

Commercial Paper Rating Models

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Abstract

This paper extends previous work in the area of commercial paper rating models using data for the years 1985 and 1986 and the ratings of commercial paper by Standard & Poor's and Moody's. MDA, LOGIT, and CART are the three statistical tests used. The models had a prediction rate about 85 percent. It was found that in some rating categories, the quality component (judgment by analysts) played a greater role than in other categories. Variables such as sales, earning power, return on assets, and amount of equity were identified as most important in explaining ratings of commercial paper.

Introduction

Many researchers have studied the determinants of the important variables underlying the quality ratings assigned by Moody's Investors Services and Standard & Poor's Corporation (Bolster and Srinivasan [6], Ederington [10], Peavy [24], Emery and Cogger [13], Peavy and Edgar [25], Perry *et al.* [26], Pinches and Mingo [28, 29], Rappaport *et al.* [32]). Most of these studies develop models for bond ratings.

Commercial paper ratings, however, have received much less attention because most analysts believe the major determinant of a commercial paper rating is the corresponding bond rating (Backer and Gosman [3]). Actually, rating agencies use a process for rating commercial paper that is significantly different from the one used to rate bonds (Peavy and Edgar [25]). Standard & Poor's state that although the analytical rating procedures possess similarities, additional consideration is given to the short life of a commercial paper issue.

Research conducted in this area has identified a model significantly different from the models for rating bond issues. As expected, liquidity has more weight in rating commercial paper than in similar bond rating research. Even with obvious differences in the issues and rating procedures, research has found the corresponding bond rating to be significant in determining the commercial paper rating (Bolster and Srinivasan [6]). Typically, companies whose long-term debt is rated in the upper rating categories also would have highly rated commercial paper. An additional factor considered by Standard & Poor's outside the typical

ratio analysis is the intended use of the cash flows. Companies whose commercial paper issues are tied to a well-defined working capital cycle will be rated more favorably than those where the cash flows are intended for use as a quasipermanent financing instrument.

Given the views of the rating agencies, the rating system, and the beliefs of financial analysts, it is evident that the process of rating commercial paper must be viewed as outside the well-documented arena of bond ratings. The importance of commercial paper as a financing tool and the apparent variance between agency practice and analyst beliefs document the importance of further research in this area.

The commercial paper market has grown from \$130 billion in 1980 to over \$360 billion in 1987 (Federal Reserve Bank of New York [14]). As financial institutions begin to sell and underwrite commercial paper, the need for a complete understanding of the market becomes imperative. Understanding the characteristics that are pertinent for ratings should be a concern of investors, issuers, and the rating agencies.

This paper contributes in two areas. It provides empirical results in the neglected area of commercial paper quality ratings and explores additional tests involving the use of nonparametric methods in finance. The paper uses three alternative models (MDA, LOGIT, and CART) to examine the importance of financial information in determining the quality ratings assigned to commercial paper by both Moody's and Standard & Poor's. In addition to searching for the important explanatory variables, the paper compares the three models to see which model is the most appropriate for this type of research.

A Brief Look at Commercial Paper

Short-term financing is essential to corporate operations, accounting for between 35 percent and 70 percent of external financing. Commercial paper, a short-term unsecured instrument issued by both financial and nonfinancial companies, is a major source of short-term financing for many firms. In the United States, more than 1300 companies issue commercial paper. Over the last year and a half, the relatively young Euro-commercial paper market has doubled in size to over \$50 billion (Jones [20]). Domestically, commercial paper is characterized by short maturities (usually less than nine months), the lack of SEC registration requirements, and the absence of a strong secondary market.

Five organizations provide quality ratings of commercial paper issues. Standard & Poor's, Inc. and Moody's Investors Services dominate, rating the majority of the issues. The three others (Crisanti, Maffei, Inc., Fitch Investor Services Corp., and Duff and Phelps, Inc.) rate less than half as many issues as the larger agencies.

Nonparametric Models

Bond rating methodology traditionally has involved multiple discriminant analysis (MDA) or rank transformation discriminant analysis (RTDA). More recently, a relatively new approach, recursive partitioning analysis (RPA), has been used. Nonparametric methods such as RPA have been used in an attempt to improve the restrictive parametric linking found in such methods as MDA, LOGIT, and PROBIT. Research comparing these methods has provided support for the use of nonparametric methods. Nonparametric methods, such as RPA, typically provide better results because they incorporate better real world assumptions. They also show a superior ability to handle complex data sets.

