THE PREDICTION OF INDUSTRIAL BOND RATING CHANGES:
A MULTIPLE DISCRIMINANT MODEL VERSUS A
STATISTICAL DECOMPOSITION MODEL

DISSERTATION

Presented to the Graduate Council of the
North Texas State University in Partial
Fulfillment of the Requirements

For the Degree of

DOCTOR OF PHILOSOPHY

By

Saad Abdel-Hamid Metawe, M.B.A.
Denton, Texas
December, 1985
The purpose of this study is to investigate the usefulness of statistical decomposition measures in the prediction of industrial bond rating changes. Further, the predictive ability of decomposition measures is compared with multiple discriminant analysis on the same sample.

The problem of this study is twofold. It stems in general from the statistical problems associated with current techniques employed in the study of bond ratings and in particular from the lack of attention to the study of bond rating changes.

Two main hypotheses are tested in this study. The first is that bond rating changes can be predicted through the use of financial statement data. The second is that decomposition analysis can achieve the same performance as multiple discriminant analysis in duplicating and predicting industrial bond rating changes.

To explain and predict industrial bond rating changes, statistical decomposition measures were computed for each company in the sample. Based on these decomposition
measures, the two types of analyses performed were (a) a univariate analysis where each decomposition measure was compared with an industry average decomposition measure, and (b) a multivariate analysis where decomposition measures were used as independent variables in a probability linear model.

In addition to statistical decomposition analysis, multiple discriminant analysis was used in duplicating and predicting bond rating changes. Finally, a comparison was made between the predictive abilities of decomposition analysis and discriminant analysis.

The findings of this study indicate that, first, the individual decomposition measures for the companies that experienced bond rating changes during 1977-1981 are larger and more unstable than decomposition measures for companies that did not experience bond rating changes during the same period. Second, the incorporation of more than one decomposition measure in a multivariate decomposition model achieves a better predictive accuracy in the prediction of industrial bond rating changes. Third, statistical decomposition analysis performed as well as discriminant analysis in duplicating and predicting industrial bond rating changes.
TABLE OF CONTENTS

LIST OF TABLES .................................. v

Chapter

I. INTRODUCTION .............................. 1

Objective of the Research
Background
The Problem
Hypotheses
Delimitations
The Importance of Bond Ratings
Significance of the Study
Methodology
Outline of the Study

II. REVIEW OF THE LITERATURE ............... 13

Introduction
Bond Rating Studies
Studies Related to the Stability of Financial Variables
Studies that Used Information Theory-Derived Decomposition Measures in the Analysis of the Financial Statement Data and in the Prediction of Corporate Events

III. METHODOLOGY ............................. 41

Null Hypothesis
Appropriateness of Information Theory Concepts to the Study of Bond Rating Changes
Computation of Information Theory-Derived Decomposition Measures
Univariate Statistical Decomposition Analysis
Multivariate Statistical Decomposition Analysis
Test of Significance
Multiple Discriminant Analysis
| Variables in the Multiple Discriminant Model               | 69 |
| Sample Selection                                           |    |
| Validation                                                 |    |
| Comparison of Classification Accuracy of the Decomposition Model with the Discriminant Model |    |

**IV. ANALYSIS AND RESULTS**

- Univariate Decomposition Analysis
- Evaluation of Univariate Analysis
- Univariate Analysis
- Multivariate Decomposition Analysis
- Discriminant Analysis
- Two-Group Discriminant Analysis
- Three-Group Discriminant Analysis
- Comparison of the Classification and Predictive Accuracy of the Decomposition Measures with the Discriminant Models
- Summary

**V. SUMMARY AND CONCLUSIONS**

- Summary
- Conclusions
- Suggestions for Future Research

**APPENDICES**

- 137

**BIBLIOGRAPHY**

- 153
# LIST OF TABLES

<table>
<thead>
<tr>
<th>Table</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>I. Results of the Univariate Analysis Size Attribute for Two Selected Firms</td>
<td>72</td>
</tr>
<tr>
<td>II. Results of Univariate Decomposition Analysis</td>
<td>75</td>
</tr>
<tr>
<td>III. Comparison Between Classification Accuracy of Decomposition Measures and A Chance Model in Predicting Bond Rating Changes</td>
<td>80</td>
</tr>
<tr>
<td>IV. Results of the Univariate Analysis: Instability Attributes for Two Selected Companies</td>
<td>82</td>
</tr>
<tr>
<td>V. Results of the Univariate Analysis—Instability Attribute—For the Two Groups and the Sample</td>
<td>83</td>
</tr>
<tr>
<td>VI. Comparison Between Classification Accuracy of the Instability of Decomposition Measures and A Chance Model</td>
<td>84</td>
</tr>
<tr>
<td>VII. Statistics for Independent Variables Included in the Linear Probability Model (LPM)</td>
<td>87</td>
</tr>
<tr>
<td>VIII. Classification Results of the Linear Probability Model (LPM)</td>
<td>90</td>
</tr>
<tr>
<td>IX. Comparison Between Classification Accuracy and Prediction Results of the LPM and A Chance Model</td>
<td>94</td>
</tr>
<tr>
<td>X. Classification Results of the Two-Group Discriminant Analysis (based on two different sets of independent variables)</td>
<td>98</td>
</tr>
<tr>
<td>XI. Standardized and Unstandardized Discriminant Function Coefficients: Four-variable Model</td>
<td>99</td>
</tr>
<tr>
<td>Table</td>
<td>Description</td>
</tr>
<tr>
<td>-------</td>
<td>-------------</td>
</tr>
<tr>
<td>XII.</td>
<td>Standardized and Unstandardized Discriminant Function Coefficients: Ten-variable Model</td>
</tr>
<tr>
<td>XIII.</td>
<td>Prediction Results of the Two-Group Discriminant Analysis</td>
</tr>
<tr>
<td>XIV.</td>
<td>Results of the Three Alternative Rating-Change Strategies</td>
</tr>
<tr>
<td>XV.</td>
<td>Percentage of Correct Predictions for Two-Group Discriminant Analysis</td>
</tr>
<tr>
<td>XVI.</td>
<td>Classification Results of the Three-Group Discriminant Analysis Based on Two Sets of Independent Variables</td>
</tr>
<tr>
<td>XVII.</td>
<td>Standardized and Unstandardized Discriminant Function Coefficients (Ten-variable Model)</td>
</tr>
<tr>
<td>XVIII.</td>
<td>Standardized and Unstandardized Discriminant Function Coefficients: Four-variable Model</td>
</tr>
<tr>
<td>XIX.</td>
<td>Prediction Results: Three-Group Discriminant Analysis</td>
</tr>
<tr>
<td>XX.</td>
<td>Comparison of the Correct Classification Percentages Produced by the Individual Decomposition Measures with Correct Classification Percentages of the Two-Group Discriminant Analysis</td>
</tr>
<tr>
<td>XXI.</td>
<td>Comparison of the Classification Percentages of the Individual Decomposition Measures with Correct Classification Percentages of the Three-Group Discriminant Analysis</td>
</tr>
<tr>
<td>Table</td>
<td>Title</td>
</tr>
<tr>
<td>-------</td>
<td>----------------------------------------------------------------------</td>
</tr>
<tr>
<td>XXII.</td>
<td>Comparison Between the Two-Group Multiple Discriminant Analysis and the Multivariate Decomposition Analysis (classifications and predictions)</td>
</tr>
<tr>
<td>XXIII.</td>
<td>Comparison Between the Three-Group Multiple Discriminant Analysis and the Multivariate Decomposition Analysis (classifications and predictions)</td>
</tr>
</tbody>
</table>
CHAPTER I

INTRODUCTION

Objective of the Research

The purpose of this study is to investigate the usefulness of statistical decomposition measures in the prediction of industrial bond rating changes. Further, the intention is to compare the predictive ability of this technique with that of a multiple discriminant analysis which will be used on the same sample. This study may assist in answering the long-standing question of how successful bond rating agencies are in their rating-change decisions since study results can be used to determine whether companies that did not experience rating changes have maintained a financial stability that warranted the continuity of their original rating.

Background

In theory, a bond rating is considered an ex ante probability of default. However, this ex ante probability is difficult to measure absolutely (4). Recognizing this difficulty, Moody's Industrial Manual defines a bond rating as "a simple system of gradation by which the relative investment qualities of bonds may be noted" (19, p. v).
Today, corporate bond ratings are prepared by three rating agencies—Fitch, Moody's Investor's Service, and Standard and Poor's Corporation. These rating agencies provide the financial community with a regular record of their opinions of the quality of most large, publicly held corporate, municipal, and government issues. Of the three rating agencies, Moody's and Standard and Poor's are the most important in terms of both the variety and number of securities rated and the agencies' power and importance in the market. Although the rating agencies use different labels, their rating systems are similar in that they use both quantitative and qualitative data to reach their rating decisions.

Several studies have attempted to predict or duplicate bond ratings by using financial ratios and certain statistics of financial statement data. These studies can be classified into two main groups. The first group of studies (2, 6, 7) was done during the 1940s and 1950s. Most of the studies in this group are primarily descriptive in nature and relate corporate bond ratings solely to the frequency of default of a bond issue (18). They added little to the knowledge about how the risk premium on bonds is determined or about the mechanism (analysis and reevaluation) of the rating process.

Publication of the second group of studies began in the late 1950s and continues to the present time. This
group began with a study by Fisher (5) in which he employs a multiple regression model to predict the default risk. Fisher's study was followed by Horrigan's (8) study in 1966. Horrigan also employs a multiple regression model to predict the long term credit standing of firms.

Both Fisher's and Horrigan's studies were criticized by many researchers, particularly Kaplan and Urwitz (11). The main criticism of these studies is that both assumed that the dependent variable was interval scale type data; specifically, they assumed that the distance between an Aaa rating and an Aa rating is equal to the distance between a Baa rating and a Ba rating. The nature of the dependent variable does not provide any assurance that this assumption can be made.

Because of the criticism of the use of multiple regression for the study of bond ratings, researchers turned to multiple discriminant analysis (3, 13, 21, 22). They argued for the appropriateness of the use of multiple discriminant analysis to the study of bond ratings on two bases. First, a bond rating is a categorical variable, and it can be predicted by a set of metric variables; in that respect the problem appears to be fitted for the use of the discriminant analysis. Second, from both the theoretical and practical points of view, bond ratings appear to be
influenced by several variables or factors that make the use of multiple discriminant analysis appropriate to the study of those ratings.

Although the use of multiple discriminant analysis enabled researchers to overcome the interval scale problem that was present in the studies that employed multiple regression analysis, they faced other statistical problems. The first problem stems from the multivariate normality assumption required for the application of discriminant analysis. Mardia's (14) study concludes that business data which was analyzed did not meet the multivariate normality assumption. Second, the discriminant model gives a score to each case (firm); on the basis of that score the case will be assigned to one of a predetermined set of groups. This scoring scheme may cause interpretation problems if the score reported by the model falls into what is known as the range of ambiguity or the indecision zone. In that case the researcher has to investigate further in order to decide to which group the case belongs (11).

Finally, to avoid the problems associated with the use of multiple regression and discriminant analysis in the study of bond ratings, some researchers, particularly Kaplan and Urwitz (13), suggest the use of a probit model. However, the suggested model appears to be unpopular because of (a) the limitations on the acceptance of cumulative probability function as a solid basis for the model, and (b) the
limitations on the acceptance of the threshold utility
concepts as a means of describing and analyzing bond ratings.
In addition to the studies previously discussed, some studies
have been done in which the authors relate bond ratings to
stock prices (9), to systematic risk (15), and to bond yield
and financial regulation (23).

The Problem

The problem of this study is twofold. It stems from the
statistical problems associated with current techniques
employed in the study of bond ratings in general and the lack
of attention to the study of bond rating changes in particular.

The statistical problems associated with the existing
techniques employed in the study of bond rating were dis-
cussed briefly in the previous section. Regarding the lack
of attention to the study of bond rating changes, the
researcher has found that most of the studies in the bond
rating area have dealt with explanations and the prediction
of bond ratings. A limited number of studies are related
either to the impact of bond rating changes to the borrowing
cost of the issuer (10) or to price adjustment (12). Only
one study has been found that focuses on the determinants and
predictability of industrial bond quality rating changes;
according to Bhandari (4), this lack of attention to the rating
changes by academicians can be attributed to three main reasons.
1. The increased belief in market efficiency. In an efficient market, a rating change announcement does not bring new information to the participants in the market and, therefore, has a limited impact on market variables;

2. The low predictive power of existing bond rating models. Most of those models did not correctly classify more than 70 per cent of the bonds used in those studies;

3. Officials in rating agencies have always insisted that the criteria they use in their rating or rating change decisions cannot be duplicated because the rater's judgment plays an important role in the rating assignment:

Investors using the ratings should not, therefore, expect to find them a reflection of statistical factors alone. They are not statistical ratings but an appraisal of long term risks, such appraisal giving recognition to many non-statistical factors (15, p. v).

None of the above reasons appear to be so strong that they should discourage academicians from the study of bond rating changes. Bhandari (4) concludes that the rating agencies' claim about the importance of their judgment, and the qualitative factors in duplicating the bond ratings, may have a substantial empirical basis, but this claim is not substantiated in the case of duplicating their rating-change decisions. Bhandari's conclusion suggests that quantitative techniques can perform well in duplicating bond rating changes. This conclusion supports this researcher's
view that bond ratings changes can and should be studied through the use of quantitative techniques that use financial statistics as a basis for explaining those changes.

Hypotheses

Two main hypotheses are tested in this study. The first hypothesis predicts that industrial bond rating changes can be predicted through the use of financial statement data. The second hypothesis predicts that statistical decomposition analysis can achieve the same performance as multiple discriminant analysis in duplicating and predicting industrial bond rating changes.

Delimitations

This study analyzes only industrial bond ratings that were changed during the 1977-1981 period. Convertible bonds are excluded because of their special nature. Moody's Bond Survey (18) is used to obtain the list of rating changes.

The Importance of Bond Ratings

A bond rating is an important economic event. Following are several reasons for this importance.

1. A bond rating is a measure of default risk, and as such it affects the investment decisions of both institutions and individuals (4). In making rating decisions, rating agencies adopt a conservative view of ratings as the minimum
level of overall bond quality that a firm can expect to maintain given the present conditions. This view is reflected in the following note from Moody's Bond Record.

Since ratings involve a judgment about the future, on the one hand, and since they are used by investors as a means of protection on the other, the effort is made when assigning ratings, to look at "worst" potentialities in the "visible" future rather than solely at the past record and the status of the present (17, p. 11).

2. Bond ratings are useful because they have been found to be highly correlated with bond yields to maturity (2). The higher the bond rating, the lower the average yield to maturity in that group.

3. Bond ratings are useful to borrowers, bond dealers, and underwriters. For the borrowers, the rating affects the interest cost they pay on their bonds. Bond dealers and underwriters use the rating as an assessment and marketing mechanism in their efforts to match borrowers and investors (1).

4. Bond ratings are used in the regulation of the investment decisions of some financial institutions. The following order issued by the Comptroller of the Currency in 1963 to all national banks indicates this fact.

The purchase of investment securities in which the investment characteristics are distinctly and predominantly speculative, or investment securities of a lower designated standard than those which are distinctly and predominantly speculative, is prohibited . . . the terms applied herein may be found in recognized rating manuals. (6, p. 30).
Significance of the Study

It is expected that this study will provide the following contributions, as follows:

1. To demonstrate that industrial bond rating changes can be predicted;

2. To provide insights into financial statement changes that can be used in the prediction of certain corporate events;

3. To extend the use of statistical decomposition analysis into a new area—predicting bond rating changes.

Methodology

To explain and predict bond rating changes, statistical decomposition measures (see Appendix A) are computed for each company. Based on these decomposition measures (DMs), the two types of analyses to be performed are (a) a univariate analysis where each decomposition measure will be compared with an industry decomposition measure computed for this purpose, and (b) a multivariate analysis where the decomposition measures will be used as independent variables in a probability linear model (PLM) or a special regression model to predict the bond rating changes.

