversely classified.

With the extensive and frequent reviewing of commercial loans by many interested parties, it is disappointing how little research has been done to understand and capture the loan classification decision. Lev [1974], in a chapter surveying analytic models for credit evaluation by banks, summarized the meager state of the art, "Given that banks are probbably the major users of financial statement information, it is striking that so few models have been developed for bank credit operations" (p. 173). It is especially striking because extensive research has been conducted to develop formal models that successfully predict bankruptcy[2] and bond ratings[3] based on financial and accounting data.

In contrast to the extensive study of bankruptcy and bond ratings (helped, no doubt, by the ready public availability of such data), hardly any studies have been reported on the loan classification decision. Orgler (1970) developed a simple regression model for commercial loans where the dependent variable was a simple dummy variable (1 for a criticized loan—categories IA, II, and III above—

[2] For example, see Beaver [1966; 1968] for comparisons of selected ratios for failed and nonfailed firms. Altman (1968) used the multiple discriminant analysis technique to estimate a bankruptcy prediction model. Wilcox [1973] derived and tested a bankruptcy prediction model based upon a Markov process. Sometimes referred to as the "gambler's ruin problem," the model estimates the probability that future cash outflows will exceed the firm's financial resources, based upon its historical performance.

[3] One recently developed bond rating model is described in Kaplan and Urwitz [1979]. Other efforts to develop bond rating models are referenced therein.

and 0 if uncriticized—category I). The explanatory and predictive power of Orgler's model was not impressive; the R^2 of the regression was only .36 and on a holdout sample of 120 loans, less than 60 percent were correctly classified. Even these results were achieved using a set of independent variables that would not be helpful in predicting changes in the classification status of existing loans or the classification of new loans.

Virtually all financial ratios were insignificant in explaining the difference between criticized and uncriticized loans. Five of the six independent variables were dummy variables to represent whether the loan was: (1) secured or unsecured, (2) current or past-due, and (3) previously criticized on the last examination; and whether the company had (4) audited financial statements, and (5) positive income. Certainly, the first four of these dummy variables were already providing direct evidence on the current status of the loan or its perceived riskiness. They hardly constitute an interesting set of independent variables from which to develop an explanatory or predictive model.

Haslem and Longbrake [1972] criticized Orgler's use of examiners' loan classification as the dependent variable for several reasons: "First, the use of this dependent variable implicitly assumes the relative superiority of examiner evaluation over a model based on a more objective measure of loan quality" (p. 734). Although a "more objective measure" was not explicitly defined, Haslem and Longbrake stated that "there is little reason to assume that bank examiners make more accurate appraisals of credit quality than loan officers" (p. 734). Perhaps loan officers' assessments are this "more objective measure." A second objection to Orgler's dependent variable was that "a heuristic model simulating examiner procedural behavior [may] provide a more direct approach . . ." (p. 734). Thus, Haslem and Longbrake concluded that Orgler's model "is primarily useful in indirectly explaining how bank examiners judge loan quality" (p. 734).

Other studies have examined commercial lending activities more generally. That is, rather than concentrate on the assessment of loan risk, other aspects of lending activities are also studied. Cohen, Gilmore and Singer [1966], for example, developed a computer model that was intended to simulate the decision process of a loan officer in processing a loan application. One part of this process was analyzing the credit rating of the applicant. Using historical and pro forma financial information, several ratios were compared with industry parameters. These ratios were:

1. Net Worth to Total Debt
2. Funds for Debt Service to Funds Provided by Operations (Three-Year average)
3. Liquidity measures such as Cash to Current Liabilities, Cash plus Receivables to Current Liabilities, Current Inventory to Three-Year-Average Inventory.
4. Profitability measures such as Three-Year Average of Net Profits and Trend in Net Profits.

The Cohen, Gilmore and Singer study did not directly estimate a loan risk function, but the financial ratios identified were used in estimating loan risk in their simulation of the lending process. The study thus indicates potentially relevant variables, or categories of variables, in assessing default risk.

Other discussions of default risk evaluation often list financial ratios that

analysts can (or should) use as predictors of loan risk.[4] It is somewhat surprising that, given these widely discussed financial ratios, Orgler's study relied on independent variables that are almost tautologically related to his dependent variable.[5] Perhaps loan officers do not analyze financial ratios in any systematic fashion; then statistical analysis of the classification of default risk would indicate no significant financial ratios. Libby [1975] presented evidence, however, that refutes this hypothesis. Using variables that other researchers have found to be predictors of bankruptcy,[6] Libby asked loan officers to select which of two matched firms was more likely to fail. The selections were compared with the actual failure/survival record of the firms. Libby concluded that the "accounting ratios allowed bankers . . . to make highly accurate and reliable predictions of business failure" (p. 160). Thus, it seems quite plausible that a model of loan risk, incorporating financial ratios, can be developed.

The loan classification decision is very similar to the bond rating decision. Both involve placing a company in one of a set of ordinally ranked risk categories based on financial data and judgments about future prospects. Previous bond rating studies provide strong evidence on the ability of relatively simple linear models to capture the complex decision-making processes of sophisticated users of financial information. Other evidence of linear models to provide excellent representations of expert judgment appears in the psychological literature.[7] It would be contradictory with prior evidence if an expert judgment such as the classification of a loan, on which there must be a fair degree of consensus among diverse interest groups, including loan officers, auditors, and bank examiners, could not be similarly represented by a relatively simple linear model.

We were able to obtain access to the 1975 and 1976 classifications of a set of commercial loans from the national department (primarily firms operating wholly within the U.S.) of a large money-center commercial bank. From these data, we constructed a model to explain and predict the loan classification decision. Section 2 describes the statistical procedure used to estimate the model. The source data for the independent and dependent variables are presented in Section 3. Section 4 describes the best set of models for explaining and predicting loan classification and presents various validation tests that were performed. The paper ends with a summary and the implications of the research effort.

2. Methodology

Both ordinary least squares (OLS) regression and multiple discriminant analysis (MDA) have been applied to the bond rating decision with some degree of success and would appear to be prime candidates for developing a loan classification model. Unfortunately, both methods make inappropriate assumptions

[4] For example, the National Association of Bank Loan and Credit Officers issued a publication in 1964 listing eight ratios as predictors of failure. The ratios were: quick, current, and fixed assets to net worth; total debt to net worth; sales to receivables; cost of sales to inventories; and sales to net worth. Other examples are given in Smith [1974] and Houget [1975].

[5] That is, Orgler's variable for current or past-due loan status often indicates a criticized loan, since a loan with a past-due payment is very likely to be criticized. Orgler's variable indicating that the loan was criticized on the last examination provides no insight into the classification decision; it only shows that a serial correlation exists.

[6] Libby selected five variables that Beaver [1968] and Deakin [1972] found to be associated with business failure.

[7] See Slovic and Lichtenstein [1971] for an extensive survey of the literature concerning human information processing.

about the nature of the dependent variable—the loan classification category. OLS regression requires coding the dependent variable (I, IA, II, III in this case; Aaa, Aa, . . . , B for bond ratings) as an integer variable (e.g., 0, 1, 2, 3) to represent the different categories. This coding assumes that the dependent variable is measured on an interval scale in which the loan categories represent equal intervals on a risk scale from almost certain repayment to high risk of default. The loan categories, however, only provide ordinal information (category I is less risky than IA, which, in turn, is less risky than II, etc.). It is a heroic assumption to infer that we can use these categories directly to obtain a dependent variable measured on an interval scale. McKelvey and Zavoina [1975] discuss the errors that arise when OLS regression is applied to an ordinal dependent variable.