Other nonparametric classification techniques suggested in past literature include the kernel density estimation procedure (Breiman *et al.* [5]), the k th nearest neighbor rule (Hills [19]), rank transformed discriminant analysis (Conover and Iman [8, 9]), the ID3 algorithm (Quinlan [31]), and goal programming (Freed and Glover [15]). The recursive partitioning algorithm (CART) used in this research was introduced originally by Freidman [16] and is discussed in detail by Breiman *et al.* [5].

As its name implies, RPA belongs to a class of nonparametric partitioning methods that yield a binary classification tree allowing objects to be assigned to one of k known groups. The construction of such a tree takes two steps:

1. Growing the tree;
2. Pruning the tree.

The unclassified data represented by x vectors are allowed to filter down the tree and go either left or right at the various splits as illustrated in Figure 1. The data are split into subsets in an attempt to improve their homogeneity. The data set exhibits the highest degree of impurity or heterogeneity at the top of the tree, with each subsequent split contributing to the purity of the individual subset.

Formally, the sample impurity can be considered a function θ of the node proportions $[p(1/t), p(2/t)]$ where $p(n/t)$ is the proportion of group n profiles found in node t . The function θ has the following properties:

- Is maximized when a node includes group 1 and group 2 cases in equal proportions;
- Is minimized when all the cases in the node belong to the same group;
- Is a symmetric function of $p(n)$.

With θ representing the impurity function, the impurity of a given node can be expressed as

$$i(t) = \theta [(p_l/t), p(2/t)].$$

The objective of a partitioning algorithm is to split the data and decrease heterogeneity. The sample impurity will be lowest when the following function is maximized:

$$i(t) = i(t) - p(r)i(tr) - p(l)i(tl).$$

In this equation, $i(tr)$ and $i(tl)$ denote the impurity of the subsets. Further splitting of the nodes continues until no additional reduction in impurity results. This final tree will be referred to as TREEop.

CART vs. MDA

This research compares results from three alternative models. The capability of each model can be evaluated by comparing the sets of assumptions that underlie them with the less restrictive assumptions of CART. Each model has the same basic goal: to classify with minimal resubstitution cost and error.

Breiman *et al.* [5] compare CART and MDA, identifying the following set of MDA distributional assumptions:

- The explanatory variables are multivariate normally distributed;
- The group covariances are equal;
- The groups are discrete, nonoverlapping, and identifiable.

In many cases the first two assumptions are violated in empirical data sets, which can lead to biased classification results. CART incorporates only the third assumption listed above; the CART methodology should result in fewer violations and have greater applicability.

CART vs. LOGIT

LOGIT is a strong parametric competitor for the nonparametric methodology.¹ Most studies have shown LOGIT to be applicable over a wider

¹If the probability function is in the form of a normal distribution, then the model is known as PROBIT. The LOGIT and PROBIT distributions differ only at the extreme tails. These data had a better fit with LOGIT than with PROBIT. Hence, LOGIT was used in the current study.

range of distributional assumptions than MDA, even though LOGIT assumes variables are multivariate normally distributed, dichotomous, or both. If there is a possibility that the variables may follow some other distribution, LOGIT-based predictions also may be biased. This restrictive assumption, absent from the nonparametric methodology, offers the potential for CART to be appropriate over a broader range of applications because of its complete lack of distributional assumptions.

This brief comparison and explanation of the underlying assumptions develops the framework for testing the three models used in this research. Besides providing empirical comparisons of the models, the results also test the appropriateness of the models as predictors of commercial paper ratings.

The Sample

The ratings come from both Moody's and Standard & Poor's. Commercial paper ratings of all companies were used as published in the December 1985 and December 1986 issues of Moody's *Bond Guide* and Standard & Poor's *Commercial Paper Record*. The inclusion of two years of data allows examination of the reliability and stability of the procedures. The sample was restricted to the companies with complete data available on the Compustat annual industrial tape. Most of the firms possessed dual ratings, with Standard & Poor's having the larger list of firms. Table 1 shows the number of companies in each rating class by year for both rating agencies.

A discussion of the criteria used by Standard & Poor's to assign the various ratings is presented in Table 2.