In addition to the statistical decomposition analysis, a multiple discriminant analysis model is used to predict the bond rating changes. Finally, a comparison is made of the predictive ability of the two models in predicting bond rating changes.
Outline of the Study

This study contains five chapters. The first chapter introduces the study, stating the problem, background, significance, and methodology. Chapter II reviews the relevant literature. Chapter III presents the methodology used in the study. Chapter IV presents the data analysis and results, and Chapter V presents a summary of the study and the conclusions drawn from the data analyses.
CHAPTER BIBLIOGRAPHY


CHAPTER II

REVIEW OF THE LITERATURE

Introduction

This chapter presents a survey of the various attempts to develop bond rating models using financial statement data and other financial statistics. The statistical techniques used in previous bond rating studies include regression analysis, dichotomous probability functions, multiple discriminant analysis, and the multivariate probit model. The statistical techniques and the lists of variables used in each study are evaluated.

As stated in Chapter I, this study proposes the use of information theory-derived decomposition measures in the prediction of bond ratings. Several studies have been done using decomposition measures in the prediction of certain corporate events, mainly corporate failure. These studies are reviewed in this chapter because they provide a better understanding of the contributions and limitations on the use of the information theory-derived decomposition measures in the prediction of corporate events.

Finally, this chapter includes a review of several studies that reveal variability in the values of some
corporate financial variables. These studies are important for the purpose of this study because they measure the degree of instability over time of some important financial variables that are strongly related to the quality of corporate bonds.

The chapter is divided into three primary sections. The first section includes a review of previous bond rating studies. The second section includes a review of the studies in which information theory-derived decomposition measures are used in the prediction of corporate events, mainly corporate failures. The third section includes a review of the studies that reveal the instability of some important financial statistics over time.

Bond Rating Studies

This section of the literature review includes five subsections. These sections cover the early research, studies using regression analysis, studies using dichotomous probability functions, studies using multiple discriminant analysis, and studies using multivariate probit analysis.

**Early Research**

The research on bond quality and bond ratings was begun by three research studies. The authors of these studies are Harold (10), Hickman (12), and Atkinson and Simpson (3).

The Harold study.—In an early study, Harold (10) compared the performance of agency-rated corporate bonds
from 1929 through 1936. He used a sample of 363 corporate bonds to evaluate the rating procedures of Standard and Poor's, Fitch, and Moody's. He examined the yield and the default records of each class of bonds in the sample and concludes that "on the whole, the principle of more defaults as the ratings proceed step by step downward is conditionally confirmed; that is, scars were found, but in view of human fallibility the record is surprisingly good" (10, p. 221).

In addition, Harold discussed rating changes and their importance to the investors and the causes of those rating changes. He argued that the change in the rating of an outstanding security was not due to changing conditions of the issuer but was due to "the lack of alleged perfection on part of raters" (10, p. 225). He also says that "rating agencies succeed in anticipating market change, but they usually announce a change in rating after part of the market change has already taken place" (10, p. 225).

The Hickman study.--Hickman's (12) study was sponsored by the National Bureau of Economic Research. In his study, Hickman analyzed the experiences of all straight (non-convertible) corporate bond issues of $5 million or more issued from 1900 through 1943 plus a 10 per cent sample of 1900-1943 issues below $5 million. He related four measures of investor experience—default rate, promised yield, realized yield, and loss rate—to nine measures of bond
quality—industry, agency rating, legal status in Maine, Massachusetts, and New York, gross income, lien position, market rating, time charges earned ratio, size of the issue and asset size, and the ratio of net income to total income. Hickman found a consistent inverse relationship between the agency bond ratings and default rates. Therefore, he concluded that "the record of the agencies over the period studies was remarkably good insofar as their ratings pertain to the risk of default" (12, p. 209). Also, he found that the errors in ratings of corporate bonds can be traced mainly to the business cycle and the difficulty of forecasting business trends.

The Atkinson and Simpson study.—Atkinson and Simpson's (3) study was also sponsored by the National Bureau of Economic Research, and it is an extension of Hickman's study into the post-World War II era, with some modifications. They used such standard measures as earnings coverage, agency ratings, market rating, and security in the comparison of postwar corporate bond quality with the prewar corporate bond quality. They found that the post-World War II default experiences were considerably fewer than the 1900-1943 default experiences. They also found that bond quality, as measured by agency ratings, increased significantly during the post-World War II period.
Studies Using Regression Analysis

Regression analysis was used in three studies in developing a bond rating prediction model (8, 13, 27). The use of regression analysis in the prediction of bond ratings assumes that the relationship between the dependent variable \( Y \) (or bond rating) and the independent variables \( X \) is additive and linear.

The Horrigan study. -- In his study, Horrigan (13) used a multiple regression analysis to duplicate the agency bond ratings financial ratios as predictors. His original sample includes 201 corporations with Moody's rating and 151 corporations with Standard and Poor's ratings that did not change during the 1959-1964 period. He used a coded bond rating as the dependent variable. The independent variables in the model, except for the subordination status of the bond issue, are all derived from accounting data. The study was conducted in two phases.

In the first phase, Horrigan used various combinations of financial ratios as independent variables. These variables came from six main categories: (a) short term liquidity, (b) long term liquidity, (c) short term capital turnover, (d) long term capital turnover, (e) profit margin, and (f) return on investment. The subordination status was represented by a dummy variable (0, 1). Each ratio employed in the study was divided by the respective industry average.
ratio. Six variables were finally selected to be the most important in bond rating prediction model. These variables include (a) subordination, (b) total assets, (c) working capital to sales, (d) net worth to total debt, (e) sales to net worth, and (f) net operating profit to sales. Approximately 50 per cent of the cross-sectional variation in bond ratings is explained by the above variables.

In the second phase of the study, Horrigan uses the coefficients that were obtained in the first phase in the prediction of new bond ratings and changes in ratings in the 1961-1964 period. The model correctly predicts 58 per cent of Moody's new ratings, 52 per cent of Standard and Poor's new ratings, 54 per cent of Moody's changed ratings, and 57 per cent of Standard and Poor's changed ratings.

The Fisher study.—Fisher (8) empirically examined the determinants of risk premium on corporate bonds. He defined the risk premium of a bond as the difference between the market yield to maturity and the corresponding pure rate of interest, or the market yield on a riskless bond maturing on the same day as the bond under study. He recognized the default risk of bonds as one of the determinants of the risk premium on corporate bonds. He also considered the market-ability of the bond as another determinant of the risk premium on the bond.

Fisher used four variables as proxies for default risk: $X_1$ = the variability of the firm's earnings (as measured by
the coefficient of variation of earnings after tax of the most recent nine years); $X_2$ = the reliability of the firm in meeting its obligations (measured by the number of years the firm operated without forcing its creditors to take a loss); $X_3$ = the strength of the firm's capital structure (measured by the ratio of the market value of the firm's equity to the par value of its debt); and $X_4$ = marketability risk as measured by the total value of the firm's bonds. These four variables were used as independent variables in a multiple regression model with the logarithm of the average yield differential between a riskless bond and the firm's bond as the dependent variable. Several regressions were run cross-sectionally on bond observations collected in 1927, 1932, 1937, 1949, and 1953. The regression run on all 366 bonds in the sample showed that 75 per cent of the total variations in the logarithm of the yield differential are explained by the default and marketability measures, thus indicating a good explanatory power for the model.

The West study.—West (27) criticized Horrigan's bond rating model for its extensive use of accounting data and suggested that Horrigan's bond rating model can be improved by using less data. He suggests the use of Fisher's (8) model and defends its use on two grounds. First, Fisher's model is theoretically and empirically supported. Second, the risk premium used in Fisher's model is a better surrogate for default risk than are bond ratings.
In his study, West used the same independent variables that Fisher used (earnings variability, reliability in meeting financial obligations, bond marketability, and capital structure) in the prediction of bond rating. He also used the same five cross sections of data as used by Fisher (1927, 1932, 1937, 1949, and 1953). He used non-subordinated bonds rated by Moody's agency.

West found that for each of the five years observed, the four independent variables in the regression equation accounted for 70 per cent of the variability in the logarithm of ratings. He then used a model based on 1949 data in predicting the ratings on bonds in the 1953 sample. His model correctly predicts 48 out of 77 ratings (about 62 per cent accuracy).

Study Using Dichotomous Probability Functions

The Pogue and Soldofsky study.—Pogue and Soldofsky (24) used a linear probability model in the prediction of bond ratings. They define $Y_1$ (the dependent variable in the model) as the probability that a bond issued by firm 1 will be given the higher of two ratings. Some of the independent variables in the model were expressed as six-year means. These variables were long term debt over total capitalization, net income after tax over total assets, net assets, net income after tax plus interest over interest. They added an additional dummy variable to distinguish the broad industry as
an independent variable. They also used the coefficient of variation of the return on assets as an independent variable.

In the Pogue and Soldofsky study, the dependent variable was stated as probability of either Aaa rather than Baa rating, probability of either Aaa rather than Aa rating, probability of either Aa rather than A rating, and probability of either A rather than Baa rating. Several regression runs were performed for each pair of successive ratings. Their model predicted correctly fifty out of fifty-three bonds in the experimental sample, and it predicted eight out of ten bonds in a holdout sample from the same period (1961-1966).

Pogue and Soldofsky conclude that leverage and profitability appear to have a significant influence on corporate bond ratings, and that readily available information about the company can be employed to predict whether its bond will be assigned the higher of a pair of ratings.

Studies Using Multiple Discriminant Analysis

The Pinches and Mingo study.—Pinches and Mingo (22) used a multiple discriminant analysis in the prediction of bond ratings. They used a sample of 180 newly issued bonds rated B or above by Moody's rating agency. The sample was divided into an estimation sample of 132 bonds and a hold-out sample of 48 bonds.

Pinches and Mingo employed factor analysis to screen the financial data in order to choose the most appropriate
independent variables in the prediction of bond rating. The factor analysis transformed the original set of thirty-five financial variables into seven significantly separate factors. These seven factors include (a) size, (b) financial leverage, (c) long-term capital intensiveness, (d) return on investment, (e) short-term capital intensiveness, (f) earnings stability, and (g) debt and debt coverage stability.

Pinches and Mingo employed multiple discriminant analysis to develop their bond rating model which include five of the seven factors reached in the earlier stage. Their model included the independent variables of $X_1 = \text{subordination};$ $X_2 = \text{years of consecutive dividends};$ $X_3 = \text{issue size};$ $X_4 = \frac{\text{net income} + \text{interest}}{\text{interest}}: \text{five-year mean};$ $X_5 = \text{long term debt/total assets};$ and $X_6 = \text{net income/total assets}.$

Pinches and Mingo's model was first used to classify the 132 bonds in the estimation sample. The model correctly classified 92 of the 132 in that sample (69.7 per cent accuracy).

The model was then used to classify the 48 bonds in the holdout sample. The hit ratio is 31 out of 48 bonds in that sample. Misclassified ratings were within one rating higher or lower than the actual bond rating.

Pinches and Mingo concluded that the subordination status is the most important variable affecting bond ratings in their study. Other independent variables ranked according to their perceived importance were years of consecutive
dividends, issue size, earnings coverage, profitability, and leverage. Pinches and Mingo concluded their study by stating that "we believe that much of the rating process can be captured by an appropriately specified model, but . . . it is still very difficult to predict more than 75 per cent of the actual ratings" (22, p. 18).

The Long Study.—Long (18) used multiple regression analysis to test the hypothesis that Moody's rating can be explained by the information available in financial statements. The dependent variable was represented by the alphabetical ratings. Long used two surrogate series in the specification of that variable. The first surrogate was based on the assumption that each rating category represents an equal amount of risk. The second surrogate series was based on the assumption that each rating category represents an increasing increment of risk.

Long used five independent variables in his study. These variables include (a) seven-year moving average of total assets, (b) times fixed charges earned, (c) debt to capital ratio, (d) coefficient of variation of times charges earned, and (e) a dummy variable to identify communication and noncommunication utility companies. He used a sample of 228 firms covering the period from 1958 through 1961.

Long's model explained 50 per cent of the variation in the dependent variable. Because of the poor performance of
his model, Long concludes that two hypotheses may account for the unexplained variations: (1) the reported error terms from the model are simply larger than the true error terms by virtue of the numerical surrogate construct, and (2) some process occurs within the rating agency that is not reflected in the information publicly reported on the rated firm. Within this category there were two possibilities: (a) the agency does in fact have access to inside information unknown to the market place or not reflected in published financial statements, or (b) the agency simply does not keep ratings current, possibly for a variety of reasons (18, p. 151). Long analyzed the residuals in relation to rating changes and decided in favor of hypothesis 2(b), which refers to the rater's inability to keep the ratings updated.

The Bhandari study.—Bhandari (5) used a multiple discriminant analysis to predict industrial bond rating changes. The dependent variable was represented by the three rating categories—upgraded, downgraded, and no-change bond ratings. The independent variables used in his model were (a) fixed charges coverage, (b) fixed charges coverage trend, (c) return on assets, (d) return on assets trend, (e) long-term debt to capitalization, (f) long-term debt to capitalization trend, and (g) earnings instability. Bhandari determined the trend variables by fitting a least squares linear regression line on the five-year data preceding the rating change.
Bhandari used a sample of 158 bond rating changes that took place during the 1971-1975 period. This sample was obtained from the Final Cumulative Index of Moody's Bond Survey covering that period. He found the return on assets, the return on assets trend, and the fixed charges coverage trend to be the most important variables in the prediction of industrial bond rating changes.

Bhandari performed two types of discriminant analysis: a two-group analysis where the dependent variable was represented only by upgraded or downgraded bond ratings, and a three-group analysis where the dependent variable is represented by three groups of bond ratings—upgraded, downgraded, and no-change groups. He found that the two-group discriminant model performed better than the three-group discriminant analysis. The two-group model correctly classified 89.8 per cent of industrial and 87.2 per cent of utility companies in the estimation sample. Bhandari then applied the two-group discriminant analysis to predict a holdout sample of bond rating changes. The model correctly predicted 55 per cent of the industrial bond rating changes and 90 per cent of the utility bond rating changes. The three-group discriminant model correctly classified 58.9 per cent of industrial bond rating changes and 73 per cent of the utility bond rating changes.
The Belkauoi study.—Belkauoi (4) used multiple discriminant analysis to develop a bond rating model. He criticizes previous studies in the bond rating area for the lack of economic rationale in the choice of independent variables used. He used an economic rationale in selecting firm-, market-, and indenture-related variables to be used as predictor variables in the bond rating prediction model. The independent variables in the Belkauoi study included (a) the size of the firm, (b) the total size of the debt, (c) the long-term capital intensiveness, (d) the short-term capital intensiveness, (e) the total liquidity, (f) the debt coverage, (g) subordination status, and (h) stock price/common equity per share.

Belkauoi used a sample of 275 industrial corporate bonds rated B or above by Standard and Poor's in 1978. He divided the sample into an estimation sample of 160 bonds and a holdout sample of 97 bonds. The model correctly classified 62.8 per cent of the estimation sample and 65.8 per cent of the holdout sample. On a univariate basis, subordination appeared to be the most important variable, but in a multivariate context, current ratio became the most important variable followed by fixed charges coverage.

Studies Using Multivariate Probit Analysis

The Kaplan and Urwitz study.—Kaplan and Urwitz (14) criticized previous bond rating studies that used regression
analysis as the basis for the development of a bond rating model because the dependent variable (bond rating) was treated as if it were an interval scale. They also criticized multiple discriminant analysis models used in previous bond rating studies because of the restrictive assumptions of the multiple discriminant analysis. They suggested that the ordinal nature of bond ratings makes it more appropriate to study such ratings through the application of a multivariate probit model.

Kaplan and Urwitz used their probit model to rate 120 outstanding bonds and 207 newly issued bonds. The independent variables used in the model include (a) interest coverage ratio, (b) leverage ratio (measured by long term debt/net worth), (c) profitability ratio (measured by net income/total assets), (d) size variable (measured by the size of the firm of the size of the issue), (e) stability variables (coefficient of variation of total assets or coefficient of variation of net income), and (f) subordination status. Their model correctly predicted 70 per cent of a holdout sample of 67 newly issued bonds. However, Kaplan and Urwitz concluded that, contrary to their expectations, the regression model employed on the same sample performed slightly better than the probit model.