MDA treats loans in different categories as essentially different populations and estimates a series of functions that are used to predict in which category a loan should belong. By treating each category as a different population, MDA does not have to make strong assumptions about the nature of the loan classification variable. But this technique does does not exploit the ordinal nature of the classification variable. It treats the various categories as different outcomes but does not recognize that the different categories can be viewed as partitions, of perhaps unequal widths, of a single risk dimension, the probability of default. Thus, MDA avoids the interval scale assumption required to do OLS but does not use all of the structure available from the classification decision. MDA also requires strong distributional assumptions on the independent variables (financial ratios and trends) which need not be satisfied when a regression analysis is performed.

Fortunately, a procedure has recently been developed (see McKelvey and Zavoina [1975]) that permits us to estimate a model when the dependent variable is measured on an ordinal, but not interval, scale. The McKelvey-Zavoina procedure has been successfully applied to the bond rating decision (see Kaplan and Urwitz [1979] and seems especially well suited to the ordinal loan classification variable. Details of this statistical procedure can be found in either reference. For this paper, we provide only a summary of the technique.

We assume that there is a fundamental variable, Y, which measures the riskiness or probability of default of each loan. We assume that Y is a continuous variable, measured on an interval scale, and, if it could be observed, a linear function of a set of independent variables describing the financial condition of the company. The loan officers, however, do not attempt to estimate Y directly. Instead, they estimate an ordinal version of Y, the loan classification category (which we denote by Z). Z takes on values I, IA, II, and III. We assume that these four categories correspond to unequal width partitions of the continuous variable Y.

Formally, these assumptions can be described by:

$$Y = X\beta + \varepsilon \qquad (1)$$

where X is the matrix of independent variables (e.g., financial ratios), β is the coefficient vector, and ε is the vector of residuals or error terms assumed to be identically and independently normally distributed; $\varepsilon \sim N(0, \sigma^2 I)$. The category, Z, is determined by assuming four intervals on the real line: $(-\infty, 0]$, $(0, \mu_1]$, $(\mu_1, \mu_2]$ and (μ_2, ∞) where μ_1 and μ_2 are constants to be estimated from the data. These intervals correspond to the loan classification categories in the following way:

If $Y_i = 0$, then Z_i = category I
$0 < Y_i \leq \mu_1$, then Z_i = category IA
$\mu_1 < Y_i \leq \mu_2$, then Z_i = category II
$\mu_2 < Y_i$, then Z_i = category III

The vector of coefficients β and the two constants μ_1 and μ_2 are estimated using a maximum likelihood procedure. Since we are using maximum likelihood estimates of these coefficients, rather than obtaining estimates from a discriminant analysis, we know the statistical properties of the estimators. Details on these statistical issues are provided in McKelvey and Zavoina [1975], which also contains an actual application in which substantially different conclusions are reached when the correct analysis on ordinal dependent variables is used rather than ordinary least squares regression.

3. Selection of Independent Variables

Initially, discussions were held with about ten bank lending officers and executives in the controller's department of the commercial bank to learn which variables they consider to be most important in evaluating the riskiness of a loan. Variables were also suggested by reading the description of credit rating models developed by the Wells Fargo Bank of America.

Finally, we used variables found in the traditional financial statement analysis literature to measure risk, and variables that had been successful in explaining bond-ratings.[8]

Tested variables included profitability indicators (return on assets, dividend, trend in net income), debt-equity ratios, funds flow ratios, liquidity and activity ratios (current ratio, quick ratio, working capital to total assets, sales to assets), size variables (total assets, net worth), and abnormal increases in receivables and inventory. Ideally, one would prefer to have a model to suggest relevant financial variables rather than have to test many different possibilities for their explanatory power. But models of corporate loan default as a function of observable financial indicators are not well developed. Also, we are using a dependent variable, Z_i, which arises from the judgment of individual experts. Thus, even with a well-specified model, we might still find that the experts were using quite a different set of variables to classify loans. While the data-fitting exercise we performed is always subject to selecting variables unique to a particular sample, there is a compensating factor. New companies are constantly being added to and subtracted from the set of outstanding loans. Thus, by going further back in time or obtaining a new sample after a year has passed, we can re-estimate the model on new data and, if it is consistent with the original model, we can have more confidence in the robustness and predictive ability of our estimated relationships.

Financial variables were obtained from the COMPUSTAT Annual Industrial Tape. This machine readable source provides convenient access to many data items for 2,700 firms for up to 20 years into the past. Despite the richness of data items on the COMPUSTAT tape, including a detailed breakdown of the three major financial statements and, for recent years, data from footnote disclosure, this source still does not give us access to some key indicators that are readily accessible to the loan officer and could influence the loan classification decision.

Examples of such qualitative variables are whether the company received a qualified audit opinion, the type and effect of particular accounting procedures

[8] Variables that were found to be significant predictors of bond ratings (e.g. Kaplan and Urwitz [1979]), and bankruptcy (e.g., Altman [1968], Wilcox [1973], Beaver [1968]) were tested. More generally, variables identified as potentially relevant to commercial loan officers (Cohen, Gilmore and Singer [1966], Hester [1962], Smith [1974]) were examined.

used by a firm (e.g., LIFO or FIFO, accelerated or straight-line depreciation, flow-through or deferral of the investment tax credit), a missing interest or principal payment, and a division in financial difficulty, indicating future trouble for the consolidated company.

Also, occasionally there are missing or non-reported data items for particular companies on COMPUSTAT. When this occurs, surrogate values need to be estimated for the missing variable. Thus, the restriction to COMPUSTAT data places the computer-based model at a slight disadvantage relative to the rich array of data available to the loan officer. These limitations make positive findings from the model more difficult. Hence, the useful conclusions that are obtained from analysis of this limited data source are more impressive, considering the omission of these potentially relevant factors.

Initially, we did not anticipate performing industry adjustments of the data. We restricted our sample to industrial and retailing firms, excluding utilities, finance and real estate firms and regulated transportation companies. Analysts and loan officers claim to adjust financial ratios for industry effects, but previous modeling attempts to introduce industry adjustments have not been uniformly successful. The process of classifying complex companies into narrow industry categories and constructing industry averages can introduce errors that more than offset potential increases in explanatory power. By excluding industries, such as utilities and finance companies, with known differences in financial structure and operation, we hope to avoid the necessity of introducing formal industry adjustments into the model.