Twenty-six separate variables were used to search for the most important set of determinants. (See Appendix A for a complete list of the variables.) Most of the variables reflect conventional approaches to the use of financial statement data in analysis. Traditional financial ratios are grouped as operating, financial, liquidity, profitability, and activity ratios. Several of the ratios were collected on the basis of market-determined values and necessarily are related to the market value of equity. It is assumed that a relationship between equity values and commercial paper exists. The ratios used here are derived from Compustat and closely follow earlier research (Peavy and Edgar [25]) in the area of commercial paper. This was done in order to provide comparisons between the two studies.

Results

The results of each model were examined separately and then as a group. First, the MDA model was used on both sets of data in an attempt to classify correctly each company with its appropriate rating. Peavy and Edgar initially

used a two tier rating system for the 83 bank holding company commercial paper issues in their sample. As they expanded the ratings to the three tiers used by Moody's, they found little change in predictive ability, with no issue classified incorrectly by more than one category. This analysis uses the commercial paper ratings assigned by both agencies with no attempt made to separate the firms further.

Results from MDA

For the Moody's data set, the results calculated under an MDA approach show that the model was able to assign the rating correctly 79.3 percent of the time in 1985 and 85.7 percent of the time in 1986. Of the ratings classified incorrectly, the most common type of error was for the model to classify the issue lower than its actual rating. The most common type of error was for a rating of '2' to be assigned when the actual Moody's rating should have been '1.' Table 3 provides complete analysis of the occurrence of errors for the Moody's data using MDA.

Although the Standard & Poor's rating system consists of a six-tier classification, few of the issues in the data set had ratings below the three highest. One negative effect of the expanded rating system appears to be that the MDA model loses much of its accuracy in this application. The 1986 data sample avoids this complication, as it does not have any ratings in the lower three tiers. For the larger data set, 63 of the 184 observations were misclassified in 1985, for a correct classification rate of 65.8 percent. With the use of only three tiers for the 1986 sample the accuracy rate improves to 74 percent. This result, however, pales in comparison to the higher rate found with the use of the Moody's classification system. A similar asymmetry in correctly classifying the firms is found for each of the three models used in this research. The second rating appears to be the most troublesome for both datasets. For the total sample in this study, MDA misclassified Moody's second rating an average of 23 percent of the time and Standard & Poor's second rating an average of 33 percent of the time. The errors are split approximately equally, with incorrect ratings both higher and lower than the second classification. Table 4 shows the classification and predictions for the Standard & Poor's data.

The use of the discriminant procedure allowed determination of the set of most significant explanatory variables for both sets of data. Although several procedures are available for examining the independent variables, this research used a method that examines all possible combinations of variables. The final result is a subset of variables that provides the greatest explanatory power (highest R^2) for a specified number of variables. Typically, the methodology revealed that more than seven or eight independent variables resulted in the

addition of variables not significant at the 10 percent level. The method of finding the best N variable model is considered better than stepwise procedures, as it examines all possible combinations of variables and produces the best combination. The results in Table 5 show the sets of variables for Moody's and Standard & Poor's and their F values.

Results from LOGIT

The LOGIT methodology improved the results. Through the use of the stepwise procedure involved in LOGIT, a set of important independent variables was revealed. By minimizing the gain/loss function, the LOGIT model was able to classify correctly 82.3 percent in 1985 and 87.1 percent in 1986 of the ratings for the Moody's data set. These results are the best set of predictions provided by the LOGIT procedure. Beside allowing the user to choose the cutoff point that provides the best predictive ability, the LOGIT program also examines the importance of individual variables in a stepwise fashion.² This reiteration eliminates the unimportant variables and identifies the most significant set of variables.

Again, in the expanded rating system of Standard & Poor's, lower predictive accuracy than that obtained earlier with Moody's was expected. The classification accuracy using the LOGIT model for this data set was 72.8 percent in 1985 and 83.8 percent in 1986. Although this classification rate is higher than the one with MDA, it is again lower than the classification rate of the Moody's data set with the LOGIT model. The comparison of results for both data sets is found in Tables 6 and 7.

The explanation for these differences seems to lie in the Standard & Poor's expanded rating system. The errors for Standard & Poor's rating system still are found in the three higher categories, not in the lower ones. The models appear to have more difficulty in differentiating the two highest categories for both rating systems. As the rating system is expanded, the quality differences narrow. The models developed here find it increasingly difficult to correctly classify the highest categories. The results appear to point to a similarity of characteristics for the two highest ratings, indicating small differences in the values of the independent variables for these two classifications. Table 8 shows the set of variables for both data sets identified as being most significant and also the variables deleted by the LOGIT procedure.