The Wingler and Watts study.—In their study, Wingler and Watts (28) examined the financial characteristics that prompt
rating changes for electric utilities. They compared a multiple discriminant model with a probit model in terms of the models' abilities to predict bond rating changes. The independent variables used in both models were (a) profitability, (b) leverage, (c) cash flows, (d) growth in assets, (e) recovery of capital costs, (f) a five-year trend in construction expenditures to total assets, and (g) allowances for funds under construction.

Both the discriminant model and the probit model were applied to a sample of 68 firms (30 firms where bonds were upgraded, 30 firms whose bonds were downgraded, and 8 firms whose bonds remained unchanged). Both the discriminant model and the probit model ranked the allowances for funds under construction, return on assets, and leverage as the most important variables in the prediction bond rating changes. A comparison between the predictive ability of the two models indicated that both models correctly classified 71 per cent of the sample. However, the probit model provided greater accuracy for both unchanged and downgraded bonds, 81 per cent and 71 per cent versus 69 per cent and 64 per cent for the discriminant analysis for the same groups. On the other hand, Wingler and Watts found that the discriminant model is more accurate than the probit model in the prediction of the upgraded bond ratings, 68 per cent for the discriminant model versus 25 per cent for the probit model for the same group.
Studies Related to the Stability of Financial Variables

Empirical studies on the stability (instability) of financial variables are relevant to the purpose of this study because this study is devoted to the explanation and prediction of the bond rating changes that are normally preceded by some degree of variability (instability) in the financial variables of a firm. As a result a review of these studies will aid in the selection of the independent variables to be used in the bond rating changes model.

The Pinches, Mingo, and Caruthers Study

In their study, Pinches, Mingo, and Caruthers (23) made a detailed examination of the stability of financial variables for industrial firms over the 1951-1969 period. The two purposes of their study were, first, to obtain an empirically-based grouping of financial ratios, and second, to measure the long term stability or change in their groupings over a period of time.

Using financial ratios for 221 industrial firms and employing factor analysis, Pinches, Mingo, and Caruthers found seven statistically significant factor patterns (or groups). These groupings include return on investment, capital intensiveness, inventory intensiveness, financial leverage, receivables intensiveness, short-term liquidity, and cash position. In addition, they found that most of the financial ratios were unstable over the 1951-1969 period,
with some ratios increasing over time and others decreasing over time. The ratios that increased over the study period included financial leverage, receivables intensiveness, and capital intensiveness. The ratios that declined over time included cash flows and return on assets. Both inventory intensiveness and short-term liquidity showed no significant trends over the period of the study.

**The Melicher and Rush Study**

Melicher and Rush (19) studied the stability of twenty-eight selected financial variables for a sample of electric utility firms. They used a sample of seventy-one firms over the 1962-1971 period. Melicher and Rush used a factor analysis in their study. The results of the study show that the original financial variables were grouped into seven factor patterns or groups. Those groups are firm size, earnings trend and stability, operating efficiency, financial leverage, financing policy, return on investment, and common stock market activity.

Melicher and Rush also examined the stability of the financial variables over the 1962-1971 period. They found that leverage, total assets, and the volatility of equity increased. The study found that bond ratings declined substantially during that period, perhaps due to the increase in risk level associated with electric utility bond issues.
The Ang and Kiritkumer Study

In their study, Ang and Kiritkumer (2) were interested in determining whether statistical models or agencies' ratings are superior to "naive" models. They compared four statistical models and two naive models for their ability to duplicate Moody's bond ratings. The four statistical models used in the comparison are by Horrigan, West, Pogue and Soldofsky, and Pinches and Mingo. The results of the comparison showed that the model of Pogue and Soldofsky ranked first, followed by those of Pinches and Mingo, West, and Horrigan; the naive models ranked fifth and sixth.

Ang and Kiritkumer also compared Moody's actual ratings, along with the ratings predicted by four statistical models and two naive models, to ex-post measures of bond default and loss rate on investment yield. They found that various bond rating methods performed better than the naive models when the lead time was long. They also found that over longer lead times, the differences between all methods appeared to be insignificant. An important finding of Ang and Kiritkumer's study is that both the Pogue and Soldofsky and the Pinches and Mingo models were able to outperform Moody's ratings in two of the five years examined.
Studies that Used Information Theory-Derived Decomposition Measures in the Analysis of the Financial Statement Data and in the Prediction of Corporate Events

There are a limited number of empirical studies on the use of the information-theory-derived decomposition measures on financial statement data analysis. There have been attempts to apply decomposition measures in the study of various aspects of corporate activities. These attempts include (a) the Lev and Theil study (17) on the use of decomposition measures in choosing the depreciation method that best reflects the available information about an asset's pattern of use; (b) the Lev study (16) on the use of the entropy as a measure of information loss due to aggregation of financial statement items; (c) the Theil study (25) on the use of the entropy in the measurement of the deviation of the actual pattern of expenditures from the budget one; (d) the Nakano (21) study on the use of the decomposition measures in the measurement of the information conveyed by the financial statement; and (e) the Abdel-Kalik (1) study on the relevance of the entropy law and accounting data to corporate decision-making. Five studies were found in which decomposition measures are used in financial statement data analysis.

The Lev Studies

Lev's studies on the use of the decomposition measures in the financial statement data analysis are widely recognized. In his first study, Lev (16) examined the
relationship between balance sheet decomposition measures, firm size, and type of industry. His sample included all the firms on the COMPSTAT tapes over the 1947-1966 period. He classified all firms into manufacturers of durables, producers of nondurables, and services. The balance sheet decomposition measure was also computed for every firm in the sample. Lev found that the balance sheet decomposition measures for manufacturers of durables were larger than the same measures for the producers of nondurables or services. This conclusion recognizes the large effect of business cycle forces on manufacturers of durables. In addition, Lev found that the balance sheet decomposition measures for small firms were larger than those for the large firms.

In his second study, Lev (15) used decomposition measures and a matched pairs design to predict corporate failure. The study's sample included 74 companies—37 failed and 37 nonfailed. He computed asset decomposition measures, liability decomposition measures, and balance sheet decomposition measures over a five-year period prior to the corporate failures. He then compared those measures for the failed companies with those of the nonfailed companies. In more than 50 per cent of the cases, Lev found that the decomposition measures for the failed firms were larger than they were for the nonfailed companies (70% for balance sheet decomposition measures, 62% for asset decomposition measures, and 66% for liability decomposition measures). These results were improved
when consecutive balance sheet measures were averaged (89\% for balance sheet decomposition measures, 76\% for asset decomposition measures, and 73\% for liability decomposition measures).

The Moyer Study

In his study Moyer (20) reexamined the forecasting of the financial failure technique proposed by Altman. He reestimated the parameters of Altman’s model using a new data set. He found that the predictive ability of Altman’s model could be improved if sales/total assets, and the variables for market value of equity and book value of debt were eliminated from the model.

In this study Moyer also compared the reestimated Altman’s model with an alternative model in which Beaver’s cash flow/debt and Lev’s balance sheet decomposition measure were used. He found that the reestimated Altman’s model compared well with that alternative model.

The Walker, Stowe, and Moriarity Study

In their study, Walker, Stowe, and Moriarity (26) used statistical decomposition measures in the prediction of corporate failure. Using a sample from one industry, decomposition measures were computed for both failed and nonfailed companies. They found that the decomposition measures for failed companies were generally larger than those for the
nonfailed companies, and the liability decomposition measure was better than the asset decomposition measure in the prediction of corporate failure.

The ability of the decomposition measures to predict corporate failure was also compared with that of ratios. Walker, Stowe, and Moriarity concluded that decomposition measures have about the same ability as that of ratio analysis in the prediction of corporate failure. They suggest that decomposition analysis can be used to augment or replace the traditional monitoring procedures that are used by banks and other institutions.

The Booth Study

In his 1983 study, Booth (6) employed statistical decomposition measures in the prediction of corporate failure. Both individual and average decomposition measures were computed for both failing and nonfailing companies. Both the magnitude and the stability of decomposition measures were used in the comparison between decomposition measures for matched pairs of failed companies and nonfailed companies. Booth concluded that the four-year average balance sheet decomposition measure, and the second, third, and fourth year balance sheet decomposition measures (for the failed company) were larger than those for the nonfailed matched company. He also found that the four year asset decomposition measure and the first and the fourth year asset decomposition
measures (for the failed company) were larger than those for the nonfailed matched company. Finally, he found that the equities decomposition measure for the average and all years prior to failure (for the failed company) was larger than that for its matched nonfailed firm.

Booth also used the instability of the decomposition measure (measured by the coefficient of variations) in the prediction of corporate failure. He found that the decomposition measures for failed companies were more unstable than those for the nonfailed companies. Further, Booth used the decomposition measures as independent variables in a multiple discriminant analysis model to predict corporate failure. He found that the model did not have a significant ability to classify nonfailed companies.

The Hatten Study

Hatten's (11) unpublished doctoral dissertation, "A Multivariate Analysis of Financially Distressed Computer Firms," used multiple discriminant analysis and statistical decomposition analysis for the predictions of corporate failure in the computer industry. She compared the predictive ability of multiple discriminant analysis with that of statistical decomposition analysis and concluded that statistical decomposition analysis appears to be as successful as discriminant analysis in the classification of failed firms, and much more successful in the classification of nonfailed firms than is discriminant analysis.
The Hamer Study

Hamer's (9) unpublished doctoral dissertation, "An Investigation of the Usefulness of Information Theory-Derived Decomposition Measures in the Prediction of Business Failure," used a sample of 88 pairs of failed and nonfailed firms, over the 1972-1975 period, to evaluate the usefulness of decomposition measures in the prediction of business failure. The predictive ability of each decomposition measure was compared on a univariate basis with each of Beaver's "best" six ratios. The study revealed that few decomposition measures produced significant differences in the means of the two groups (failed and nonfailed), while three of Beaver's ratios produced significant differences in the means of the two groups (failed and nonfailed firms).

Hamer also employed decomposition measures as additional independent variables in some existing failure-prediction models (Altman's, Denkin's, and Blum's models). Her conclusion is that the equity information measures improves the performance of the existing failure-prediction models in the second year prior to failure.


This chapter presents the research design that is used in the study of Industrial Bond Rating Changes (IBRC). Sections of this chapter include statements of the hypotheses in testable form, a discussion of the statistical techniques that are used in the study, and the basis for the selection of the appropriate sample.

Null Hypotheses

As stated in Chapter I, the two main hypotheses for this study are, first, bond rating changes can be predicted based on financial statement data, and, second, statistical decomposition measures can achieve the same performance of the multiple discriminant analysis in duplicating and predicting industrial bond rating changes. In order to test these two hypotheses, they must be subdivided into the following five null hypotheses:

\( H_0^1 \): Decomposition measures for companies that experienced bond rating changes will be larger than the decomposition measures for companies that did not experience bond rating changes.
$H_0^2$: Decomposition measures for companies that experienced bond rating changes will be more unstable than the decomposition measures for companies that did not experience bond rating changes.

$H_0^3$: A company's bond rating change can be predicted on the basis of an index or score that incorporates the size and stability of that company's decomposition measures.

$H_0^4$: There will be no significant differences among the means for the three groups of bond ratings that were upgraded, unchanged, or downgraded.

$H_0^5$: Both the statistical decomposition analysis and the multiple discriminant analysis will achieve the same performance in duplicating and predicting bond rating changes.

A univariate statistical decomposition analysis is used for testing the first two hypotheses. A multivariate decomposition analysis is used for testing the third hypothesis. The fourth hypothesis, which is a standard statement of the null hypothesis when the discriminant analysis is used, is tested by a multiple discriminant model. The fifth hypothesis is tested by a chi-square test which is discussed later in this chapter.

Appropriateness of Information Theory Concepts to the Study of Bond Rating Changes

Information theory concepts appear to be appropriate to the study of bond rating changes for several reasons. First, the application of the entropy concept in social science can
be illustrated by the case of a decision-maker who has some expectations about certain events. If the decision-maker receives a signal reflecting a change in the data, then his choice expectations are altered, and he may take a different course of action. In such a case, the entropy concept can be used by the decision-maker in the evaluation of the change.

Bond raters may be perceived as the decision-maker in the above case. Thus, when decomposition measures carry a signal to the raters about a change in the asset-liability structure of the firm, it becomes likely that the raters will review the company's current bond rating in the light of this new information. If the information reveals that the firm's conditions have improved (or deteriorated) significantly, then the rating agency may raise or lower the firm's bond rating.

A second reason why information theory concepts may be appropriate to bond rating changes is that there is empirical evidence to support the use of trends in financial ratios as a cause of a change in rating (4). Bhandari (3) uses multiple discriminant analysis in his study of bond rating changes. In his model, he uses trends in some financial ratios as independent variables. His conclusion is that both the return on asset trend and the fixed charges coverage trend are very important in their contribution to the discriminant model and to the prediction of bond rating changes. This evidence suggests that information theory-derived
decomposition measures appear to be appropriate to the study of bond rating changes because both financial ratio trends and information theory-derived decomposition measures can be used in the measurement of the changes in a firm's financial position and its asset-liability structure from one period to another as a basis for the prediction of corporate events (30).

In addition to this empirical evidence, officials in the rating agencies have admitted several times that changes in a firm's financial ratios over time represent a real cause for rating-change decisions. For example, one official of Moody's Corporate Bond Research (20) admits that a major cause for the lowering of Borg-Warner's bonds from a Aa rating to an A rating was the company's declining earnings and increasing indebtedness. This reinforces the researcher's belief that information theory-derived decomposition measures can be used in the study of bond rating changes since such measures are considered indicators of structural changes in a company's assets, liabilities, revenues, and expenses from one period to another.

A third reason for the appropriateness of this application is that information theory-derived decomposition measures are simple, less expensive to generate (30), and have no restrictive assumptions as do other previously discussed statistical techniques. These measures are simple because they rely on the entropy concept, which is well known in information
theory, and they are less expensive because they can be computed from financial statement data which are readily available at little additional cost. In addition, the use of decomposition measures does not require restrictive assumptions. The only restriction that must be met for the computation of these measures is that the set data used in the computation should not include negative numbers since the logarithm of a negative number is undefined (17, 18, 29).

A fourth reason for the use of this technique is that information theory-derived decomposition measures may be superior to ratio analysis in the study of bond rating changes for three main reasons. First, ratio analysis is usually applied to individual items (e.g., net income over equity) while decomposition measures focus on the partitioning of financial statements (i.e., on the relationships within a set of items); therefore, decomposition analysis seems to add dimension to ratio analysis and is more informative than conventional ratio analysis (24). Second, the simplicity of ratios can be misleading to the user. For example, a change in a ratio could result from a change in the numerator, a change in the denominator, or both; therefore, further investigation may be needed to identify the source of the change. On the other hand, if there is no change in the ratio, it does not mean that conditions are the same since both numerator and denominator could have been changed by the same proportion (29). Third, decomposition measures
appear to be more comprehensive than the conventional ratios. A decomposition measure can include a number of items (assets, liabilities, or both); therefore, it is more comprehensive than a conventional ratio because the latter normally includes two pieces of information (e.g., net income over sales).

A fifth reason for the appropriateness of using information theory concepts to predict bond rating changes is that there is empirical evidence to show that information theory-derived decomposition measures are highly correlated with changes in ratios that measure the same financial aspects of a company (24). This evidence reinforces the researcher's belief that information theory-derived decomposition measures can be used in the study of bond rating changes—an area that has been frequently studied through the use of financial ratios and changes in these ratios (3).

Furthermore, a sixth reason is that information theory-derived decomposition measures have been used in several studies to predict firm failure (6, 11, 12, 18). These studies show that decomposition measures are capable of signaling the event of failure with a reasonable degree of accuracy—about 70 per cent in Booth's study (6) and 73 per cent in Lev's study (18).

In addition one study (11) shows that decomposition measures are as successful as multiple discriminant analysis in the prediction of firm failure. This evidence adds more justification to the use of information theory-derived
decomposition measures in the study of bond rating changes because corporate failure and bond rating changes are similar in that each is expected to be preceded by significant changes in a company's asset-liability structure.

Computation of Information Theory-Derived Decomposition Measures

Information theory-derived decomposition measures can be computed from a firm's financial statements. These measures may be used to examine the relationship among the items in the firm's income statement and balance sheet \(11, 18, 29\). When used to compare the financial statements for two periods, such measures can provide the user with information about whether or not a change has taken place in the firm's asset-liability and revenues-expenses structure \(17\). In addition, the decomposition measures, as Theil suggests \(29\), can be used in a comparison of the firm's financial statement decompositions with the industry average.