A total of 545 outstanding loans from the commercial bank were identified in an April 30, 1976 loan report. Only 192 of these could be matched with firms on the COMPUSTAT tape. Many of the excluded loans were to foreign companies, to divisions of larger firms, or to non-corporate entities. After eliminating utilities, finance and real estate companies, and regulated transportation companies, we had a final sample of 140 loans. These loans had the following classification status:

Classification	*Number of Loans*
I	109
IA	16
II	10
III	5

Financial data from 1975 financial statements (and earlier) which would have been available by April 30, 1976 were used to estimate the model[9]

4. Model Estimates

We soon found that two ratios, leverage and funds flow, consistently had important explanatory power. The leverage, or debt-equity, ratio was measured as:

$$D/E = (\text{Long Term Debt} + \text{Current Liabilities})/\text{Total Assets}.$$

[9] To insure that the financial statements were available by April 30, 1976, we checked the filing date of the Form 10-K for all companies whose loans were classified as IA, II, or III. We also checked a sample of the type I companies. (If the 10-K was not available, the annual report was used. In four instances, neither the 10-K nor the annual report could be checked. For these companies, the earnings announcement date in *The Wall Street Journal* was checked.) The financial information was available for every company examined in this way by April 30, 1976.

To insure that the COMPUSTAT information was comparable to the information to the loan officer, we used a COMPUSTAT tape prepared in June, 1976. Therefore, the COMPUSTAT information would not be affected by reporting changes made in subsequent fiscal years. That is, no pre-1976 COMPUSTAT items were adjusted because of events subsequent to 1975.

The funds flow ratio used funds from operation in the numerator and a measure of fixed commitments in the denominator. In addition to the usual interest expense term in the denominator (yielding the "Times Interest Earned" ratio) we included minimum rental commitment (from non-cancellable leases) and a three-year average of principal repayments of debt. This latter term represented the ability of the firm to meet its maturing obligations from current operations without having to depend on a rollover of maturing debt. Formally, this fixed charge coverage ratio was:

$$\text{FCC} = \frac{\text{Funds From Operations}}{\begin{array}{l}(\text{Interest Expense} + \text{Minimum}\\ \text{Rental Commitment} + \text{Average}\\ \text{Debt Maturing Within Three}\\ \text{Years})\end{array}}$$

Once we included these two variables, it was hard to find a third variable that added much explanatory power. Net income, size, and working capital ratios were insignificant once the D/E and FCC variables were in the model. A small improvement was obtained by including a sales trend variable. This variable was measured initially as:

$$\text{SD} = \begin{array}{l}\text{Number of Consecutive Years}\\ \text{of Sales Decline}\end{array}$$

The linear function using these three variables to explain loan classifications was:[10]

$$\begin{array}{l} Y = -3.90 + 6.41\ \text{D/E} \\ \qquad (3.91)\ \ (4.59) \\ \quad -1.12\ \text{FFC} + .664\ \text{SD} \\ \qquad (4.08)\ \ \ \ (2.65) \end{array} \qquad (2)$$

where Y is the predicted score for a given loan. A loan is classified into the four categories by the following rule:

TABLE 1

1976 CLASSIFICATIONS ACTUAL AND ESTIMATED USING EQUATION (2)

		Actual			
		I	*IA*	*II*	*III*
Estimated (Using Eq. 2)	I	101	9	0	0
	IA	7	7	2	1
	II	1	0	8	1
	III	0	0	0	3
	Total	109	16	10	5

$Y \leq 0$	Category I
$0 < Y \leq 1.255$	Category IA
$1.255 < Y \leq 2.79$	Category II
$2.79 < Y$	Category III

Thus, a company with a high fraction of debt in its capital structure, with one or two years of declining sales, and with minimum coverage of fixed commitments will tend to be in a high-risk category.

With this model, the 140 loans in the sample population were classified as shown in Table 1.

Of the 109 unclassified (category I) loans, 101 are correctly classified into category I, seven are incorrectly classified into category IA, and one is incorrectly classified into category II. The ideal structure in Table 1 is to have positive entries just along the main diagonal, indicating perfect classification by the model. Overall, 119 of the 140 loans, or 85 percent, are correctly classified. This high figure is mildly misleading since it arises from a 93 percent success rate on category I loans but a less than 60-percent success rate on the remaining loans. The category IA loans are particularly hard to identify reliably.

[10] The values in parentheses are the maximum likelihood estimate divided by the standard error of the estimate. Asymptotically, this ratio is a t-statistic.

Most importantly, though, only two loans were misclassified by more than one category and all adversely classified loans (categories II and III) were signaled as substandard loans. Further, eight out of the ten category II loans are correctly classified, and four of the five category III loans are predicted to be in either category III or II. Thus, even though an extremely naive model of predicting all loans as category I would correctly classify 78 percent of all loans (109/140), such a procedure would misclassify all of the substandard loans, some by an error of two to three categories. Since these loans are of the greatest interest and concern to the bank, the performance of the model given by Equation (2) relative to the naive model is much better than is suggested by merely reporting the increase in the percentage of correctly classified loans from 78 to 85 percent. The most important test of the model is to distinguish high risk (category II and III) loans from low risk (category I) loans. The model generally does well by this criterion.

Of additional interest, while developing and estimating Equation (2), we examined all misclassified loans. In this process, we discovered two loans that were misclassified in the bank's records. In both cases, the correct classification of the loans was in the direction predicted by the model. Thus, the model not only could be used to explain the classification of most of the bank's loans, it could also identify loans whose classification status was most suspicious and likely to be in error.

In an initial attempt to validate the model, we obtained the classification status of a sample of 187 loans outstanding in March 1975. These were matched with the financial statements for the calendar year 1974 and earlier. Using the model estimated on 1976 classifications, the predictions[11] of the 1975 loan classifications is presented in Table 2. As in the 1976 sample, about 85 percent of the loans (160/187) are correctly classified. This is again caused by doing an excellent job on category I loans and a mediocre job on the riskier classifications. Nevertheless, the model did tend to identify the higher risk loans. The two category III loans and half of the category II loans were classified into the two highest risk categories.

TABLE 2

1975 CLASSIFICATIONS ACTUAL AND PREDICTED USING EQUATION (2)

		Actual			
		I	*IA*	*II*	*III*
Predicted (Using Eq. 2)	I	152	8	3	0
	IA	9	4	2	0
	II	0	2	3	1
	III	0	0	2	1
	Total	161	14	10	2

Of more interest for this sample, we were able to look one year ahead to see the 1976 classification status of the loans.[12] Of the ten category II loans in 1975, we predicted three as category I loans. Of these three, two were upgraded (one to IA, one to I) and one was paid off. The two predicted in category IA did remain as category II loans, but both category II loans predicted by the model to be in category III were reclassified by the bank to category III loans by April

[11] We will use the term "prediction" to indicate that the classification model parameters were "estimated" on a different sample of data. That is, one sample is used to "estimate" the model parameters. Those parameters are then used on another sample to "predict" the classifications.

[12] This test is biased in favor of the model since the model was estimated using 1976 classification data.

TABLE 3A

1976 CLASSIFICATIONS ACTUAL AND ESTIMATED USING EQUATION (3)

		Actual (4/76)			
		I	*IA*	*II*	*III*
Estimated (Using Eq. 3)	I	105	11	0	0
	IA	3	4	1	1
	II	1	1	9	0
	III	0	0	0	4
	Total	109	16	10	5

TABLE 3B

1975 CLASSIFICATIONS ACTUAL AND PREDICTED USING EQUATION (3)

		Actual (3/75)			
		I	*IA*	*II*	*III*
Predicted (Using Eq. 3)	I	155	7	3	0
	IA	5	4	2	0
	II	1	3	3	1
	III	0	0	2	1
	Total	161	14	10	2

1976. Thus, for this category, the discrepancies between the predicted and the actual classification were generally resolved in favor of the model's predictions. Similar predictive ability was noted in other categories. Of the nine category I loans predicted by the model to be IA, four were subsequently reclassified to IA. The two IA loans, predicted by the model to be in category II, were both downgraded to category II within the next year. Thus, the model's classifications appear to be including information that has not yet been incorporated in the loan officer's evaluation. A favorable bias is present in this analysis, however, since the model was estimated on 1976 classification data.