²The average cutoff point in the study for both the Moody's and the Standard & Poor's data set averaged approximately 65 percent.

Results from CART

Two sets of results were obtained using the CART methodology. With the first trial, linear combinations of the independent variables were allowed. A second run was conducted to examine the relative importance of the results allowing nonlinear combinations. Examining the two sets, one can note a variable's importance when judged on a stand alone basis versus its power of predictability when combinations are allowed. In the CART results for the Moody's data, the nonlinear results show the predictive ability and the importance of the individual data items. The nonlinear assumption yields an accuracy rate ranging from 68 percent to 94 percent, with an overall correct classification rate of 86.6 percent in 1985 and 79.6 percent in 1986. The CART program had much better success in classifying the top ratings correctly, an important result, as over 75 percent of the observations are assigned a rating of '1.' Tables 9 and 10 show that CART encountered the same difficulty as the MDA and LOGIT in correctly classifying the firms rated '2.' The CART program incorrectly classified this group 32 percent of the time in 1985 and 37 percent in 1986. For the 311 firms in the Moody's sample over the two year period, only two of the misclassifications were incorrect by more than one rating. The linear combination mode of the CART program yielded disappointing results, as the model misclassified 32 percent of the observations. Although the different assumptions yield different levels of predictions, the importance of the variable rankings changes also.

The CART methodology was used on the 1986 data to provide a further test of its reliability. The 1985 sample was used to generate the tree and provide test sample results. The 1986 data then were filtered down the tree as a cross validation test. The results confirm the validity of the initial tree developed from the 1985 data, as the cross validated results of 1986 are similar to the 1985 results in terms of classification rates.

In the CART results for the Standard & Poor's data set, a lower level of accuracy is seen again as compared to the results for the Moody's data set. CART's accuracy in predicting the two highest classes for Standard & Poor's ranged from 61 percent to 72 percent in 1985. The model's poor success rate of 52 percent in 1985 is caused by the difficulty in correctly assigning the proper rate to the third class. The CART program misclassified all the firms in this third class, with the entire group being assigned a higher rating. An examination of the results shows that of the 71 firms in the sample with a rating of '2,' the CART model assigned 28 firms a ranking of '1.' This observation is similar to results from the other models, which also had difficulty differentiating rankings of '1' and '2' for the Standard & Poor's data set. The validation results, however, show an improvement in the prediction accuracy of the Standard &

Poor's model. This improvement results in an increased accuracy rate in the second rating class for 1986. The model had an overall prediction rate of 69 percent in 1986.

As was observed with the Moody's data, the use of linear combinations reduced predictive ability. CART showed a strong preference for assigning the issues a rating of '1.' Table 11 shows the ten most important variables for both the Standard & Poor's and Moody's data. These particular sets of variables are the ten most important as classified by CART in helping purify the data and construct the best tree for classification purposes.

Discussion of the Results

In examining the results of this research, two areas are considered: the performance of the models and the identification of important variables. Because of the lack of restrictions that CART places on the data as well as the known problems of MDA and LOGIT in dealing with violations of normality and parametric linkages, CART was expected *a priori* to outperform the alternative models. For the Moody's data set over the two year period, CART correctly classified an average 84 percent of the issues, while LOGIT correctly classified an average 85 percent of the issues and MDA 82 percent. The results show a close range of predictive ability for the three methodologies. Positive aspects of the CART results were the accuracy of the '1' classification and the closeness of the misclassifications.

Two additional steps in the research were taken in an attempt to avoid the problems of the lower rating classes. The first step was to eliminate the small number of observations in the P-3 classification of Moody's and the B, C, and D classifications of Standard & Poor's. The two observations receiving an A-3 rating by S&P in 1986 also were removed. As these observations appeared to be outliers, it was hoped that the accuracy of the various models could be improved by concentrating on the more important classes. All three prediction models were used for both the 1985 and 1986 data sets. Initially it seems that the removal of these rather insignificant observations would tighten the sample and improve the results. Significant improvement, however, did not occur. The small improvements that did occur were due to improvement in the accuracy of predicting the second rating. The overall classification rate still hovered in the 80 percent to 87 percent range.