The basic formula that is used in the computation of the decomposition measures can be stated as follows:

\[
DM = q_i \log \frac{q_i}{p_i} \quad \text{Eq. (1)}
\]

where: \(q_i\) = represents the fraction of an asset (liability) as a fraction of the total assets (liabilities) in the most recent year.

\(p_i\) = represents the fraction of an asset (liability) as a fraction of total assets (liabilities) in the earlier year.
\( i \) is a subset of the appropriate total or liabilities.

The above equation is used in the computation of the following decomposition measures:

1. Assets Decomposition Measure (ADM);
2. Liabilities Decomposition Measure (LDM);

These three decomposition measures can be computed from balance sheet items.

Theoretically, the greater the number of categories into which a total can be divided, the more informative the decomposition measure will be. However, empirical research in this area does not provide the optimal number of subsets into which a total can be broken down—whether this total is a total of assets or a total of liabilities. As a result, the researcher uses the same number of categories suggested by researchers in the area (6, 17, 24, 26, 28). Therefore, the following system will be used for the partitioning of each of the following totals:

1. The total of assets will be divided into current assets and noncurrent assets;
2. The total of liabilities will be divided into current liabilities, long-term liabilities, and shareholders' equity.

In a functional form, the three decomposition measures to be computed (ADM, LDM, and BSDM) can be stated as follows:
1. ADM = \[ \sum_{i=1}^{n} q_{i1} \log \frac{q_{i1}}{p_{i1}} \] Eq. (2)

2. LDM = \[ \sum_{i=1}^{n} q_{i1} \log \frac{q_{i2}}{p_{i1}} \] Eq. (3)

3. BSDM = \[ \sum_{i=1}^{n} \sum_{j=1}^{2} (\cdot5) q_{ij} \log \frac{q_{ij}}{p_{ij}} \] Eq. (4)

where: \(q_{i1}\) = represents the fraction of current or non-current assets as a fraction of total assets in the most recent year; \(p_{i1}\) = represents the fraction of current or non-current assets as a fraction of total assets in the earlier year; \(q_{i2}\) = represents the fraction of current liabilities, long-term liabilities; or shareholders' equity as a fraction of total liabilities in the most recent year; \(p_{i2}\) = represents the fraction of current liabilities, long-term liabilities and shareholders equity as a fraction of the total liabilities in the earlier year.

The three decomposition measures that the researcher proposes to use in this study (ADM, LDM, BSDM) are expected to provide information about the extent to which a company's asset-liability structures have changed over one period. As discussed in the review of the literature in Chapter II, these three decomposition measures (ADM, LDM, and BSDM) are used in several studies for the prediction of corporate failure (5, 11, 18, 29), and they appear to be useful in signaling the event of failure.
Univariate Statistical Decomposition Analysis

For companies that experienced a bond rating change, the five years prior to the change are referred to as $t_1$, $t_2$, $t_3$, $t_4$, $t_5$, where $t_1$ is the first year prior to the rating change, $t_2$ is the second year prior to the change and the same sequence will continue down to $t_5$, or the fifth year prior to the change. For companies that did not experience bond rating changes during the 1977-1981 period, a cut-off year is designated. The last year in the period of study, 1981 is chosen as a cut-off year. The five years preceding that cut-off year are referred to as $t_1$, $t_2$, $t_3$, $t_4$, $t_5$ and are used in the computation of the decomposition measures for these companies.

Theoretically, the choice of another cut-off point may produce different results because of changes in economic conditions prior to that cut-off point that affect all companies in different industries. However, the research design of this study includes a comparison between the individual decomposition measures and their respective industry averages and not with other individual decomposition measures. As a result, the choice of 1981 (or any other year in the period of study) as a cut-off point is a defensible one because the changes in economic conditions prior to that cut-off point will affect all companies in the industry;
therefore, the individual decomposition measures as well as the industry average decomposition measures are expected to reflect such changes.

In computing the first decomposition measure, \( t_1 \) is referred to as the most recent year while \( t_2 \) is referred to as the earlier year. That distinction is essential for computing \( p_i \) and \( q_i \) in equation 1.

The same order will be followed in computing the second, third, and fourth decomposition measures. The computed decomposition measures are used in the analysis for the measurement of both the size and the stability attributes.

The size of each decomposition measure is used in testing Hypothesis 1, which predicts that decomposition measures for companies that experienced bond rating changes will be larger than the decomposition for companies that did not experience bond rating changes. The size of each decomposition measure is computed using the appropriate equation. Since this study does not utilize a matched-pair design, which was used in most of the empirical studies in this area, it is necessary to establish criteria against which each decomposition measure for each company is compared; the criteria are the industry average decomposition measures. These industry average decomposition measures are computed using the set of equations 2, 3, and 4 as discussed earlier.
The instability of each decomposition measure is measured by the coefficient of variation of that measure. For the computation of that coefficient of variation, a five-year average decomposition measure and a standard deviation of that measure are calculated. The following equation is used in the computation of the coefficient of variation.

\[ \text{CV} = \frac{\sigma}{\bar{X}} \]

where: \( \text{CV} \) = the coefficient of variation; \( \sigma \) = the standard deviation of the decomposition measure; \( \bar{X} \) = the five-year average decomposition measure.

The computed coefficient of variation is then used as a measure of the instability of the decomposition measure. After a preliminary review of the data, a cutoff level of the coefficient of variation is chosen; if the particular decomposition measure falls above the cutoff level, it will indicate that the measure is relatively unstable; if, however, it falls below the cutoff level, it indicates that the measure is relatively stable.

In regard to the structure of univariate analysis, most of the empirical research to date is limited to intertemporal decomposition measures (6, 11, 18). Only one study utilizes the industry average decomposition measures [cross-sectional decomposition analysis] (12). However, this current study utilizes both intertemporal decomposition measures and cross sectional decomposition analysis. The use of these two
methods is illustrated by the following contingency table format; from this point, this format will be referred to as the intertemporal cross-sectional decomposition analysis (ICSDA).

<table>
<thead>
<tr>
<th>Year</th>
<th>Company's DM</th>
<th>Industry Average DM</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st Year</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2nd Year</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3rd Year</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4th Year</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

According to the proposed method (ICSDA), the individual decomposition measures are computed for every company in each of the years prior to the rating change or cut-off point (Column 2 in the format table). The individual decomposition measures are used for three purposes. First, the individual decomposition measures for each company are used as a measure of the size attribute. Second, the individual decomposition measures for each company are used in the calculation of the five-year average decomposition measure, the standard deviation, and the coefficient of variation of that measure (equation 6). Third, the individual decomposition measures for each company in the sample are used in conjunction with
the decomposition measures for the rest of the companies in the same industry in the computation of the industry average decomposition measures (column 3 in the format table). These industry average decomposition measures are used as the criteria against which the individual decomposition measures for each company are compared. Such a comparison is used in testing the size attribute previously discussed.

Multivariate Statistical Decomposition Analysis

Although the empirical research to date is limited to the use of individual decomposition measures (univariate analysis), this study theorizes that if two or more decomposition measures, along with their respective instability measures, are combined in an "index," then that index may be more informative than the individual decomposition measure in signaling a particular event, which, for this study, is the bond rating change. Furthermore, although the proposed index can be computed in different ways, it is necessary that this index be computed in a form that is suitable for statistical testing and comparison with the multivariate models that were reviewed in Chapter II. After reviewing different statistical techniques, a special regression equation has been selected for the computation of that index.

The proposed model is similar to the special regression model developed and used by Pogue and Soldofsky (25) in their 1969 study. The two models are similar in that both
use a dichotomous dependent variable that can be predicted by a set of independent variables. However, the models differ in two respects. First, the Pogue and Soldofsky model is used in the prediction of bond ratings, while the model for this study will be used in the prediction of bond rating changes. Second, in the Pogue and Soldofsky model, financial ratios are used as independent variables, which in the model for this study only statistical decomposition measures and their respective measures of instability are used as independent variables.

In this study's regression model, the dependent variable $Y_j$ is defined as the probability that the rating of an outstanding bond for firm $J$ will be changed (either upgraded or downgraded) or remain unchanged. If the relationship between $Y_j$ and the statistical decomposition measures and their measures of instability is linear and additive, then the model is stated as follows:

$$Y_j = a + b_1 x_{1j} + b_2 x_{2j} + \cdots + b_n x_{nj} + E (e_j)$$

In their study Pogue and Soldofsky (25) found that a linear relationship exists between financial ratios and bond ratings. Another study by Walker, Stowe and Moriarity (30) shows that financial ratios and decomposition measures are highly correlated. Based on the findings of these two studies, it can be argued that the decomposition measures may have a linear relationship with the bond rating changes and as result they can be used in the prediction of those rating changes.
In this equation, $Y_j$, or the dependent variable, can be viewed as the conditional probability that the bond rating will change or remain unchanged, and $E(e_j)$, or the error term, represents the effect of all variables that affect the rating change decision other than the statistical decomposition measures and their measures of instability.

Theoretically, a positive relationship may exist between the level and the instability of the statistical decomposition measures on one hand, and the probability of a bond rating change on the other hand (i.e., the higher the level of those measures and the more unstable they are, the higher the probability of a rating change). This theoretical relationship is based on some empirical evidence (16) that supports the existence of such a relationship between the level and instability of decomposition measures on one hand and corporate failure on the other hand. Bond rating changes and corporate failure are similar in that each of the two events is expected to be preceded by some pronounced changes in the company's asset-liability structure. Because of this similarity, it may be argued that the positive relationship that exists between the level and instability of the decomposition measures on one hand, and corporate failure on the other hand, may exist between the level and instability of the decomposition measures on one hand, and the probability of bond rating change on the other hand.
Models like that in equation 8 are called linear probability models (LPM). In an LPM, \( E(Y_i/X_s) \), or the conditional expectation of \( Y_i \) given a set of \( X_s \), can be interpreted as the conditional probability that an event will occur given a set of \( X_s \). Thus, in the case of a bond rating change, \( E(Y_i/X_s) \) is the probability of a bond rating change, given a set of independent variables or decomposition measures.

The linear probability models (LPMs) have some unique problems that need special consideration. These problems are as follows:

1. The disturbances are non-normal since (like the dependent variable \( Y_i \)) \( U_i \) takes only two values. However, this problem does not represent a major threat to the reliability of the results because the estimates obtained from the LPM are still unbiased (10, 32).

2. An LPM model will have a heteroscedastic variance because it depends on the conditional probability of \( Y \), which, of course, depends on the value taken by \( X \). Thus, ultimately the variance of \( U_i \) depends on \( X \) and is thus not homoscedastic. This heteroscedasticity problem can be solved by transforming the data through the application of any transformation form (15, 29).

3. A special problem that arises in the application of LPM is that the estimated conditional probability may not lie between the 0 and 1 limit. Two remedies are available for this problem. First, if some of the estimated \( Y_i \) are less
than 0, they are assumed to be 0, and if some of the estimated \( Y_i \) are greater than 1, they are assumed to be 1. Second, some special estimating techniques may be used to guarantee that the estimated conditional probability lies between 0 and 1 (32).

Test of Significance

In evaluating the predictive accuracy of the decomposition measures—size attribute or stability attribute—it is useful to know whether the misclassification rate is smaller than would be expected by chance. Should the statistical model yield a percentage of correct classifications higher than the percentage of correct classifications achieved by random assignment, it may be concluded that the classification accuracy of the model is better than that of the chance model. The proportional reduction in error statistic, \( \tau \), which will give a standardized measure of improvement regardless of the number of groups, is computed as follows:

\[
\tau = \frac{n_c - \sum_{i=1}^{g} p_i n_i}{n - \sum_{i=1}^{g} p_i n_i}
\]

where:

- \( n_c \) = the number of cases correctly classified;
- \( p_i \) = the prior probability of group membership;
- \( n \) = the number of cases in the analysis;
Multiple Discriminant Analysis

Discriminant analysis is a statistical technique that allows the researcher to study the differences between two or more groups of objects with respect to several independent variables simultaneously (14). The technique can be used for the interpretation of group differences or for the classification of cases into the groups. When applying the discriminant analysis for interpretation, the researcher's interest is to study the ways in which the groups differ from one another on the basis of some set of characteristics. Also, the researcher's interest may include the study of which characteristics are the most powerful discriminators. On the other hand, when applying the discriminant for the classification of cases into the groups, the researcher's interest is to derive one or more mathematical equations to be used in the classification. These equations, referred to as discriminant functions, combine the group characteristics in a way that will allow the researcher to identify the group that most closely resembles a case (1, 5, 7, 14, 21, 22, 23, 27). A more detailed discussion of the discriminant analysis is presented in Appendix B.
Variables in the Multiple Discriminant Model

Two types of variables are discussed in this section. These are the dependent variables and the independent variables.

The Dependent Variable

The dependent variable in the multiple discriminant analysis is represented by three groups of bond rating change. These groups of bond rating change are upgraded, downgraded, and no change.

Independent Variables

Previous bond rating studies by Belkaoui (2), Bhandari (3), Fisher (9), Horrigan (13), Long (19), Pinches and Mingo (23), Pogue and Soldofsky (25), and West (31) show that bond ratings may be reasonably estimated using financial statement data and a summary of financial statistics (3). A survey of the different lists of variables used in these studies shows that the following list includes several variables that are considered the main determinants of bond rating. These variables are (a) firm's size, (b) liquidity, (c) fixed charges coverages, (d) leverage, (e) profitability, (f) earnings variability, and (g) subordination (see Appendix C).

Since the purpose of this study is the prediction of bond rating changes, it appears that changes in these variables over time (trends), as well as their current level, should be considered in the analysis (5). Since the
subordinating status is not likely to change over time, the change in variable \( g \) will be 0. Also, any computation of variable \( f \)—earnings variability—will consider the changes in earnings over time. As a result, this study will not compute an earnings variability trend.

The importance of the changes (trends) in the above variables for the prediction of bond rating changes can be defended on two grounds. First, officials in rating agencies have indicated that they consider changes in financial ratios in making their rating change decisions (20). Second, previous bond rating change studies used changes (trends) in financial ratios as well as current levels of those ratios in the prediction of the rating changes (3, 4).

Although changes in the financial ratios represent a solid basis for the prediction of bond rating changes, it appears that the current levels of those ratios, if included in the model, will improve the prediction of those changes. There are several justifications for the inclusion of the current levels of the financial ratios in the bond rating change model. According to Bhandari (3), first, the current levels of financial ratios have an important information content in making the rating change decision. Officials in the rating agencies have indicated that both the change in the financial ratios and the current level of those ratios are important in the rating decision. Second, in many cases, the rating change decision is made when there is an imminent
new bond issue by the company. In these cases, the decision to change the rating of an outstanding bond will be strongly linked to the quality or the rating of the imminent new issue, which in turn will be strongly influenced by the current and future levels of the financial ratios.

Based on the review of bond rating studies and the changes in corporate credit studies, as discussed above, this study uses the following set of eleven independent variables in the prediction of bond rating changes.

1. Firm size ($X_1$) measured by total assets ($TA$);
2. Total assets trend ($X_2$) or ($TRT$);
3. Financial leverage ($X_3$) measured by book value, total debt to total assets ($DR$);
4. Debt ratio trend ($DRT$) or ($X_4$);
5. Liquidity ($X_5$) measured by current ratio ($CR$);
6. Current ratio trend ($CRT$) or ($X_6$);
7. Profitability ($X_7$) measured by the return on assets ($ROA$);
8. Return on assets trend ($X_8$) or ($ROAT$);
9. Fixed charges coverage ($X_9$) or ($FCC$);
10. Fixed charges coverage trend ($X_{10}$) or ($FCCT$);
11. Earnings variability ($X_{11}$) measured by return on assets residuals ($RDAR$).

All the trend variables in the above list ($X_2$, $X_4$, $X_6$, $X_8$, $X_{10}$) will enter the analysis in the form of annualized change in their respective ratios:
Annualized change = \frac{\text{Change over the period of study}}{n},

where n is five years. The annualized change is used because it measures the change in the firm's financial position from one year to another.