A further validation was done by directly estimating a 1975 classification model using 1974 financial data. As with the 1976 model, the debt-equity and funds-to-fixed-expense ratios were highly significant. Unlike the 1976 model, the number-of-years-of-sales decline variable was not at all significant. This suggested that this particular form of the variable may have been specific to the 1976 population and economic events. After experimentation with many sales trend definitions, including even price-level adjusted data, we obtained a relatively simple weighted average of past changes in sales:

Let

S_t = Sales in year t

and

ST_t = Sales Trend Variable for year t.

Then

$$ST_t = 100*[.6*(S_t - S_{t-1}) + .3*(S_{t-1} - S_{t-2}) + .1*(S_{t-2} - S_{t-3})]/S_t$$

Companies with consecutive sales decline years using our previous sales trend variable would have a negative score with this variable since S_{t-1} would be greater than S_t and S_{t-2} would be greater than S_{t-1}.

The model estimated on 1976 classifications and 1975 financial data now appears as:

$$Y_{1976} = \underset{(3.54)}{-3.17} + \underset{(4.44)}{6.01}\ \text{D/E} - \underset{(3.65)}{1.03}\ \text{FCC} - \underset{(2.00)}{.033}\ \text{ST} \qquad (3)$$

The performance of this model is presented in Table 3A. Comparing this table to Table 1 reveals an even better classification record except for the troublesome IA category.

A separate estimation done on 1975 classifications and 1974 financial data yielded:

TABLE 4A

1975 CLASSIFICATIONS ACTUAL AND ESTIMATED USING EQUATION (4)

		Actual (3/75)			
		I	*IA*	*II*	*III*
Estimated (Using Eq. 4)	I	160	10	5	0
	IA	0	1	0	0
	II	1	3	4	2
	III	0	0	1	0
	Total	161	14	10	2

TABLE 4B

1976 CLASSIFICATIONS ACTUAL AND PREDICTED USING EQUATION (4)

		Actual (4/76)			
		I	*IA*	*II*	*III*
Predicted (Using Eq. 4)	I	107	13	1	1
	IA	0	0	0	0
	II	2	3	9	3
	III	0	0	0	1
	Total	109	16	10	5

$$Y_{1975} = \underset{(3.07)}{-2.75} + \underset{(3.36)}{4.61}\ \text{D/E} - \underset{(3.84)}{1.03}\ \text{FCC} - \underset{(1.57)}{.019}\ \text{ST} \qquad (4)$$

The performance of this model is summarized in Table 4A. Again, loans in the IA category are difficult to classify correctly. The apparently high misclassification rate in category II, though, actually gets resolved in favor of the model. For the ten category II loans in 1975, the one loan predicted by the model to be a III was subsequently reclassified to a III by the bank. Of the five loans predicted to be a I, one was subsequently reclassified to a I, one to a IA, and a third was paid off (the other two remained as category II loans). Thus, the discrepancies between estimated and actual classifications are frequently resolved in the model's favor. This finding is a cleaner validation test than the previously reported one since the 1975 model is shown to have predictive power in the subsequent year.

A further cross-validation was performed. The 1976 estimated model (Equation 3) was applied to the 1974 financial statements of firms to predict loans classified in 1975. Similarly, the 1975 model (Equation 4) was applied to 1975 financial statements to predict loans classified in 1976. Such an exercise simulates an actual classification system in which a model estimated in one year is applied to a population of loans in a different year. The predictions are presented in Tables 3B and 4B, respectively. In both cases, the models estimated in one year did almost as well in explaining the classification status of the other year as did the model specifically estimated for that year.

Firms with Negative Funds Flow

A peculiar problem arises in computing the funds-flow-to-commitments ratio (FCC) when the numerator, funds flow from operations, is negative. In the normal case, when funds from operations is positive, larger values of the ratio imply a stronger financial condition for the firm. For a given value of funds from operations, large values of the denominator (of fixed charges) yield small values of the ratio and, hence, indicate a weaker financial position. When funds from operation is negative, the ratio is negative and the effect of increases in the denominator of fixed commitments works in an opposite direction. That is, decreases in fixed charges make the denominator smaller and, hence, the FCC ratio more negative (algebraically smaller). Thus when funds from operation is negative,

smaller values of fixed commitments make the firm seem riskier. This is counter to how we wish the FCC ratio to behave.

This problem arises for any ratio when the numerator can take on negative as well as positive values. The effect of a decrease in the denominator works to increase the ratio when the numerator is positive but to decrease the ratio when the numerator is negative. There appears to be no simple way of adjusting the ratio formulation to overcome this perverse effect.[13]

We defined two alternatives to the FCC ratio to handle the situation when a company's funds flow could be negative. One possibility was to use the difference rather than the ratio between funds from operations and fixed charges:

R = Restated Coverage
= [Funds from operations— (interest expense + minimum rental commitment + average debt maturing within three years)]/Total Assets.

We divide by total assets to control for the size of different firms. In effect, the variable R measures the net return on assets not encumbered by previous commitments. Firms with small (less than 1 or 2 percent) values of R are operating on thin profitability ratios.

The second re-definition involved estimating the mean and variance of next year's funds from operations, based on historical trends, and computing:

P = Probability that next year's funds from operations will be negative.

This variable concentrates solely on the likely sign of the funds from operations and ignores the fixed commitments of the firm.

The basic model was re-estimated using these two alternative specifications of the funds flow variable. All three models (using FCC, R, or P) had similar explanatory and predictive ability. Thus, the peculiar behavior of the FCC variable did not lead to significant distortions. Of course, there were only a few firms that had negative funds from operation. At this stage, the choice from among the three models must be determined from testing on more extensive data.

Probit Versus Regression Analysis

The probit analysis used in this study is a more complex statistical procedure than ordinary least squares (OLS) regression. Even though the structure of the dependent variable implies that the probit analysis is most appropriate for analyzing the loan classification decision, it still may turn out that OLS regression performs almost as well in this situation. For example, in a previous study [Kaplan and Urwitz, 1979] on bond ratings, the more correctly specified probit procedure did not perform much better than an OLS regression approach.

To compare the probit model with a regression model, regression models were estimated on the 1975 and 1976 data samples. The loan category was coded as follows: I = 0, IA = 1, II = 2, III = 3. The estimated regression models were:

$$\begin{array}{lllll} R_{1976} = -.982 + 2.74 & \text{D/E} & -.0076 & \text{FCC} & \\ \quad (4.71) \quad (8.32) & & (.29) & & \\ \quad -.019 & \text{ST} & & & (5) \\ \quad (4.87) & & & & \end{array}$$

[13] Lev and Sunder [1979] have examined a ratio formulation when the numerator can take on both positive and negative values. They suggest that if the numerator is a flow variable (e.g., net income) and the denominator is a stock (e.g., end-of-period owners' equity), then the ratio can be restated as the beginning-of-period stock divided by the end of the period stock. Our FCC ratio, however, is not amenable to this treatment. While the numerator (funds from operations) is a flow, the denominator is *not* the associated stock variable.