The second step was an attempt to investigate the recurring problem of the second rating classification. As previously discussed, all the models had difficulty in classifying the A-2 and P-2 rating. To circumvent this problem, all firms with an A-2 or P-2 rating were combined. A small number of firms had different ratings by the two agencies. These firms with conflicting ratings were

eliminated from the combined data set. The deletion of these firms had a minimal effect and left a sample of 146 firms in 1985 and 139 firms in 1986. This sample then was used to determine the classification accuracy of firms rated the same by both agencies. Again, the accuracy rate showed minor improvements in some models and offsetting effects in others. The accuracy rate of the three models remained close and continued to fluctuate around 85 percent. This indicates that in some rating categories the qualitative component of rating (judgment by analyst) plays a greater role than in other categories.

A byproduct of these attempts to improve the prediction accuracy was a further look at the important deterministic variables. The group of significant variables did fluctuate, but as a group proved to be robust. Basically, most of the variables identified in this part of the research were the same core group found in the initial classification efforts. Again, the absence of liquidity variables is noted, with more importance placed on activity, profitability, size, and leverage factors. All the models did have the same problem in classifying the '2' and '3' ratings for the Standard & Poor's data set. The fact that this particular distinction presented problems throughout the study raises questions about the merits of the expanded Standard & Poor's rating. Intuitively, such a system seems to provide more and better information on the quality of a particular issue, as the ranking requirements for a particular issue are specified more narrowly. While this is surely the case, the results of this study reveal identification variables that are so close in value that it is difficult to differentiate classifications with these variables.

Although not as significant a problem as in the S&P data, the '2' rating for Moody's was also more difficult to classify correctly. All the models had a strong tendency to assign a quality rating of '1' to most of the commercial paper issues. A partial explanation for this can be found in the overall quality of the commercial paper issues, with a large number of the rating (75.6 percent of Moody's and 39.1 percent of S&P) for both samples in the highest quality category.

The other result generated by this research is the identification of important independent variables for classifying quality ratings. With commercial paper being a short-term money-market investment, it is important for the issue to be a highly liquid, low risk investment. These factors emphasize the importance of liquidity and short-term coverage in the balance sheet of the issuer. Past research (Peavy and Edgar [25] and Perry and Cronan [27]) has shown that the most important factors for classification of commercial paper include net income, equity/assets, and return on equity. Although these figures are linked directly with the liquidity of the issuer and its ability to cover its short-term obligations, missing from this list are the more common measures of liquidity such as current and acid ratios.

The results provided in Tables 5, 8, and 11 document the importance of variables such as sales, earning power, return on investment and assets, and the amount of equity. These results confirm earlier research. Typically absent from these results are current ratio and interest coverage ratios. Although it is essential that the commercial paper be highly liquid and low risk, it is the overall set of financial statements, not just the short-term assets, that is important in determining the quality of a commercial paper rating.

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Table 1
Number of Firms in each Rating Category

Standard & Poor's			Moody's	
		1985		
A-1	72		P-1	124
A-2	71		P-2	38
A-3	39		P-3	2
B	1			
C	0			
D	1			
TOTAL	184		TOTAL	164
		1986		
A-1	113		P-1	102
A-2	46		P-2	43
A-3	2		P-3	2
B	0			
C	0			
D	0			
TOTAL	161		TOTAL	147

Table 2
Explanation of Ratings Assigned by Standard & Poor's

- A** Issues assigned this highest rating are regarded as having the greatest capacity for timely payment. Issues in this category are delineated with the numbers 1, 2, and 3 to indicate the relative degree of safety.
- A-1 This designation indicates that the degree of safety regarding timely payment is either overwhelming or very strong. Those issues determined to possess overwhelming safety characteristics will be denoted with a plus (+) sign designation.
- A-2 Capacity for timely payment on issues with this designation is strong. The relative degree of safety, however, is not as high as for issues designated A-1.
- A-3 Issues carrying this designation have a satisfactory capacity for timely payment. They are, however, somewhat more vulnerable to the adverse effects of changes in circumstances than obligations carrying the higher designations.
- B** Issues rated B are regarded as having only an adequate capacity for timely payment. Such capacity, however, may be damaged by changing conditions or short-term adversities.
- C** This rating is assigned to short-term debt obligations with a doubtful capacity for payment.
- D** This rating indicates that the issue is either in default or is expected to be in default upon maturity.