Sample Selection

The sample for the study will include all the industrial nonconvertible bond rating changes that took place during the 1977-1981 period. Moody's Bond Survey is the main source of information about rating changes. Each company is represented by only one bond issue of its outstanding bond issues. If a company has experienced more than one bond rating change during the 1977-1981 period, the earliest bond rating change is included in this study.

The sixty-two unchanged bond ratings were randomly selected from Moody's Industrial Manual for the 1977-1981 period. Since it is recognized that a degree of difficulty is involved in the selection of a representative sample of firms that have maintained the same bond ratings during the 1977-1981 period, the following approach was followed in the selection of the study sample.

1. An alphabetical listing of all companies that have maintained the same bond ratings over the 1977-1981 period will be assigned a number from 1 to n.

2. A random number table will be used to identify the sixty-two companies to be included in the study.
Validation

There are two main ways to validate discriminant functions. The first one is known as a hold-out sample, and it requires a discriminant function derived from a set of observations known as the analysis sample to be used in the prediction of another sample, referred to as a hold-out sample. A second way to validate the discriminant function is known as the Lachenbruch validation technique (16); according to this technique a discriminant function is developed from all observations except one (i.e., n-1). The developed function is then used in the prediction of the observation that was excluded from the sample in the development of the function. The procedure will be repeated several times until each observation has a chance to be predicted by a discriminant function developed from other observations. The validation procedure for the multi-variate decomposition analysis is the same as that used for the validation of the discriminant analysis results.

Comparison of Classification Accuracy of the Decomposition Model with the Discriminant Model

As stated in Chapter I, one of the main objectives of this study is the comparison of classification accuracy of the decomposition model with that of the discriminant model. A chi-square test will be used to determine whether the difference in classification accuracy of the two models is significant. This test is also used in previous studies.
in the comparison of the predictive accuracy of two different models used in the prediction of corporate failure. The test is based on the following contingency format:

<table>
<thead>
<tr>
<th></th>
<th>Number of Firms Correctly Classified</th>
<th>Number of firms Misclassified</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>0_{11}</td>
<td>0_{12}</td>
<td>n_1</td>
</tr>
<tr>
<td>Model 2</td>
<td>0_{21}</td>
<td>0_{22}</td>
<td>n_2</td>
</tr>
<tr>
<td>Total</td>
<td>n_3</td>
<td>n_4</td>
<td></td>
</tr>
</tbody>
</table>

\[
T = \frac{(n_1 + n_2) \left(0_{11}0_{22} - 0_{12}0_{21}\right)^2}{n_1 \cdot n_2 \cdot n_3 \cdot n_4}
\]

Since this study hypothesizes that the predictive ability of the decomposition model is not different from the predictive ability of the discriminant model, this hypothesis will be rejected at significance level \( \alpha \) if \( T \) is greater than \( (1 - \alpha) \) quantile of the chi-square distribution with one degree of freedom (a two-tail chi-square test).


CHAPTER IV

ANALYSIS AND RESULTS

The results of the decomposition analysis are reported in this chapter, and statistical tests are undertaken to determine if statistical decomposition measures can be used in the classification and the prediction of bond rating changes. In addition, the results of the multiple discriminant analysis are reported, and statistical tests are undertaken to evaluate the accuracy of this technique for the classification and prediction of industrial bond rating changes. Finally, the predictive abilities of statistical decomposition analysis and that of multiple discriminant analysis are compared using the chi-square test discussed in the previous chapter.

The sample used in this study includes a total of 134 firms; 33 of these firms had bond ratings that were upgraded during the 1977-1981 period, 39 of these firms had bonds that were downgraded during the 1977-1981 period, and 62 of these firms maintained their bond ratings without a change during the 1977-1981 period. The procedure for the selection of the 62 nonchanged firms was discussed in Chapter III.

The number of firms that experienced bond rating changes during 1977-1981 period is higher than the 72 firms used in
this study. Several factors contributed to this discrepancy. First, any firm that experienced a bond rating change had to be listed on COMPSTAT tapes before it could be included in the sample. Second, changes of the ratings of convertible bonds were excluded from the selection because of the special nature of these bonds. Third, some firms which experienced bond rating changes on their nonconvertible bonds and which are listed on COMPSTAT were excluded from the sample because the financial data of those firms were either incomplete or did not enable the researcher to compute other measures (namely, statistical decomposition measures). The research design employed in this study requires that the sample used in the discriminant analysis be the same sample used in the statistical decomposition analysis.

Univariate Decomposition Analysis (Size Attribute)

Statistical decomposition measures, which are assumed to gauge the structural changes in the balance sheets for 72 changed bond firms that experienced bond rating changes and for 62 firms that did not experience bond rating changes over the period of study, were computed using the set of equations presented in Chapter III. Each of the computed statistical decomposition measures for each firm in the sample was then compared with an industry average statistical decomposition measure each year for four years before the rating
change (or the cut-off year) in order to determine if the firm's decomposition measures deviated from their respective industry average decomposition measures.

The comparison of the firms' statistical decomposition measures with those of the industry was made by constructing the contingency format shown in the previous chapter. Table I presents the results of the univariate analysis for two selected firms: Harper & Row Publishers, Inc., which experienced a bond rating change in 1980, and Macmillan, Inc., which did not experience any bond rating change during the 1977 to 1981 period. Since two firms belong to the same industry, the computed decomposition measures for each firm are compared with that of the industry for each year for four years before the rating change year (for Harper & Row) or before the cut-off year (for Macmillan).

The data in Table I show that first, the asset decomposition measure for Harper & Row, which experienced a bond rating change in 1980, was higher than the industry average asset decomposition measures for the first, second, and third year before the rating change. In contrast, the same decomposition measure (ADM) for Macmillan, which did not experience any bond rating change during the study period, was lower than the industry average decomposition measure for all four years prior to the cut-off year. Second, the liability decomposition measure for Harper & Row was higher than the industry average liability decomposition measure
for the first year before the rating change and below the industry average for the second, third, and fourth years before the change; for Macmillan, the liability decomposition measure was far below the industry average for all the four years before the cut-off year. Third, the balance sheet decomposition measure for Harper & Row was higher than the industry average decomposition measure for the first and second year before the rating change and below the industry average for the third and fourth year; however, for Macmillan, the balance sheet decomposition measure was far below the industry average for all four years before the cut-off year.

TABLE I

RESULTS OF THE UNIVARIATE ANALYSIS SIZE ATTRIBUTE FOR TWO SELECTED FIRMS

<table>
<thead>
<tr>
<th>Year Before Rating Change or Cut-Off Year</th>
<th>Harper &amp; Row Publishers, Inc.</th>
<th>Macmillan, Inc.</th>
<th>Industry Average</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ADM*</td>
<td>LDM</td>
<td>BSDM</td>
</tr>
<tr>
<td>First</td>
<td>20.4</td>
<td>41.5</td>
<td>31.9</td>
</tr>
<tr>
<td>Second</td>
<td>28.1</td>
<td>7.7</td>
<td>17.8</td>
</tr>
<tr>
<td>Third</td>
<td>18.3</td>
<td>10.2</td>
<td>14.2</td>
</tr>
<tr>
<td>Fourth</td>
<td>.1</td>
<td>.4</td>
<td>1.26</td>
</tr>
</tbody>
</table>

*All decomposition measures are expressed in \(10^{-4}\) nits.

Although Table I is prepared to illustrate the type of univariate decomposition analysis that was performed, it may
be inferred from these data that the asset decomposition measure signalled the rating change for Harper and Row three years before the change took place, with stronger accuracy in the first year before the change. The balance sheet decomposition measure for Harper and Row gave the same signal in the two years preceding the rating change, with stronger accuracy shown in the first year before the rating change. The liability decomposition measure for Harper and Row, however, signalled the rating change only one year before the change. For Macmillan, which did not experience any bond rating change during the period of study, none of the three decomposition measures—ADM, LDM, and BSDM—show any increase above their respective industry average decomposition measures in any of the four years covered in this study. As a result, the decomposition measures for Macmillan shows that the firm did not experience major changes in the industry over the same period. Therefore, one can infer that the relative stability of Macmillan's asset-liability structure over the period of study, along with other financial and operating factors, contributed to the maintenance of the firm's bond rating over the period of study.

Univariate decomposition analysis, as illustrated in the above example, was performed for each of the 72 firms that experienced bond rating changes during the 1977-1981 period and for each of the 62 firms that were randomly
selected from the firms that did not experience any bond rating change during the 1977-1981 period. Since the purpose of performing univariate decomposition analysis is to test the null hypothesis that the decomposition measures for firms that experienced bond rating changes are greater than those for the firms that did not experience bond rating changes, the classification procedure that was followed in the analyses was to classify the firm into a "change" or "nonchange" group on the basis of the size of the firm's decomposition measure relative to the respective industry average decomposition measure. According to that classification procedure, the firm is assigned to the change group if the decomposition measure for that firm is larger than the respective industry average decomposition measure, and the firm is assigned to the nonchange group if the decomposition measure for that firm is equal to or smaller than the respective industry average decomposition measure.

The above classification procedure is repeated four times for each firm in the sample because the study covers the four years prior to the rating change or the cut-off year for firms that did not experience bond rating changes. (This type of analysis is referred to as intertemporal cross-sectional analysis.)

Table II data show the percentage of correct classification that resulted from performing intertemporal cross-sectional analysis on all firms in the sample. These data
### TABLE II
RESULTS OF UNIVARIATE DECOMPOSITION ANALYSIS

<table>
<thead>
<tr>
<th>Decomposition Measure</th>
<th>Year Before the Change or the Cut-Off Year</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>First Year</td>
<td>Second Year</td>
<td>Third Year</td>
<td>Fourth Year</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>No Change</td>
<td>Change</td>
<td>No Change</td>
<td>Change</td>
<td>No Change</td>
</tr>
<tr>
<td>ADM N</td>
<td></td>
<td>43</td>
<td>35</td>
<td>78</td>
<td>43</td>
<td>39</td>
</tr>
<tr>
<td>%</td>
<td></td>
<td>59.7</td>
<td>56.5</td>
<td>58.2</td>
<td>59.7</td>
<td>62.9</td>
</tr>
<tr>
<td>LDM N</td>
<td></td>
<td>45</td>
<td>36</td>
<td>81</td>
<td>47</td>
<td>34</td>
</tr>
<tr>
<td>%</td>
<td></td>
<td>62.5</td>
<td>58.1</td>
<td>60.4</td>
<td>65.3</td>
<td>54.8</td>
</tr>
<tr>
<td>BSDM N</td>
<td></td>
<td>46</td>
<td>37</td>
<td>83</td>
<td>48</td>
<td>40</td>
</tr>
<tr>
<td>%</td>
<td></td>
<td>63.9</td>
<td>59.7</td>
<td>61.9</td>
<td>66.7</td>
<td>64.5</td>
</tr>
</tbody>
</table>
show the percentage of correct classification for the group of firms that experienced bond rating changes, the percentage of correct classification for the group of firms that did not experience bond rating changes during the study period, and the percentage of correct classification for the whole sample.

The data in Table II show that for the firms that experienced bond rating changes during the 1977-1981 period, both the liability and the balance sheet decomposition measures show the highest classification accuracy in the second year before the rating change. This accuracy declines as the analysis moves to the third and fourth year prior to the change. The asset decomposition measure follows a similar pattern except that it maintains its highest classification accuracy in the first and second years before the rating change.

These results confirm this study's anticipated results for the second, third, and fourth year prior to the rating change because they show the classification accuracy of all decomposition measures improving as the analysis moves from the fourth to the third to the second year prior to the rating change. However, the above results do not confirm the anticipated results for the first year prior to the rating change. Instead of commanding their highest classification accuracy in the first year before the rating
Previous studies show that the agency's decision to change a bond rating lags behind the actual changes in the firm's conditions. For instance, Pinches and Singleton (13) estimated the lag in the rating change decision to be between 12 and 18 months. The results of this study confirm the findings of Pinches and Singleton since the decomposition measures show their highest classification accuracy in the second year and not in the first year before the rating change.

Table II also presents the percentage of correct classifications for decomposition measures for the firms that did not experience bond rating changes during the 1977-1981 period. The data suggest that decomposition measures for the firms that maintained their original bond rating did not follow any consistent pattern relative to their respective industry average decomposition measures over the study period. The lack of consistency in the pattern for these decomposition measures in relation to their respective industry average decomposition measures is due in part to the heterogeneous nature of the firms in that group. Since this group includes firms that were randomly selected from several industries, it is probable that there are firms in this group that experienced some structural changes.
in their asset-liability structure because they are fast-growing firms that have different growth patterns in their assets and liabilities.

In addition, the finding of Pinches and Singleton (13) regarding the 12- to 18-month lag in the bond rating change decision justifies the existence of the inconsistent classification pattern for decomposition measures for firms that maintained their bond ratings. In this group, there may be some firms that experienced some structural changes in their asset-liability structure, but did not experience a bond rating change because of the inability of the rating agency to keep the ratings updated. It also indicates that rating revisions are inadequate.

Evaluation of Univariate Analysis

To evaluate the classification accuracy of the statistical decomposition measures presented in Table II, it was necessary to compare the misclassification rate for each decomposition measure with the misclassification rate that would occur had observations been assigned by chance between the two groups. Since there are two groups in the analysis—changed and nonchanged bond ratings—one would expect to correctly classify 50 per cent of the predictions by pure random assignment. Should the classification process yield more than 50 per cent correct, it may be concluded that the classification accuracy of the decomposition
measure(s) is better than that of the chance model. The proportional reduction in the error statistic, \( \tau \), which will give a standardized measure of improvement regardless of the number of groups, is computed as follows:

\[
\tau = \frac{n_c - \sum_{i=1}^{q} p_i n_i}{n - \sum_{i=1}^{q} p_i n_i}
\]

where,
- \( n_c \) = the number of cases correctly classified;
- \( p_i \) = the prior probability of group membership,
- \( n \) = the number of cases in the analysis,
- \( S \) = the number of groups,
- \( n_i \) = case \( i \) in a particular group.

Table III presents a comparison of data between the classification accuracy of each decomposition measure and that of a chance model for each year prior to the rating change. The data in Table III suggest that each decomposition measure produced fewer errors than would be expected by random assignment. In the second year prior to the rating change, the three decomposition measures commanded the highest superiority over the chance model. The balance sheet decomposition measure produced 31 per cent fewer errors than would be expected by random assignment, while the liability decomposition measure produced 21 per cent fewer
<table>
<thead>
<tr>
<th>Decomposition Measure</th>
<th>Year Before the Change</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>First Year</td>
<td>Second Year</td>
<td>Third Year</td>
<td>Fourth Year</td>
<td></td>
</tr>
<tr>
<td></td>
<td># Cases Correctly Classified by DM</td>
<td># Cases Correctly Classified by Chance</td>
<td>Tau</td>
<td># Cases Correctly Classified by DM</td>
<td># Cases Correctly Classified by Chance</td>
</tr>
<tr>
<td>ADM</td>
<td>78</td>
<td>67</td>
<td>.16</td>
<td>82</td>
<td>67</td>
</tr>
<tr>
<td>LDM</td>
<td>81</td>
<td>67</td>
<td>.21</td>
<td>81</td>
<td>67</td>
</tr>
<tr>
<td>BSDM</td>
<td>83</td>
<td>67</td>
<td>.24</td>
<td>88</td>
<td>67</td>
</tr>
</tbody>
</table>

TABLE III

COMPARISON BETWEEN CLASSIFICATION ACCURACY OF DECOMPOSITION MEASURES AND A CHANCE MODEL IN PREDICTING BOND RATING CHANGES
errors, and the asset decomposition measure produced 22 percent fewer errors than would be expected by chance model.

Univariate Analysis
(Stability Attribute)

The second form of the univariate decomposition analysis involves the use of the instability attribute of those measures to discriminate between changed and nonchanged bond ratings. The instability of each decomposition measure is computed using the coefficient of variation that measures the fluctuation of each decomposition measure about its mean for a maximum of four years before the rating change. The coefficient of variation (CV) is computed using the following equation:

$$CV = \frac{\sigma}{\mu}$$

where,

$\sigma$ = the standard deviation,

$\mu$ = average decomposition measure (sample considered as a total population).