TABLE 5A

1976 CLASSIFICATIONS ACTUAL AND ESTIMATED USING EQUATION (5)

		Actual (4/76)			
		I	*IA*	*II*	*III*
Estimated Using Eq. (5)	I	85	7	0	0
	IA	24	9	10	2
	II	0	0	0	2
	III	0	0	0	1
	Total	109	16	10	5

TABLE 5B

1975 CLASSIFICATIONS ACTUAL AND PREDICTED USING EQUATION (5)

		Actual (3/75)			
		I	*IA*	*II*	*III*
Predicted Using Eq. (5)	I	139	5	1	0
	IA	21	9	6	2
	II	1	0	3	0
	III	0	0	0	0
	Total	161	14	10	2

$$R_{1975} = \underset{(3.45)}{-.693} + \underset{(6.43)}{2.03}\ \text{D/E} - \underset{(.40)}{.010}\ \text{FCC} - \underset{(3.39)}{.013}\ \text{ST} \qquad (6)$$

The largest difference between Equations (5) and (6) and the previously estimated probit Equations (3) and (4) is that the fixed-charge-coverage (FCC) ratio is now statistically insignificant.

In order to examine the performance of the regression models, we need to specify a procedure to convert from the numerical score R to a particular loan classification category. Theoretically, this could be done based on a benefit-cost approach relative to the costs of making Type I and Type II errors in each of the four categories. Lacking a formal model of these costs, we adopted the simple, intuitively reasonable, but somehat arbitrary procedure of using the mid-point between each category value to define the interval for that category. That is, loans were classified by their R-score using the following procedure:

Score	*Category*
$R < 0.5$	I
$0.5 \leq R < 1.5$	IA
$1.5 \leq R < 2.5$	II
$2.5 \leq R$	III

The performance of the model estimated on 1976 classifications and 1975 financial data is presented in Table 5A. In comparison with the probit model (see Table 3A), the regression model classifies only 68 percent correctly rather than 87 percent with the probit model. When Equation (5) is used to predict the 1975 classifications from 1974 financial data, 36 firms are misclassified (see Table 5B). The corresponding number of misclassifications with the probit model was 22. Also, a much higher incidence of misclassifications occurs in the critical category II and III loans. Thus, the 1976 probit model outperforms the 1976 regression model in both an explanatory and predictive sense.

Similar results are obtained using the models estimated from the 1975 classifications. Tables 6A and 6B summarize the performance of model (6). Comparing Table 6A with Table 4A, the regression model misclassified 35 loans, whereas the probit model only misclassified 22. Similarly, Table 6B shows 36 classification "errors" instead of 23 for the probit model. Also, the regression model is particularly faulty with respect to category II and III loans. None of the ten category II loans in either 1975 or 1976 had an R-score in excess of 1.5 and only one of the seven category III loans in the two years had an R-score larger than 1.5. The OLS regression approach compresses all of the risk scores of the loans, making it difficult to discriminate among

TABLE 6A

1975 CLASSIFICATIONS ACTUAL AND ESTIMATED USING EQUATION (6)

		I	*IA*	*II*	*III*
	I	145	7	3	0
Estimated	IA	16	7	7	2
Using Eq. (6)	II	0	0	0	0
	III	0	0	0	0
	Total	161	14	10	2

TABLE 6B

1976 CLASSIFICATIONS ACTUAL AND PREDICTED USING EQUATION (6)

		I	*IA*	*II*	*III*
	I	95	8	0	0
Predicted	IA	14	8	10	4
Using Eq. (6)	II	0	0	0	0
	III	0	0	0	1
	Total	109	16	10	5

the different risk classes. We conclude, from this comparison, that at least for the loan classification analysis, the probit analysis is a superior procedure to OLS, and its better performance should justify the additional cost and complexity required to implement it.

Comparison with Bankruptcy Models

The loan classification decision can be viewed as an attempt to predict the financial distress or bankruptcy of a firm. As a loan gets classified into a higher category (say, II or III), there is presumably a higher likelihood of the borrowing firm going into bankruptcy. Therefore, an interesting comparison can be made of how well bankruptcy models developed by Altman [1968] and Wilcox [1973] can classify our population of commercial loans.[14]

The Altman and Wilcox models have generally been developed and tested on a matched-pair sample of healthy and bankrupt firms. Their reportedly good performance is certainly influenced by testing on a population where 50 percent of the firms are known to have entered bankruptcy. (One commentator has described this procedure as an autopsy of deceased firms rather than as a prediction of business failures [Benishay 1973, p. 181].) Testing the Altman and Wilcox models on our loan population is a more realistic test of the model's performance on a representative sample of firms currently in business.

The Altman model produces a Z-score:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 - 0.6X_4 + 1.05X_5$$

where

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 debt
X_5 = Sales/Total assets.

Altman uses a cutoff score of 2.675 (firms with scores below 2.675 are classified as bankrupt-prone) although classification errors are considered likely for Z-scores in the interval 1.81 to 2.99. The Z-scores for companies in the 1976 loan sample are computed and presented in Table 7. Since the Altman model does not give cutoffs for loan classifications, it cannot be used directly to classify loans. But since low Z-scores imply a high probability of bankruptcy, low scores should correlate with category III or category II loans.

If the cutoff of 2.5 (instead of the suggested 2.675) is used to signal category II and III loans, 80 percent of the category II and III loans are properly classified.

[14] Bankruptcy models have also been developed by Beaver [1966] and Deakin [1972], but the performance of these models was not evaluated in this context. Also, the Z-score model has been extended into a "Zeta model" (Altman, Haldeman and Narayanan [1977]. The zeta model is available commercially but the published article did not disclose coefficient estimates. Hence, the extended model could not be evaluated by us.

TABLE 7
Z-SCORES FROM ALTMAN MODEL

	Actual Classification			
Z score range	*I*	*IA*	*II*	*III*
.5–1.0	4	0	1	2
1.0–1.5	6	4	1	1
1.5–2.0	8	1	4	1
2.0–2.5	18	4	2	0
2.5–3.0	22	3	1	1
3.0–3.5	20	1	0	0
3.5–4.0	9	3	0	0
4.0–4.5	10	0	0	0
4.5–5.0	5	0	1	0
>5.0	7	0	0	0
	109	16	10	5

TABLE 8
PROBABILITY SCORE FROM WILCOX MODEL

	Actual Classification			
Probability of failure	*I*	*IA*	*II*	*III*
0–.1	45	3	6	3
.1–.2	2	2	1	1
.2–.3	4	1	0	0
.3–.4	2	2	0	0
.4–.5	3	0	2	0
.5–.6	3	0	0	0
.6–.7	0	0	0	0
.7–.8	2	0	1	0
.8–.9	1	0	0	0
.9–1.0	47	8	0	1
	109	16	10	5

But 33 percent of the current loans (category I) are misclassified as category II or III. If 2.0 is used instead, the number of category I loans misclassified drops to 17 percent, but the number of correctly classified category II and III loans decreases to 67 percent. The actual number of category II and III loans correctly classified using the cutoff of 2.0 is 10, while the number of misclassified category I and IA loans is 23. Thus, using this cutoff would misclassify over twice as many loans into serious classes than it would properly classify. Even lower *Z*-score cutoffs would yield similar results. Because of these misclassification errors, the Altman model seems overly severe in its adverse classifications, although it does indeed provide some level of risk measurement.