Table 3
Classification Results Using Moody's Ratings
MDA Procedure

Actual Class	1	2	3	Percent Correctly Classified
1985 Predicted Class				
1	100	24	0	81
2	7	28	3	74
3	0	0	2	100
1986 Predicted Class				
1	89	13	0	87
2	7	35	1	81
3	0	0	2	100

Table 4
Classification Results Using Standard & Poor's Ratings
MDA Procedure

Actual Class	1	2	3	Percent Correctly Classified
1985 Predicted Class				
1	50	18	4	69
2	13	40	18	56
3	3	5	31	79
4	0	0	1	0
5	1	0	0	0
1986 Predicted Class				
1	82	29	2	73
2	9	36	1	78
3	0	1	1	50

Table 5
Significant Variables from MDA Procedure

Moody's	F Value	Standard & Poor's	F Value
	1985		
Cash Turnover	7.54	Current Ratio	5.30
Earning Power	7.66	Inventory Turnover	2.21
EBIT/Total Assets	5.74	Sales per Dollar of Working Capital	5.49
EBIT/Sales	8.69	Profit Margin	12.18
Net Income/Total Assets	6.24	Net Income/Total Assets	3.59
Long-Term Debt/Total Invested Capital	28.71	Long-Term Debt/Total Assets	19.93
Net Sales	7.55	Common Stock Price/Cash flow Net Sales	9.66 7.06
	1986		
Receivables Turnover	3.51	Receivables Turnover	6.14
Inventory Turnover	7.65	Inventory Turnover	2.30
Receivables/Total Assets	8.85	Receivables/Total Assets	6.95
Inventory/Total Assets	5.92	EBIT/Total Assets	9.65
Return on Equity	8.84	Long-Term Debt/Total Assets	
	11.26		
Long-Term Debt/Total Assets	47.59	Common Stock Price/ Cash Flow	4.32
Sales/Total Assets	3.54	Sales/Net Worth Total Assets	3.40 2.25

Table 6
Classification Results Using LOGIT Procedure

Moody's Ratings (1985) Predicted Class						Percent Correctly Classified
Actual Class	1	2	3			
1	115	9	0			93
2	20	18	0			53
3	0	0	2			100
Standard & Poor's Ratings (1985) Predicted Class						Percent Correctly Classified
Actual Class	1	1	3	4	5	
1	57	15	0	0	0	79
2	15	51	5	0	0	72
3	5	8	24	2	0	62
4	0	0	0	1	0	100
5	0	0	0	0	1	100

Table 7
Classification Results Using LOGIT Procedure

Actual Class	1	2	3	Percent Correctly Classified
Moody's Ratings (1986) Predicted Class				
1	95	7	0	93
2	9	31	3	72
3	0	0	2	100
Standard & Poor's Ratings (1986) Predicted Class				
1	105	8	0	93
2	12	29	5	63
3	0	1	1	50

Table 8
Summary of Stepwise Results
LOGIT Procedure

Data Item Entered	Moody's Ratings		Approximate F	
	Removed	To Enter	To Remove	
Long-Term Debt/Total Assets		20.25		
Earning Power		9.04		
Total Assets		4.26		
Return on Capital		4.39		
Earnings Before Interest and Taxes/Total Assets		2.85		
Cash Turnover		3.04		
Net Sales		4.92		
	Total Assets			1.28
Standard & Poor's Rating				
Data Item Entered				
Inventory/Total Assets		10.72		
Common Stock Price/Cash Flow		9.97		
Total Assets		8.46		
Long-Term Debt/Total Assets		6.85		
Return on Capital		8.27		
Net Sales		2.74		
Long-Term Debt/Total Invested Capital		3.65		

Table 9
Number of Observations and Percent
Classified Into Group
Recursive Partitioning

Actual Class	1	2	3	Percent Correctly Classified
Moody's Ratings (1985) Predicted Class				
1	116	8	0	94
2	12	26	0	68
3	2	0	0	0
Standard & Poor's Ratings (1985) Predicted Class				
1	52	20	0	72
2	28	43	0	61
3	9	30	0	0

Table 10
Number of Observations and Percent
Classified Into Group
Recursive Partitioning