The instability attributes of each decomposition measure for all the firms in the sample are then compared with the average coefficient of variation for the sample. Table IV presents the coefficients of variation for two selected companies, Harper & Row Publishers, Inc., and Macmillan Company, and the average coefficient of variation for the sample, which is used as a cut-off point for evaluating the
instability of decomposition measures for the changed and the nonchanged ratings.

### TABLE IV

RESULTS OF THE UNIVARIATE ANALYSIS: INSTABILITY ATTRIBUTES FOR TWO SELECTED COMPANIES

<table>
<thead>
<tr>
<th>Coefficient of Variation</th>
<th>Harper &amp; Row Publishers, Inc.</th>
<th>Macmillan Company</th>
<th>Cut-Off Coefficient of Variation</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADM</td>
<td>1.22</td>
<td>.95</td>
<td>.97</td>
</tr>
<tr>
<td>LDM</td>
<td>1.32</td>
<td>1.22</td>
<td>1.31</td>
</tr>
<tr>
<td>BSDM</td>
<td>1.38</td>
<td>1.12</td>
<td>1.29</td>
</tr>
</tbody>
</table>

The ability of the instability attribute of the decomposition measure to discriminate between changed and nonchanged bond ratings is evaluated by comparing the coefficient of variation of each decomposition measure for each firm in the sample with the cut-off coefficient of variation, which is the sample average coefficient of variation. If the coefficient of variation of the decomposition measure falls above the cut-off coefficient of variation, it is an indication that the firm belongs to the changed ratings group. However, if the coefficient of variation of the decomposition measure is less than or equal to the cut-off coefficient of variation, it is an indication that the firm belongs to the nonchanged ratings group. The
The data presented in Table IV show that all three decomposition measures for Harper & Row, which experienced a rating change in the period of study, are more unstable than the average decomposition measures for the sample. In addition, it shows that the three decomposition measures for Macmillan, which did not experience any rating change during the study period, are more stable than those of Harper & Row and the average decomposition measures for the sample.

This classification procedure was followed in the classification of the 134 firms in the sample. The results are presented in Table V.

### TABLE V

**RESULTS OF THE UNIVARIATE ANALYSIS—INSTABILITY ATTRIBUTE—FOR THE TWO GROUPS AND THE SAMPLE**

(percentage of correct classification)

<table>
<thead>
<tr>
<th>Coefficient of Variation</th>
<th>Cut-Off Coefficient of Variation</th>
<th>Group 1 (62)</th>
<th>Group 2 (72)</th>
<th>Sample (134)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADM</td>
<td>N 6%</td>
<td>.97</td>
<td>35</td>
<td>39</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>56.4</td>
<td>54.2</td>
</tr>
<tr>
<td>LDM</td>
<td>N 6%</td>
<td>1.31</td>
<td>34</td>
<td>44</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>54.8</td>
<td>61.1</td>
</tr>
<tr>
<td>BSDM</td>
<td>N 6%</td>
<td>1.29</td>
<td>34</td>
<td>41</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>54.8</td>
<td>56.9</td>
</tr>
</tbody>
</table>

The data in Table V show that the instability attribute of liability decomposition measure (LDM) has the highest power (58.2%) in discriminating between the changed and the
nonchanged bond ratings (61.1% correct classification for Group 2, the changed ratings, and 55% correct classification for Group 1, the nonchanged ratings). In addition, the data show that the instability attribute of the balance sheet decomposition measure produced a 56% correct classification for the whole sample (56.9% correct classification for Group 2 and 55% for Group 1).

One way to evaluate a certain classification scheme would be to compare the results of that scheme with those produced by a chance model. Table VI presents a comparison of data between the classification accuracy of the instability attribute with that of a chance model.

**TABLE VI**

**COMPARISON BETWEEN CLASSIFICATION ACCURACY OF THE INSTABILITY OF DECOMPOSITION MEASURES AND A CHANCE MODEL**

<table>
<thead>
<tr>
<th>Instability Measure</th>
<th>#Cases Correctly Classified by the Stability Attribute</th>
<th># Cases Correctly Classified by a Chance Model</th>
<th>Tau</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficient of Variation ADM</td>
<td>74</td>
<td>67</td>
<td>.10</td>
</tr>
<tr>
<td>Coefficient of Variation LDM</td>
<td>78</td>
<td>67</td>
<td>.16</td>
</tr>
<tr>
<td>Coefficient of Variation BSDM</td>
<td>75</td>
<td>67</td>
<td>.12</td>
</tr>
</tbody>
</table>
The data in Table VI suggest that the instability attribute for all three decomposition measures (ADM, LDM, and BSDM) does perform better than the chance model in the classification of bond rating changes.

Multivariate Decomposition Analysis

This section is devoted exclusively to the discussion and evaluation of the performance of the linear probability model (LPM) as stated in Chapter III. The model was formulated for use in testing the null hypothesis which predicts that the use of more than one decomposition measure, and its instability measure in formulating an index to predict bond rating changes, can produce a better performance than would be expected from a univariate analysis or the random assignment (chance model).

The dependent variable in the linear probability model is a coded variable (0 and 1), with 0 representing the probability that a rating will be maintained (no change) and the 1 representing the probability that the rating will be changed. The original list of independent variables includes:

- $x_1$ The average asset decomposition measure (AADM),
- $x_2$ The coefficient of variation of the asset decomposition measure (CADM),
- $x_3$ The average liability decomposition measure (ALDM),
- $x_4$ The coefficient of variation of the liability decomposition measure (CLDM),
x_5 The average balance sheet decomposition measure (ABSDM), and
x_6 The coefficient of variation of the balance sheet decomposition measure (CBSDM).

A multiple regression with coded dependent variables was employed. Since individual decomposition measures produce different degrees of classification accuracy, as shown in previous sections, a stepwise selection of the independent variables for LPM was made. A minimum tolerance level was, therefore, specified. Variables that failed to meet the minimum tolerance level were excluded from the analysis. Table VI presents a summary of these data.

Although the linear probability model (LPM) lends itself to the ordinary least squares model (OLS), it has some unique features that make it different from the ordinary least squares model, which are discussed in Chapter III. Empirical evidence suggests that the ordinary least squares' derived estimates may be robust against errors in some assumptions (2, 4, 8, 14). However, other assumptions are crucial and the difference will lead to quite unreasonable estimates. Such is the case when the dependent variable is a qualitative measure rather than a continuous interval measure. Aldrich and Nelson (1) state that regression estimates with a qualitative dependent variable may seriously misestimate the magnitude of the effects of independent variables, that all of the standard statistical inferences such as hypothesis tests or the construction of confidence intervals are unjustified . . . .
TABLE VII

STATISTICS FOR INDEPENDENT VARIABLES INCLUDED IN THE LINEAR PROBABILITY MODEL (LMP)

<table>
<thead>
<tr>
<th>Variable</th>
<th>B</th>
<th>SE.B</th>
<th>Beta</th>
<th>T</th>
<th>Sign. T</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABSDM</td>
<td>.2209</td>
<td>.1134</td>
<td>.1795</td>
<td>1.949</td>
<td>.050</td>
</tr>
<tr>
<td>CBSDM</td>
<td>.1451</td>
<td>.1322</td>
<td>.10168</td>
<td>1.097</td>
<td>.274</td>
</tr>
<tr>
<td>AADM</td>
<td>-9.6238</td>
<td>14.2199</td>
<td>-.0667</td>
<td>-.667</td>
<td>.490</td>
</tr>
<tr>
<td>CADM</td>
<td>5.3230</td>
<td>5.680</td>
<td>.0943</td>
<td>.937</td>
<td>.350</td>
</tr>
</tbody>
</table>

*A* B = a measure of the change in the explained variable, probability of a rating change, for unit change in each explanatory variable, ABSDM, CBSDM, AADM, or CADM (holding other variables constant).

*b* SE . B = the standard error of the coefficient B (SE.B is used in computing the T ratio that is used to make confidence-interval statements for the coefficient B).

*Beta* = a measure of the change in the explained variable, probability of a rating change (in standard deviation units), for a unit change in each explanatory variable (in standard deviation units) holding other variables constant.

*d* T = the computed value of the T ratio.

*e* Sign. T = the level of significance at which the computed T is larger than the tabulated T.

One of the crucial assumptions of ordinary least squares (OLS) is that the \( U_i \)’s have a constant variance. However, this assumption cannot be maintained when the dependent variable is a qualitative variable because the variance of \( U_i \) varies systematically with the values of the independent
variables. As a result, the OLS estimate, $\hat{b}_k$, will be unbiased but not best (i.e., these estimates will not have the smallest possible sampling variance).

Goldberger (6) proposes a solution to the above problem that requires a simple modification of the OLS model and can be accomplished in two steps. The first step requires the researcher to perform the ordinary least squares of $Y_i$ on the $X_{ik}$; the result will be unbiased estimates $\hat{b}_k$. Then the researcher uses these estimates in the computation of a set of weights, one for each observation.

$$W_i = \left[ \frac{1}{(\sum \hat{b}_k X_{ik})(1-\sum \hat{b}_k X_{ik})} \right]^{\frac{1}{2}}$$

or,

$$W_i = \frac{1}{\sqrt{\frac{\sum \hat{b}_k X_{ik}(1-\sum \hat{b}_k X_{ik})}{(\sum \hat{b}_k X_{ik})^{\frac{1}{2}}}}}.$$

The second step requires that the weights ($W_i$) be multiplied by both sides of the regression equation, which will then be stated as

$$(W_i Y_i) = \sum_{i=1}^{n} (\hat{b}_i W_i X_{ik}) + (W_i U_i).$$

Goldberger argues that the $(W_i U_i)$ in the above equation has a constant variance; therefore, regressing $(W_i Y_i)$ on $(W_i X_{ik})$ will produce a set of estimates that are unbiased and, in the meantime, have the smallest sampling variance (6).
Although the weighted least squares (WLS) suggested by Goldberger can solve the heteroscedastic variance problem associated with LPM, it was difficult to employ the suggested method in this study because the coefficient of determination $R^2$, produced by the proposed WLS method, will be of limited use in the interpretation of the analysis results because the $R^2$ (which represents the proportion of the variance explained) does not represent the proportion of variance in the original dependent variable explained by the independent variables. Rather, it refers to the proportion of variance in the weighted dependent variable and not the original one explained by the independent variables.

Given these limitations on the use of WLS in this study, the summary of data reported in Table VII is not the main basis for the evaluation of the linear probability model. Instead, the model is evaluated on the basis of its ability to "discriminate" between changed and nonchanged bond ratings (i.e., percentage of correct classification is the basis for that evaluation). However, the information in Table VII is not disappointing from a historical viewpoint for two reasons. First, regarding the sign of each independent variable, the data in Table VII show that three independent variables (BSDM, CBSDM, and CADM) have the correct sign (i.e., the actual sign is the same as the anticipated one). The only variable that has an incorrect
sign is AADM. Second, the coefficient of ABSDM is significant at the .05 level, which supports the evidence drawn previously from the univariate analysis of the accuracy of BSDM in the prediction of rating changes.

The linear probability model, stated as

\[ Y = A + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + \epsilon, \]

was performed on all 134 ratings in the study. As discussed in Chapter III, the predicted \( Y \) represents the probability of rating change given a set of independent variables \( X \) (these variables are ABSDM, CBSDM, AADM, and CADM). A cut-off point of .5 probability was assigned in the analysis. If the predicted \( Y \) falls above .50, it will be rounded to 1 and the case will be assigned to the "change" group; however, if the predicted \( Y \) falls below .50, it will be rounded to 0 and the case will be assigned to the "nonchange" group. Table VIII presents the classification data for the linear probability model.

**TABLE VIII**

CLASSIFICATION RESULTS OF THE LINEAR PROBABILITY MODEL (LPM)

<table>
<thead>
<tr>
<th>Actual Group</th>
<th>Number of Cases</th>
<th>Predicted Group</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change N %</td>
<td>72</td>
<td>52</td>
</tr>
<tr>
<td></td>
<td></td>
<td>72.2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>20</td>
</tr>
<tr>
<td>No Change N %</td>
<td>62</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td></td>
<td>48.4</td>
</tr>
<tr>
<td></td>
<td></td>
<td>32</td>
</tr>
<tr>
<td></td>
<td></td>
<td>51.6</td>
</tr>
</tbody>
</table>
The data in Table VIII indicate that the linear probability model performs exceedingly well in the classification of rating changes. Of the 72 rating changes, 52 were correctly classified (72.2%). However, the model does not achieve the same accuracy in the classification of the non-changed bond ratings. Only 32 out of the 62 nonchanged ratings (51.6%) were correctly classified. This poor performance may be due to the fact that the nonchange group represents a heterogeneous group which may include some fast-growing firms whose balance sheets have large information values. As a result, these companies will be mistakenly assigned to the "change" and not to the "nonchange" group. However, this does not represent a serious limitation on the use of the linear probability model because the rating agency can easily discriminate between the fast-growing companies and those with a relative degree of stability through the use of other indicators (e.g., growth of share prices).

A positive aspect about the results of LPM, as reported in Table VIII, is that the number of "changed" ratings that are misclassified as a "nonchanged" rating is well below the number of "nonchanged" ratings that are misclassified as a "changed" rating (27.8% versus 48.4%). This represents a positive aspect in the performance of the LPM; mistakenly identifying a "nonchanged" rating as a "changed" one is considerably less serious to investors than the reverse because of the different losses involved. The loss that investors will suffer from holding "nonchange" rating bonds
whose ratings deserve a change will be in the form of increased risk (if the change that was supposed to take place was a downgrading one) or in the form of foregone income (if the change that was supposed to take place was an upgrading one). This loss outweighs the loss the investor will suffer if the bond is eliminated from his portfolio on the assumption that it deserves a change, which actually it does not deserve. The loss in this case will be in the form of foregone income that would have been earned from holding that bond in the portfolio. This loss is negligible because the bond can be replaced at low transaction costs with other bonds that meet the investor's risk-return preferences.

One way to evaluate the classification accuracy of the LPM would be to compare the percentage of correct classification achieved by this model with that of a chance model. Line 1 of Table IX presents the data for this comparison.

The data in Table IX, line 1, show that the LPM model produces 44 percent fewer errors than would be expected by a chance model in the classification of the changed ratings. This percentage is 3 percent in the classification of the nonchanged ratings and 25 percent for the entire sample.

Another way to evaluate the LPM is to compare the classification accuracy of that model (Table VII) with the classification accuracy of individual decomposition measures.
as shown in Table II. Such a comparison shows that the LPM outperforms all the decomposition measures (ADM, LDM, and BSDM) in all years in the classification accuracy of the changed ratings. However, LPM performed poorly in the classification accuracy of the nonchanged bond ratings. Finally, the classification accuracy of the LPM for the entire sample is higher than that of all decomposition measures and their instability measures in all the years prior to the rating change except for the BSDM in the second year prior to the change (Table II).

Since LPM demonstrated its accuracy in the classification of bond rating changes, it was also used for the prediction of bond rating changes. The procedure for employing the LPM in the prediction of bond rating changes is based on Lachenbruch (9) validation procedure. It requires that the regression equation be estimated for all cases except one (e.g., n-1), then this equation is used in the prediction of the excluded case. This procedure is repeated 134 times so that each case receives a change of prediction based on an equation estimated from all the other cases except its own. Table IX, line 2, presents the data for both the predictions achieved by LPM and those achieved by a chance model.

The data in Table IX, line 2, suggest that the LPM achieves a higher predictive accuracy than that achieved by the chance model. LPM produces 22 percent fewer errors
TABLE IX

COMPARISON BETWEEN CLASSIFICATION ACCURACY AND PREDICTION RESULTS OF THE LPM AND A CHANCE MODEL

| Comparison | Changed Group (72) | | Nonchanged Group (62) | | Entire Sample (134) | |
| --- | --- | --- | --- | --- | --- |
| Classification Accuracy | # Cases of Correct Classification by LPM | 52 | 36 | .44 | 32 | 31 | .03 | 84 | 67 | .25 |
| Prediction Results | 44 | 36 | .22 | 29 | 31 | .09 | 73 | 67 | .09 |
than would be produced by random assignment in the prediction of rating changes. This percentage is 9 percent for the entire sample. Although LPM has a predictive accuracy higher than that of a chance model for changed ratings and the entire sample, it does not have the same predictive accuracy as that of a chance model in the case of nonchanged ratings. This poor performance may be due to the fact that the nonchanged group represents a heterogeneous group which may include some fast-growing companies whose balance sheets have large information values without feasible possibility of a rating change.