The Wilcox model, based on a gambler's ruin probability model, computes the probability of bankruptcy as a function of two parameters; X and N.

$$\Pr\{\text{failure}\} = \begin{cases} 1 & \text{if } X \le 0 \\ \left[\dfrac{1-X}{1+X}\right]^N & \text{if } X > 0 \end{cases}$$

Wilcox estimates these parameters by using the following definitions:

Adjusted Cash Position = Cash + .7 (Current Assets other than Cash) + .5 (Long Term Assets) − Liabilities

Adjusted Cash Flow = Net Income − Dividends − .3 (Period-to-Period Increase in Non-Cash Current Assets) − .5 (Period-to-Period Increase in Long Term Assets) + Stock Issued in Merger or Acquisition

$$\sigma = [(\text{Mean Adjusted Cash Flow})^2 + (\text{Variance of Adjusted Cash Flow})]^{1/2}$$

Then:

N = Adjusted Cash Position/σ
X = Mean Adjusted Cash Flow/σ.

For our sample of loans, the mean and variance of adjusted cash flow were estimated for up to seven years. The adjusted cash position was calculated by using fiscal year end 1975 data. Table 8 presents the Wilcox probability measure for the 1976 population of classified loans. The Wilcox model provides no cutoff specification for loan classification, but higher probabilities of failure should correspond to higher risk loan categories.

FIGURE 1

SAMPLE COMPANY—ADVERSELY CLASSIFIED

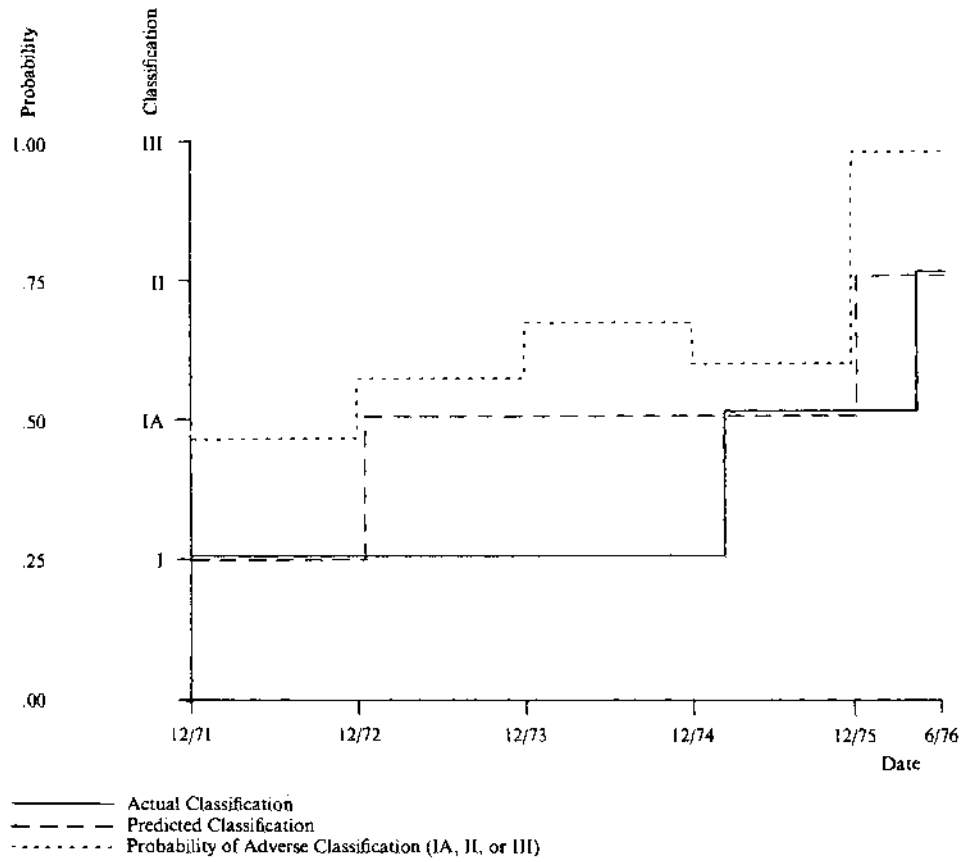


Table 8, however, does not indicate any clear trends of this sort. Instead, three of the category III loans have less than a 10 percent probability of failure, while 47 of the category I loans have a very high probability of failure.

The reason for the poor results of the Wilcox model seems to be in the definition of adjusted cash flow. Wilcox does not include debt issues and bank loans as cash inflows. Instead, the cash flow must come from net income. Firms that are growing rapidly do not show sufficient net income to support the buildup of assets. As a result, these firms, according to the Wilcox model, will fail. This explanation accounts for the large number of firms whose probability of failure is nearly 1.

It should be obvious that our loan classification model offers distinct advantages over these two bankruptcy models that have appeared in the literature.

Classification Changes Over Time

Another test of the predictive ability of the model was performed. This test involved predicting the loan classifications over a five-year period using financial data. Predicted classifications were compared with the actual classification history on a firm-by-firm basis. Time-series graphs of the actual and predicted

classifications showed the lead or lag of the prediction as well as any classification differences. Thus, on a loan-by-loan basis, the predictive ability of the model can be examined. Because the loan population in the study consisted of over 250 firms, plotting the classification history for each firm would provide so much information as to to be confusing. Instead, plots were prepared for all loans that were adversely classified during some portion of the five-year period. The loan histories indicated the model's ability to predict adversely classified loans.

A typical plot is shown in Figure 1. The actual classification of the loan is indicated by a solid line. The loan depicted in Figure 1 shows the loan to have current status[15] (category I) until March 1975. At that time, it is reclassified as category IA. It continues with that status until April 1976, when it becomes a category II loan.

The actual classification can be compared with the predicted classification which is computed from Equation (3). The predicted classification is shown by the dashed line. The predicted loan classification shown in Figure 1 is initially I. In December 1972, the prediction changes to IA. Finally, in December 1975, the status is downgraded to category II.

Classifications are predicted only at the fiscal year end of the company. Only at those times is new information made available on the annual COMPUSTAT file. Therefore, predicted classification changes appear only once per year.[16] That prediction is continued until the next fiscal year end. Financial data may not actually be available until two or three months after the year end. So a three-or four-month lead shown in predicting the transition to II may in fact be only a one- or two-month lead, or perhaps none at all. The plot shows these year-end situations with a potential bias for the model's predictions to lead the loan officer. But the model receives financial information only once per year. The loan officer may receive financial data more often. This effect tends to bias the loan officer's classification to lead the model.