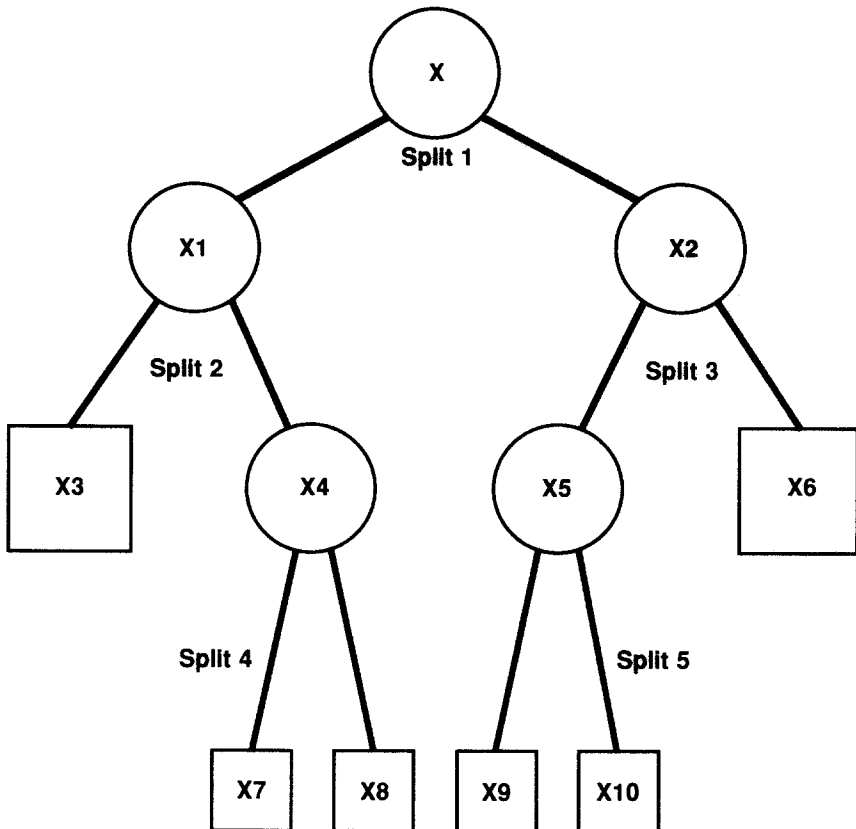
Actual Class	1	2	3	Percent Correctly Classified
Moody's Ratings (1986) Predicted Class				
1	89	13	0	87
2	16	27	0	63
3	0	1	1	50
Standard & Poor's Ratings (1986) Predicted Class				
1	77	36	0	68
2	12	34	0	74
3	0	2	0	0

Table 11
Variable Importance List from CART Program

Moody's Ratings	
Variable	Relative Importance
Common Stock Price/Cash Flow	100
Market Value of Equity/Total Debt	78
Earnings Before Interest and Taxes/Sales	72
Long-Term Debt/Total Invested Capital	68
Fixed Charge Coverage	56
Earnings Before Interest and Taxes/Total Assets	48
Net Sales	47
Profit Margin	47
Return on Equity	44
Earning Power	41

Standard & Poor's Ratings	
Variable	Relative Importance
Net Sales	100
Earnings Before Interest and Taxes/Sales	96
Return on Capital	94
Long-Term Debt/Total Assets	94
Common Stock Price/Cash Flow	89
Market Value of Equity/Total Debt	88
Profit Margin	83
Return on Equity	66
Earning Power	66
Acid Test Ratio	59

Figure 1
Sample CART Tree



Adapted from an example in Frydman, Altman and Kao (1985)

Appendix A
List of Variables Used in the Study

- X1 = Current Ratio
- X2 = Acid Test Ratio
- X3 = Cash Turnover
- X4 = Receivables Turnover
- X5 = Inventory Turnover
- X6 = Sales Per Dollar of Working Capital
- X7 = Cash/Total Assets
- X8 = Receivables/Total Assets
- X9 = Inventory/Total Assets
- X10 = Earning Power
- X11 = Profit Margin
- X12 = Return on Equity
- X13 = Earnings Before Interest and Taxes/Total Assets
- X14 = Earnings Before Interest and Taxes/Sales
- X15 = Net Income/Total Assets
- X16 = Return on Capital
- X17 = Long-Term Debt/Total Assets
- X18 = Long-Term Debt/Total Invested Capital
- X19 = Fixed Charge Coverage
- X20 = Cash Flow
- X21 = Market Value of Equity/Total Debt
- X22 = Common Stock Price/Cash Flow
- X23 = Sales/Net Worth
- X24 = Sales/Total Assets
- X25 = Total Assets
- X26 = Net Sales