In conclusion, the hypothesis is accepted that the index of more than one decomposition measure will perform better than the chance model or those decomposition measures considered individually. The linear probability model (LPM), employed for the computation of that index, achieved classification and prediction degrees of accuracy that are superior to those achieved either by the individual decomposition measures, their instability attributes, or the chance model.

**Discriminant Analysis**

This section is devoted to the discussion and evaluation of the multiple discriminant analyses performed in this study. The properties of this technique as well as its assumptions are presented in detail in Appendix B.
The purpose of employing a multiple discriminant model in this study is to predict bond rating changes. This purpose can be achieved in two ways. One is to perform a two-group discriminant analysis in which the two groups are upgraded bond ratings and downgraded bond ratings. In this case the nonchanged bond ratings can be viewed as midway between these two primary groups (upgraded and downgraded bond ratings). This two-group discriminant analysis procedure will be discussed in detail in a following section of this chapter. The second way to employ a discriminant analysis for this study is to perform a three-group discriminant analysis in which the three groups are upgraded, nonchanged, and downgraded bond ratings. The three-group discriminant analysis will also be discussed in a following section.

Two-Group Discriminant Analysis

As discussed previously, the groups used in the two-group analysis are the 33 upgraded bonds and the 39 downgraded bonds. These two a priori groups represent the dependent variable in the analysis. The original list of independent variables included fixed charges coverage (FCC), fixed charges coverage trend (FCCT), return on assets (ROA), return on assets trend (ROAT), return on asset residual (ROAR), current ratio (CR), current ratio trend (CRT), debt
ratio (DR), debt ratio trend (DRT), total assets (TA), and total asset trend (TAT).

Since the rating change decision carries a signal that the financial condition of the firm has been changed from its previous level, it appears that the trends in some financial ratios over time are likely to play an important role in the rating change decision. In addition, empirical evidence (3) suggests that earnings variability plays an important role in the rating change decision. Given that special role of both trends in some financial ratios and earnings variability in the prediction of bond rating changes, a four-variable list of independent variables is also used in the two-group discriminant analysis as presented by data in Table X. These four variables were selected from the list of eleven independent variables because they were found to be of special importance in the assignment of bond ratings and in the rating change decision (3, 12). These four variables are fixed charges coverages trend (FCCT), current ratio trend (CRT), debt ratio trend (DRT), and the return on assets residuals (ROAR).

These data show that the four-variable model produced 66.67 percent correct classification, while the ten-variable model only produced 65.28 percent correct classification. These results support the researcher's a priori assumption that the trends in some financial ratios, as well as the earnings instability of the firm, play an important role in the agencies' rating change decisions. In addition, the
discriminant function in the case of the four-variable model is significant at .06 level, while the discriminant function of the ten-variable model is significant at .29 level. Again, these data suggest that the four-variable model does a better job than the ten-variable model in the classification of bond rating changes.

TABLE X
CLASSIFICATION RESULTS OF THE TWO-GROUP DISCRIMINANT ANALYSIS
(BASED ON TWO DIFFERENT SETS OF INDEPENDENT VARIABLES)

<table>
<thead>
<tr>
<th>Actual Group***</th>
<th># of Cases</th>
<th>10-Independent Variable Model*</th>
<th>4-Independent Variable Model**</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Predicted Group Membership</td>
<td>Predicted Group Membership</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Upgraded</td>
<td>Downgraded</td>
</tr>
<tr>
<td>Upgraded</td>
<td>N</td>
<td>33</td>
<td>22</td>
</tr>
<tr>
<td></td>
<td>%</td>
<td>66.7</td>
<td>33.33</td>
</tr>
<tr>
<td>Downgraded</td>
<td>N</td>
<td>39</td>
<td>14</td>
</tr>
<tr>
<td></td>
<td>%</td>
<td>35.9</td>
<td>64.1</td>
</tr>
</tbody>
</table>

*Discriminant function significant at .29 level.

**Discriminant function significant at .06 level.

***Percentage of group cases correctly classified: 4-variable model = 66.67%; 10-variable model = 65.28%.

The next step is to determine the relative importance of the independent variables in the discriminant analysis. Tables XI and XII present the standardized and the unstandardized coefficients for the independent variables in both the four-variable model and the ten-variable model.
TABLE XI
STANDARDIZED AND UNSTANDARDIZED DISCRIMINANT FUNCTION COEFFICIENTS: FOUR-VARIABLE MODEL

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unstandardized Coefficients</th>
<th>Rank</th>
<th>Standardized Coefficients</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed Charges Coverages Trend (FCCT)</td>
<td>- .8023</td>
<td>4</td>
<td>-.5799</td>
<td>3</td>
</tr>
<tr>
<td>Return on Asset Residuals (ROAR)</td>
<td>21.548</td>
<td>2</td>
<td>.8074</td>
<td>1</td>
</tr>
<tr>
<td>Current Ratio Trend (CRT)</td>
<td>- 5.652</td>
<td>3</td>
<td>-.7311</td>
<td>2</td>
</tr>
<tr>
<td>Debt Ratio Trend (DRT)</td>
<td>-34.020</td>
<td>1</td>
<td>-.5796</td>
<td>4</td>
</tr>
</tbody>
</table>

Based on the data in Table XI, the return on asset residuals (ROAR), which is a measure of earnings variability, is the most important independent variable of all four variables used in the classification of bond rating changes. The current ratio trend (CRT) is ranked second, the fixed charges coverage trend (FCCT) ranks third, and the debt ratio trend (DRT) ranks fourth.

For the ten-variable model, Table XII presents the standardized and the unstandardized coefficients of the discriminant function. The standardized coefficients shown in Table XII indicate that the fixed charges coverage trend
<table>
<thead>
<tr>
<th>Variables</th>
<th>Unstandardized Coefficients</th>
<th>Rank</th>
<th>Standardized Coefficients</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed Charges Coverage (FCC)</td>
<td>.545</td>
<td>6</td>
<td>2.621</td>
<td>2</td>
</tr>
<tr>
<td>Fixed Charges Coverage Trend (FCCT)</td>
<td>.398</td>
<td>7</td>
<td>2.88</td>
<td>1</td>
</tr>
<tr>
<td>Return on Asset Trend (ROAT)</td>
<td>-75.833</td>
<td>1</td>
<td>- .737</td>
<td>6</td>
</tr>
<tr>
<td>Return on Asset Residuals (ROAR)</td>
<td>5.358</td>
<td>4</td>
<td>.201</td>
<td>10</td>
</tr>
<tr>
<td>Total Assets Trend (TAT)</td>
<td>- .151</td>
<td>10</td>
<td>-1.255</td>
<td>3</td>
</tr>
<tr>
<td>Current Ratio Trend (CRT)</td>
<td>- 6.516</td>
<td>3</td>
<td>- .842</td>
<td>5</td>
</tr>
<tr>
<td>Debt Ratio (DR)</td>
<td>2.365</td>
<td>5</td>
<td>.240</td>
<td>8</td>
</tr>
<tr>
<td>Debt Ratio Trend (DRT)</td>
<td>-27.119</td>
<td>2</td>
<td>- .462</td>
<td>7</td>
</tr>
</tbody>
</table>
(FCCT) is the most important variable, followed by the fixed charges coverage (FCC), the total assets (TA), the total asset trend (TAT), the return on asset trend (ROAT), the debt ratio trend (DRT), the debt ratio (DR), the current ratio (CR), and the return on asset residuals (ROAR).

The analysis of these two models, the four-variable model and the ten-variable model, indicates that the four-variable model is superior to the ten-variable model for two reasons. First, the four-variable model produces a higher classification accuracy than the ten-variable model (66.67\% versus 65.28\%). Second, the discriminant function for the four-variable model is significant at 6 percent, while the discriminant function for the ten-variable model is significant at 29 percent. These data suggest that the first function has a stronger discriminating power than the second one. Because of its superiority over the ten-variable model, the four-variable model is used for further analysis and evaluation of the two-group discriminant analysis.

**Evaluation of the Two-Group Discriminant Analysis**

The evaluation of the two-group discriminant analysis is done in three stages. The first stage involves the validation of the two-group discriminant analysis on the same sample (72 firms) using the Lachenbruch (9) technique. The second stage involves the selection of several prediction techniques.
(strategies) for using the discriminant function of the two-
group discriminant analysis in the prediction of the third
group of "nonchanged" ratings that were excluded from the
two-group discriminant analysis. Finally, the third stage
involves the use of the results of the two former stages in
the construction of the overall predictive accuracy table
for the two-group discriminant analysis.

Validation of the Two-Group Discriminant Analysis

The Lachenbruch (9) validation technique, as discussed
in Chapter III, is used in the validation of the two-group
discriminant analysis. The results are shown in Table XIII.

<table>
<thead>
<tr>
<th>Actual Group</th>
<th>Number of Cases</th>
<th>Predicted Group Membership</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Upgraded</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Upgraded</td>
<td>33</td>
<td>17</td>
</tr>
<tr>
<td></td>
<td></td>
<td>51.5</td>
</tr>
<tr>
<td>Downgraded</td>
<td>39</td>
<td>19</td>
</tr>
<tr>
<td></td>
<td></td>
<td>48.7</td>
</tr>
</tbody>
</table>

Percentage of correct classification = 51.4%.
The choice of a cut-off probability for group membership based on the probability of group membership. In this study, each case is assigned to a certain group that neutra1 zone involves the use of the probability of discriminant scores for the cases. Another way to determine the nonchange group, can be defined in terms of different groups: as a result of the neutra1 zone, which for each case may be used in assignment of the cases to the may be achieved in several ways. The discriminant score

The accommodation of the nonchange group in the analyses:

The analysis of accommodation the nonchange group in the analyses. In this section, therefore, the procedure rating change analyses, thus this group should be included grading and downgrading. In order to perform a reliable can be defined as midway between the two major groups, up to two-group discriminant analysis on the assumption that the nonchange group is assigned to the same group that includes the groups used are the upgraded and downgraded ratings. These

For two-group discriminant analysis, the only two

---

Precaution Strategies for Using the Two-Group

---

The nonchange group in the selection of the nonchange group in the study involves some degree of subjectivity on the part of the

group membership.

The neutral zone is defined in terms of the probability of group membership. In this study, each case is assigned to a certain group that neutral zone involves the use of the probability of discriminant scores for the cases. Another way to determine the nonchange group, can be defined in terms of different groups: as a result of the neutral zone, which for each case may be used in assignment of the cases to the may be achieved in several ways. The discriminant score

The accommodation of the nonchange group in the analyses:

The analysis of accommodation the nonchange group in the analyses. In this section, therefore, the procedure rating change analyses, thus this group should be included grading and downgrading. In order to perform a reliable can be defined as midway between the two major groups, up to two-group discriminant analysis on the assumption that the nonchange group is assigned to the same group that includes the groups used are the upgraded and downgraded ratings. These

For two-group discriminant analysis, the only two
XIV presents the results of three different prediction
different cut-off probabilities of group membership. Table

different and different prediction results because they have
second and the third strategies produce different "neutral"
otherwise, it is assigned to the "non-neutralized" group. The
its probability of group membership is above 65 per cent:
assigned either to the upgraded or the downgraded group if
example, according to the first strategy, the case is
each strategy produces a different "neutral" zone, for
membership, represents the least conservative strategy.
strategy, with a 55 per cent cut-off probability of group
representing the most conservative one, with the third
strategy, with a 65 per cent probability of group membership,
among the three selected strategies, the first
preliminary analysis of results for the two-group discriminant
these strategies were selected on the basis of the

55 per cent, respectively.

cut-off probabilities for group membership are 65, 60, and

different prediction strategies are employed for which the
degree of conservatism decreases. In this study, three
into the different groups), it reflects a decrease in the
group membership (as a basis for the assignment of cases
of the analyst, as the analyst assigns lower probability
groups reflects a high degree of conservatism on the part
membership for the assignment of cases into the different
analyst, the selection of a high probability of group

104
Table XIX suggests that the cut-off probability of group
7 out of the 62 unchanged ratings. Finally, the data in
rating agencies could have downgraded their ratings and upgraded
grades, and 1 downgrading. The results suggest that the
(87%) correctly classified as unchanged ratings, 7 of
the 62 „unchange“ group, this strategy leads to 54 cases
assigned to the unchanged group. However, when applied to
classified and 1 misclassified case) with 60 cases (83%)
classified cases, and 6 downgrades (5 cases correctly
duced 6 upgrades (4 cases correctly classified and 2 mis-
which is the most conservative of the three strategies, pro-
the data in Table XIX indicate that the first strategy,

<table>
<thead>
<tr>
<th>Number of Misclassified Cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>17</td>
</tr>
<tr>
<td>22</td>
</tr>
<tr>
<td>4</td>
</tr>
<tr>
<td>3</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Prediction in the unchanged sample (62)</th>
<th>Prediction in the original sample (72)</th>
</tr>
</thead>
<tbody>
<tr>
<td>17</td>
<td>14 + 5</td>
</tr>
<tr>
<td>22</td>
<td>15 + 5</td>
</tr>
<tr>
<td>4</td>
<td>5 + 1</td>
</tr>
<tr>
<td>3</td>
<td>60</td>
</tr>
<tr>
<td>1</td>
<td>65</td>
</tr>
</tbody>
</table>

Results of three alternative rating-change strategies

Table XIX

Strategies performed on the original sample of 72 changed
membership declines, more ratings will be assigned to the upgraded and the downgraded groups and fewer ratings will be assigned to the nonchanged group. This pattern exists in the predictions of both the 72 original sample and the 62 nonchanged sample.

The third stage in the evaluation of the two-group discriminant analysis is to construct a table of correct predictions based on the results reached in the two previous stages. Table XV presents the percentage of correct classifications for the two-group discriminant analysis on the original 74 and the 62 nonchanged ratings.

**TABLE XV**

PERCENTAGE OF CORRECT PREDICTIONS FOR TWO-GROUP DISCRIMINANT ANALYSIS

<table>
<thead>
<tr>
<th>Prediction in the Change Sample (72)</th>
<th>Prediction in the Nonchange Sample (62)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Upgradings</td>
<td>Downgradings</td>
</tr>
<tr>
<td>N</td>
<td></td>
</tr>
<tr>
<td>17*</td>
<td>20*</td>
</tr>
<tr>
<td>%</td>
<td>51.5</td>
</tr>
</tbody>
</table>

*numbers from Table XIII.
**number from Table XIV.

Three-Group Discriminant Analysis

Another way to perform a discriminant analysis for the classification and predictions of bond rating changes is to
employ a three-group discriminant analysis. In this analysis
the dependent variable is represented by three groups of bond
ratings: upgraded ratings, downgraded ratings, and non-
changed ratings. This section is devoted to the discussion
and the evaluation of the three-group discriminant analysis.

In the previous section, two sets of independent
variables were tried in the two-group discriminant analysis.
Those two sets produced different results, and a decision
was made to select the four-variable model. In this section,
two sets of independent variables are also used in the three-
group discriminant analysis.

The original list of independent variables used in the
three-group discriminant analysis includes fixed charges
coverage (FCC), fixed charges coverage trend (FCCT), return
on asset trend (ROAT), return on asset residuals (ROAR),
total assets (TA), total asset trend (TAT), current ratio
(CR), current ratio trend (CRT), debt ratio (DR), and debt
ratio trend (DRT). The second list of independent variables
used in this study emphasizes the importance of trends in
certain financial ratios in the prediction of bond rating
changes. In addition, the list emphasizes the special role
of earnings instability and leverage in the prediction of
bond rating changes. The four independent variables included
in this list are fixed charges coverage trend (FCCT), return
on asset residuals (ROAR), current ratio trend (CRT), and
debt ratio (DR).
The classification results of the three-group discriminant analysis are based on two sets of independent variables. These data are presented in Table XVI.