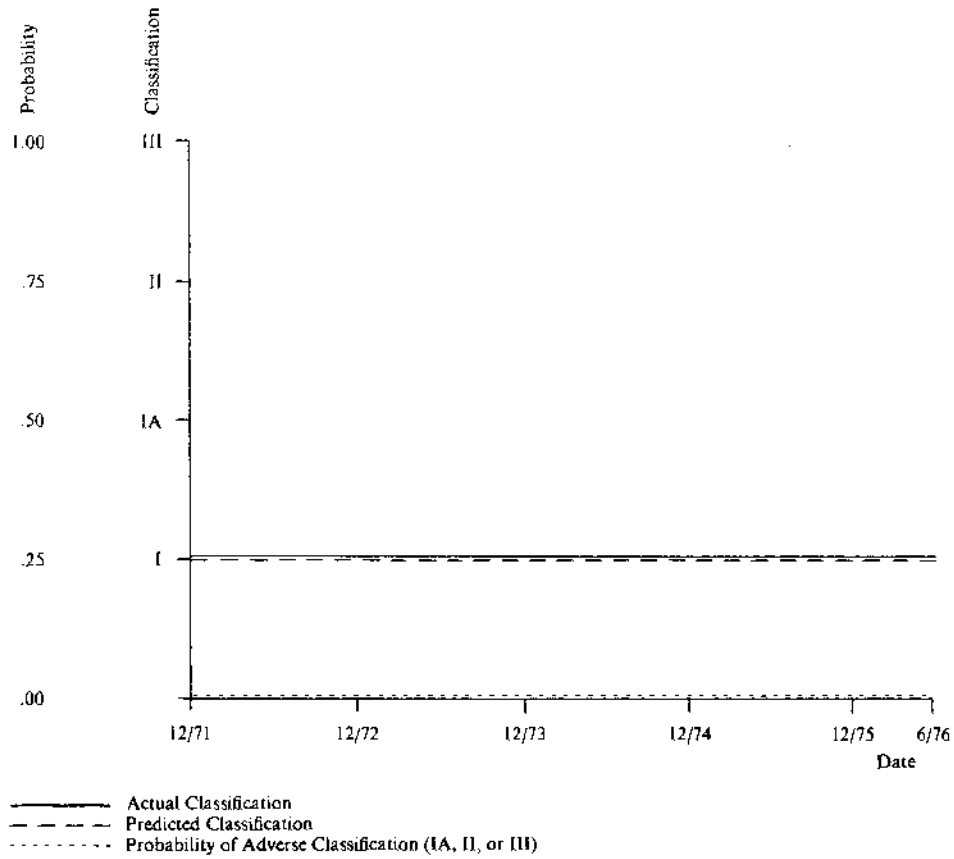
The predicted classification changes only in discrete steps; as a result, trend lines are difficult to visualize. The estimation technique we used provides two risk estimators that are continuous. These estimates may provide more information than is contained in the predicted classification line. The estimators are (i) the estimates of the underlying risk (Variable (Y) of Equation (1)) and (ii) the probability of classification into each of the classification categories. These two estimators provide similar information. To simplify the figures, we plot only the probability that a loan is adversely classified (i.e., categories IA, II, or III). The probability of adverse classification, drawn as a dotted line in Figure 1, is scaled so that a probability value of 0.50 corresponds to category IA in the figure, and a probability of 1.0 corresponds to category III. This scaling is a useful heuristic in depicting the loan status. For example, the company shown in Figure 1 is predicted to be of category I in December 1971 although the probability that it is adversely classified is about 45 percent. (This consists of a 36 percent probability that the loan is IA and a nine percent probability it is in category II.

[15] The actual loan classification line records two conditions as category I loans. One condition is an outstanding loan with a current status (classification I). A loan that is not outstanding, however, is also recorded as category I. We know only if the loans in the population are outstanding in March 1975 and April 1976. We do not know whether they are outstanding at other times unless they were adversely classified.

[16] Annual changes in the prediction is purely an artifact of the data source. If the model were estimated with quarterly financial information, predictions could then be made quarterly.

FIGURE 2

SAMPLE COMPANY—NOT ADVERSELY CLASSIFIED



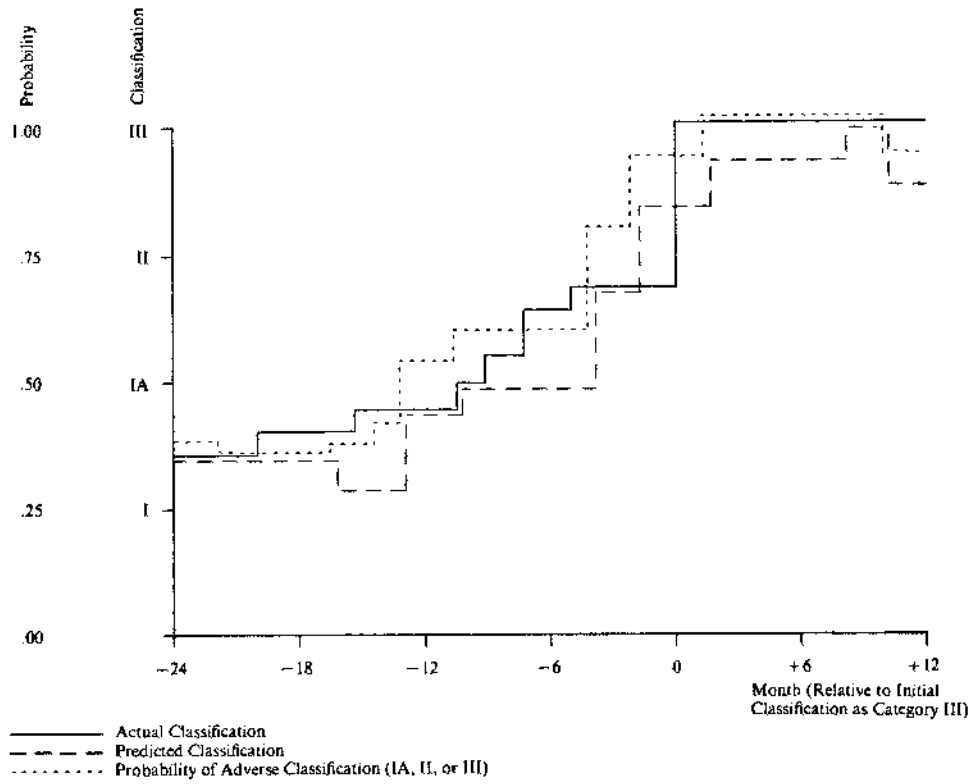
The statistical classification procedure selects the category with the highest probability as the predicted classification.) Thus, although this company is predicted to be of risk-class I, it is predicted to be riskier than a loan with a probability of adverse classification of, say, five percent. The adverse classification probability indicates that the Figure 1 loan is more likely to be adversely classified as time passes. Thus, this predictor may serve as an indicator of risk of loan default.

Figure 1 shows an example of a plot for an adversely classified loan. Plots of a random sample of firms that were not adversely classified were also made. These plots were examined for predictions of adverse classification. Figure 2 is an example of one of these plots. The actual classification is I throughout the five-year period. The dashed line indicates that the predicted classification is also I throughout and the probability estimator shows no evidence of increasing risk.

Examining predictive ability of the model in this fashion is cumbersome. Instead, the model's predictions were aggregated for the set of loans that were classified as type III in April 1976. There are several reasons for choosing these loans. They provide a rigorous test of the predictive ability because the model's

FIGURE 3

AGGREGATED CLASSIFICATION HISTORY FOR CATEGORY III LOANS FROM APRIL 1976 SAMPLE



estimation was weakest on these loans. Also, predicting difficulty of loan repayment is obviously important to banks. If the model's predictions are coincident with loan officers' classification changes, the model may be a useful tool in identifying troubled loans.

To aggregate the plots, the loan histories of the five firms were aligned on the date of initial classification to category III. That is, month 0 is defined to be the date of category III classification for each loan. Using loan histories for the preceding 24 months and the succeeding 12 months, we computed a composite classification measure for each month. This composite classification was simply an arithmetic average of the individual classifications using the transformation that I=0, IA=1, II=2, and III=3. For example, in month −4, the five firms had actual classifications of II, II, IA, II, and II. The portfolio average classification then is 1.8, or slightly less than a category II. Admittedly, this weighting scheme is arbitrary and will not, in general, provide an overall measure of default risk on the portfolio. Its use is solely to depict graphically an aggregated classification measure. The solid line in Figure 3 shows the aggregated actual classification measure. In month −24, the "average" loan in this portfolio is actually classified between I and IA. As time progresses, the classification increases. At month 0, the "average" classification rises to III. The actual classification remains as III throughout the remaining 12 months.

The actual classification can be compared with the predicted classification (using Equation (3)) which is indicated by the dashed line. The "average" predicted classification is computed by using the same method as the "average" actual classification, except that the predicted classification for each loan was employed. In month −24, the "average" loan is predicted to be classified between I and IA. In fact, the "average" predicted classification is equal to the actual classification in that month.[17] The predicted classification closely follows the actual classification throughout the 36-month period. Sometimes the predicted classification lags the actual; for example, see months −20 to −13. On the other hand, the predicted classification sometimes leads the actual; months −2 and −1 show this.

Figure 3 presents averaged predictions for the probability of adverse classification as a dotted line. This estimator tracks the actual classification very closely.

These graphs of loan classification histories show that the model is quite successful in predicting loan classification. Not only can the model perform well cross-sectionally, it can also indicate trends in loan risk changes over time. Also, to the extent that the model's predictions are leading the actual loan classification, discrepancies between predicted and actual classifications (the off-diagonal terms in Tables 1–4) are not "errors" but merely lags in the loan classification process. In these instances, the divergence between model prediction and actual classification is desirable by providing a signal to the loan officer to re-examine the status of the loan.

5. Summary and Future Work

We have been successful in developing a simple linear model that explains and predicts loan classification decisions in a large commercial bank. The model uses three independent variables—debt-equity ratio, funds-flow-to-fixed-commitments ratio, and sales trend—to compute a score that can classify a loan into one of four mutually exclusive categories. Except for a troublesome "transition" category (IA), the model generally can distinguish high risk (category II and III) loans from low risk (category I) loans with only a few errors. In many instances where the model's score differs from the actual classification, the loan is subsequently reclassified in the direction predicted by the model. The model is superior to previously developed bankruptcy models in predicting the riskiness of a loan as measured by its risk-classification status.

Future work will provide more extensive tests of the predictive ability of the model. In particular, we wish to investigate the use of quarterly data to provide an early indication of rapidly deteriorating or improving financial condition. At present, we can change the classification of a loan only once a year, when the annual report is issued. This limits the ability of the model to respond rapidly to changing financial conditions.

[17] The solid line (depicting actual classification) and the dashed line (indicating predicted classification) are drawn to not overlap in the figures so that each line can be readily distinguished.

REFERENCES

Altman, Edward I., "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy," *Journal of Finance* (September 1968), pp. 589–609.

———, Robert G. Haldeman, and P. Narayanan, "Zeta Analysis," *Journal of Banking and Finance* (1977), pp. 29–54.

Beaver, William H., "Financial Ratios as Predictors of Failure," *Empirical Research in Accounting: Selected Studies, 1966*, Supplement to *Journal of Accounting Research*, pp. 71–111.

———, "Alternative Accounting Measures as Predictors of Failure," THE ACCOUNTING REVIEW (January 1968), pp. 113–122.

Benishay, Haskel, "Discussion of a Prediction of Business Failure Using Accounting Data," *Empirical Research in Accounting: Selected Studies, 1973*, Supplement to *Journal of Accounting Research*, pp. 180–182.

Cohen, Kalman J., Thomas C. Gilmore and Frank A. Singer, "Bank Procedures for Analyzing Business Loan Applications," in *Analytical Methods in Banking*, edited by Kalman J. Cohen and Frederick S. Hammer (Richard D. Irwin, Inc., 1966), pp. 219–249

Deakin, Edward B., "A Discriminant Analysis of Predictors of Business Failure," *Journal of Accounting Research* (Spring 1972), pp. 167–179.

Haslem, John A., and William A. Longbrake, "A Credit Scoring Model for Commercial Loans, A Comment," *Journal of Money, Credit and Banking* (August 1972), pp. 733–734.

Hester, Donald D., "An Empirical Examination of a Commercial Bank Loan Offer Function," *Yale Economic Essays* (Spring 1962), pp. 3–57; reprinted in slightly condensed form in *Analytical Methods in Banking*, edited by Kalman J. Cohen and Frederick S. Hammer (Richard D. Irwin, Inc., 1966), pp. 178–215.

Houget, George R., "Techniques of Term Loan Analysis," *The Journal of Commercial Bank Lending* (March 1975), pp. 30–36.

Kaplan, Robert S., and Gabriel Urwitz, "Statistical Models of Bond Ratings: A Methodological Inquiry," *Journal of Business* (April 1979), pp. 231–261.

Lev, Baruch, *Financial Statement Analysis: A New Approach* (Prentice Hall, 1974).

———, and Shyam Sunder, "Methodological Issues in the Use of Financial Ratios," *Journal of Accounting and Economics* (December 1979), pp. 187–210.

Libby, Robert, "Accounting Ratios and the Prediction of Failure: Some Behavioral Evidence," *Journal of Accounting Research* (Spring 1975), pp. 150–161.

McKelvey, Richard D., and William Zavoina, "A Statistical Model for the Analysis of Ordinal Level Dependent Variables," *Journal of Mathematical Sociology* (Summer 1975), pp. 103–120.

National Association of Bank Loan and Credit Officers, *Financial Statements for Bank Credit Purposes* (Robert Morris Associates, 1964).

Office of the Comptroller of the Currency, *The Comptroller's Handbook of Examination Procedure* (March 1973).

Orgler, Yair E., "A Credit Scoring Model for Commercial Loans," *Journal of Money, Credit and Banking* (November 1970), pp. 435–445.

Slovic, P., and S. Lichtenstein, "Comparison of Bayesian and Regression Approaches to the Study of Information Processing in Judgment," *Organizational Behavior and Human Performance* (November 1971), pp. 649–744.

Smith, Victor D., "A Reflective Primer on Lending," *The Journal of Commercial Bank Lending* (April 1974), pp. 49–60.

Wilcox, Jarrod W., "A Prediction of Business Failure Using Accounting Data," *Empirical Research in Accounting: Selected Studies, 1973*, Supplement to *Journal of Accounting Research*, pp. 163–179.