<table>
<thead>
<tr>
<th>Actual Group</th>
<th># of Cases</th>
<th>10-Variable Model</th>
<th>4-Variable Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Predicted Group Membership</td>
<td>Predicted Group Membership</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Up-Graded</td>
<td>Down-Graded</td>
</tr>
<tr>
<td>Upgraded</td>
<td>33 N</td>
<td>18</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>% 54.5</td>
<td>9.1</td>
<td>36.4</td>
</tr>
<tr>
<td>Downgraded</td>
<td>39 N</td>
<td>10</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>% 25.6</td>
<td>51.3</td>
<td>23.1</td>
</tr>
<tr>
<td>Nochange</td>
<td>62 N</td>
<td>15</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>% 24.2</td>
<td>24.2</td>
<td>51.6</td>
</tr>
</tbody>
</table>

These data show that the ten-variable model yields a higher classification accuracy than the four-variable model (52.24% for the ten-variable model versus 45.52% for the four-variable model). Comparing these classification results with those of the two-group discriminant analysis, it appears evident that the four-variable model outperforms the ten-variable model in the two-group analysis, while the ten-variable model outperforms the four-variable model in the three-group discriminant analysis. Based on classification accuracy, the ten-variable model is selected for
further analysis and evaluation of the three-group discriminant analysis. In order to determine the relative importance of the independent variables in the three-group discriminant analysis, Tables XVII and XVIII present the standardized and the unstandardized coefficients for the two sets of independent variables used in the analysis.

**TABLE XVII**

STANDARDIZED AND UNSTANDARDIZED DISCRIMINANT FUNCTION COEFFICIENTS: TEN-VARIABLE MODEL

<table>
<thead>
<tr>
<th>Variable</th>
<th>Standardized Coefficient</th>
<th>Rank</th>
<th>Unstandardized Coefficient</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed Charges Coverage (FCC)</td>
<td>.2681</td>
<td>5</td>
<td>.7585</td>
<td>5</td>
</tr>
<tr>
<td>Fixed Charges Coverage Trend (FCCT)</td>
<td>.8906</td>
<td>1</td>
<td>.1557</td>
<td>9</td>
</tr>
<tr>
<td>Return on Assets Trend (ROAT)</td>
<td>- .0912</td>
<td>7</td>
<td>- 9.897</td>
<td>2</td>
</tr>
<tr>
<td>Return on Asset Residuals (ROAR)</td>
<td>.6825</td>
<td>3</td>
<td>-19.393</td>
<td>1</td>
</tr>
<tr>
<td>Total Asset (TA)</td>
<td>-.0304</td>
<td>10</td>
<td>-.4710</td>
<td>8</td>
</tr>
<tr>
<td>Total Asset Trend (TAT)</td>
<td>-.0758</td>
<td>9</td>
<td>-.1250</td>
<td>10</td>
</tr>
<tr>
<td>Current Ratio (CR)</td>
<td>.3969</td>
<td>4</td>
<td>.6280</td>
<td>7</td>
</tr>
<tr>
<td>Current Ratio Trend (CRT)</td>
<td>.0872</td>
<td>8</td>
<td>.7001</td>
<td>6</td>
</tr>
<tr>
<td>Debt Ratio (DR)</td>
<td>.8162</td>
<td>2</td>
<td>9.1040</td>
<td>3</td>
</tr>
<tr>
<td>Debt Ratio Trend (DRT)</td>
<td>.1383</td>
<td>6</td>
<td>8.3610</td>
<td>4</td>
</tr>
</tbody>
</table>
These results indicate that, on the basis of the standardized coefficients, the five most important variables in the ten-variable model are fixed charges coverage trend (FCCT), followed by the debt ratio (DR), the return on asset residuals (ROAR), current ratio (CR), and fixed charges coverage (FCC). However, in the four-variable model, the data in Table XVIII show that the most important variable is the return on asset residuals (ROAR), followed by the debt ratio (DR), the fixed charges coverage trend (FCCT), and the current ratio trend (CRT).

### TABLE XVIII

**STANDARDIZED AND UNSTANDARDIZED DISCRIMINANT FUNCTION COEFFICIENTS: FOUR-VARIABLE MODEL**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Standardized Coefficient</th>
<th>Rank</th>
<th>Unstandardized Coefficient</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed Charges Coverage Trend (FCCT)</td>
<td>.5693</td>
<td>3</td>
<td>.9940</td>
<td>4</td>
</tr>
<tr>
<td>Return on Asset Residuals (ROAR)</td>
<td>.8616</td>
<td>1</td>
<td>24.4448</td>
<td>1</td>
</tr>
<tr>
<td>Current Ratio Trend (CRT)</td>
<td>-.231</td>
<td>4</td>
<td>-1.8720</td>
<td>3</td>
</tr>
<tr>
<td>Debt Ratio (DR)</td>
<td>.8092</td>
<td>2</td>
<td>8.9565</td>
<td>2</td>
</tr>
</tbody>
</table>
Evaluation of the Three-Group Discriminant Analysis

The three-group discriminant analysis is evaluated using a Lachenbruch validation technique discussed in Chapter III. Table XIX presents the rating change predictions for the three-group discriminant analysis based on Lachenbruch's (9) validation procedure. These data suggest that the three-group discriminant analysis does not perform as well as the two-group discriminant analysis (48.5% prediction accuracy for the three-group discriminant analysis versus 54.5% for the two-group discriminant analysis). The poor predictive accuracy of the three-group discriminant model is due to the fact that when the dependent variable (rating change) is represented by three groups (upgradings, downgradings, and nonchange), it is to be expected that there will be more overlapping among the three groups than there would be between two groups (upgradings and downgradings) only.

Comparison of the Classification and Predictive Accuracy of the Decomposition Measures With the Discriminant Models

This study introduces the use of statistical decomposition measures in the classification and prediction of industrial bond rating changes. The two types of decomposition analyses performed are univariate decomposition analysis and multivariate decomposition analysis. The results of these two types of analyses were presented in
TABLE XIX
PREDICTION RESULTS: THREE-GROUP DISCRIMINANT ANALYSIS

<table>
<thead>
<tr>
<th>Group</th>
<th># of Cases</th>
<th>Predicted Group Membership</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Upgraded</td>
<td>Downgraded</td>
<td>Unchanged</td>
<td></td>
</tr>
<tr>
<td>Upgraded</td>
<td>33 N</td>
<td>16</td>
<td>7</td>
<td>10</td>
<td></td>
</tr>
<tr>
<td></td>
<td>%</td>
<td>48.5</td>
<td>21.2</td>
<td>30.3</td>
<td></td>
</tr>
<tr>
<td>Downgraded</td>
<td>39 N</td>
<td>7</td>
<td>19</td>
<td>13</td>
<td></td>
</tr>
<tr>
<td></td>
<td>%</td>
<td>17.9</td>
<td>48.7</td>
<td>33.3</td>
<td></td>
</tr>
<tr>
<td>Unchanged</td>
<td>62 N</td>
<td>17</td>
<td>15</td>
<td>30</td>
<td></td>
</tr>
<tr>
<td></td>
<td>%</td>
<td>27.4</td>
<td>24.2</td>
<td>48.4</td>
<td></td>
</tr>
</tbody>
</table>

Percentage of Correct Classification = 48.5%.

Tables II through VIII. In order to evaluate the usefulness of these decomposition measures in the study of bond rating changes, it is essential that the performance of these decomposition measures—on both univariate and multivariate bases—be compared with the performance of a leading statistical technique that has been used frequently in the study of bond ratings. This technique is discriminant analysis and is used in this study. This section is devoted to the comparison of the performance of these two techniques: decomposition analysis and discriminant analysis.

The complete comparison of the performance of the two techniques is made in four steps. The first step involves comparison of classification results of individual decomposition measures with the classification results of the
two-group discriminant analysis. The second step involves comparison of the classification results of individual decomposition measures with the results of the three-group discriminant analysis. The third step involves comparison of the classification and prediction results of the multivariate decomposition analysis—the linear probability model—with results of the two-group discriminant analysis. The fourth step involves comparison of the classification and prediction results of the multivariate decomposition analysis—the linear probability model—with the results of the three-group discriminant analysis.

The data in Table XX presents a comparison between the classification results of the individual decomposition measures and the classification results of the two-group discriminant analysis. The data indicate that there are differences between the percentages of correct classifications produced by the two techniques.

For the "nonchange" group, the data show that the balance sheet decomposition measure and the instability of the three decomposition measures outperformed the discriminant model consistently over the four years prior to the cut-off year. Neither the asset decomposition measure nor the liability decomposition measure outperformed the discriminant model consistently over the four-year period. For the changed bond ratings, the data show that the discriminant
TABLE XX

COMPARISON OF THE CORRECT CLASSIFICATION PERCENTAGES PRODUCED
BY THE INDIVIDUAL DECOMPOSITION MEASURES WITH CORRECT
CLASSIFICATION PERCENTAGES OF THE TWO-GROUP
DISCRIMINANT ANALYSIS

<table>
<thead>
<tr>
<th></th>
<th>Year Before</th>
<th>Change</th>
<th>Total</th>
<th>Year Before</th>
<th>Change</th>
<th>Total</th>
<th>Year Before</th>
<th>Change</th>
<th>Total</th>
<th>Year Before</th>
<th>Change</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>DM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ADM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>43</td>
<td>35</td>
<td>78</td>
<td>42</td>
<td>39</td>
<td>81</td>
<td>41</td>
<td>38</td>
<td>79</td>
<td>39</td>
<td>35</td>
<td>74</td>
</tr>
<tr>
<td>%</td>
<td>59.7</td>
<td>56.5</td>
<td>58.2</td>
<td>58.3</td>
<td>61.3</td>
<td>60.4</td>
<td>56.9</td>
<td>61.3</td>
<td>58.9</td>
<td>54.2</td>
<td>56.5</td>
<td>55.2</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ELDM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>45</td>
<td>36</td>
<td>81</td>
<td>47</td>
<td>34</td>
<td>81</td>
<td>43</td>
<td>35</td>
<td>78</td>
<td>40</td>
<td>37</td>
<td>77</td>
</tr>
<tr>
<td>%</td>
<td>62.5</td>
<td>58.1</td>
<td>60.4</td>
<td>65.3</td>
<td>54.8</td>
<td>60.4</td>
<td>59.7</td>
<td>56.5</td>
<td>58.2</td>
<td>55.5</td>
<td>59.6</td>
<td>57.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BSDM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>46</td>
<td>37</td>
<td>83</td>
<td>48</td>
<td>40</td>
<td>88</td>
<td>44</td>
<td>37</td>
<td>81</td>
<td>42</td>
<td>38</td>
<td>80</td>
</tr>
<tr>
<td>%</td>
<td>63.9</td>
<td>59.6</td>
<td>61.9</td>
<td>66.7</td>
<td>64.5</td>
<td>65.7</td>
<td>61.1</td>
<td>59.6</td>
<td>60.4</td>
<td>58.3</td>
<td>61.3</td>
<td>59.7</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Change</td>
<td>No Change</td>
<td>Total</td>
<td>Change</td>
<td>No Change</td>
<td>Total</td>
<td>Change</td>
<td>No Change</td>
<td>Total</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ADM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>%</td>
<td>59.7</td>
<td>56.5</td>
<td>58.2</td>
<td>58.3</td>
<td>61.3</td>
<td>60.4</td>
<td>56.9</td>
<td>61.3</td>
<td>58.9</td>
<td>54.2</td>
<td>56.5</td>
<td>55.2</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ELDM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>%</td>
<td>62.5</td>
<td>58.1</td>
<td>60.4</td>
<td>65.3</td>
<td>54.8</td>
<td>60.4</td>
<td>59.7</td>
<td>56.5</td>
<td>58.2</td>
<td>55.5</td>
<td>59.6</td>
<td>57.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BSDM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>%</td>
<td>63.9</td>
<td>59.6</td>
<td>61.9</td>
<td>66.7</td>
<td>64.5</td>
<td>65.7</td>
<td>61.1</td>
<td>59.6</td>
<td>60.4</td>
<td>58.3</td>
<td>61.3</td>
<td>59.7</td>
</tr>
</tbody>
</table>

*represents the number of nonchange bond ratings correctly classified according to the second strategy in Table XIV.
model consistently outperformed the asset decomposition measure and the liability measure over the four years prior to the rating change.

As for the balance sheet decomposition measure, the data show that the discriminant model outperforms the balance sheet decomposition measure in the first, third, and fourth years prior to the rating change. However, the balance sheet decomposition measure outperformed the discriminant model in the second year prior to the rating change.

Given the relative accuracy of the balance sheet decomposition measure in the classification of bond rating changes, it may be concluded that the special importance of this measure in the prediction of corporate events is once again confirmed. Previous studies (5, 7, 10, 11, 14) show the importance of the balance sheet decomposition measure in the prediction of corporate failure. This study proves its importance in the prediction of bond rating changes. The data in Table XXI for the entire sample show that the balance sheet decomposition measure demonstrates a predictive accuracy in the first three years prior to the rating change or the cut-off year that is almost equal to the accuracy of the discriminant model.

To determine if there is a significant difference between the classification accuracy of the two techniques, a chi-square test was used. The test was repeated several times in order to perform all the possible comparisons.
<table>
<thead>
<tr>
<th>DM</th>
<th>Year Before Change</th>
<th>Coefficient of Variation of DM</th>
<th>Three-Group Discriminant Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>First Year</td>
<td>Second Year</td>
</tr>
<tr>
<td>ADM</td>
<td></td>
<td>Change</td>
<td>No Change</td>
</tr>
<tr>
<td>%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>43</td>
<td>35</td>
</tr>
<tr>
<td></td>
<td>59.7</td>
<td>56.5</td>
<td>58.2</td>
</tr>
<tr>
<td>LDM</td>
<td></td>
<td>45</td>
<td>36</td>
</tr>
<tr>
<td>%</td>
<td>62.5</td>
<td>58.1</td>
<td>60.4</td>
</tr>
<tr>
<td>BSDM</td>
<td></td>
<td>46</td>
<td>37</td>
</tr>
<tr>
<td>%</td>
<td>63.9</td>
<td>59.6</td>
<td>61.9</td>
</tr>
</tbody>
</table>
between the classification accuracy of the discriminant model and that of each individual decomposition measure for each of the four years prior to the rating change.

The procedure for performing this test is discussed in Chapter III. Using a .05 level of significance, the results of the chi-square test suggest that there is no significant difference between the classification accuracy of the two-group discriminant model and the classification accuracy of any individual decomposition measure in any year prior to the change. Also, the test results show that there is no significant difference between the classification accuracy of the two-group discriminant model and the classification accuracy of the instability of the decomposition measures.

Table XXII presents a comparison between the classification accuracy of both the decomposition measures and the three-group discriminant model for each year prior to the rating change or the cut-off year. Because the disparity in the performance of the techniques is not large, a chi-square test shows that there is no significant difference between the classification accuracy of the three-group discriminant model and the classification accuracy of the individual decomposition measures or their instability measures in any year prior to the change or the cut-off year.

To complete the comparison of the decomposition analysis and the discriminant analysis performed in this study, the performance of the multivariate decomposition model (linear
TABLE XXII

COMPARISON BETWEEN THE TWO-GROUP MULTIPLE DISCRIMINANT ANALYSIS AND THE MULTIVARIATE DECOMPOSITION ANALYSIS (classifications and predictions)

<table>
<thead>
<tr>
<th></th>
<th>PERFORMACE ON CHANGE SAMPLE (72)</th>
<th>PROBABILITY MODEL</th>
<th>PERFORMACE ON NOCHANGE SAMPLE (62)</th>
<th>PROBABILITY MODEL</th>
<th>PERFORMACE ON WHOLE SAMPLE (134)</th>
<th>PROBABILITY MODEL</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MDA</td>
<td>M.DE</td>
<td>COMP</td>
<td>MDA</td>
<td>M.DE</td>
<td>COMP</td>
</tr>
<tr>
<td>Classification</td>
<td>N</td>
<td>%</td>
<td></td>
<td>N</td>
<td>%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>48</td>
<td>66.67</td>
<td>52</td>
<td>36</td>
<td>58.1</td>
<td>51.61</td>
</tr>
<tr>
<td>Prediction</td>
<td>N</td>
<td>%</td>
<td></td>
<td>N</td>
<td>%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>35</td>
<td>48.61</td>
<td>42</td>
<td>36</td>
<td>58.1</td>
<td>48.38</td>
</tr>
</tbody>
</table>

The probability model was compared with the performance of both the two-group discriminant model and the three-group discriminant model. The results of these two comparisons are presented in Tables XXII and XXIII.

Table XXII presents a comparison between the performance of the linear probability model and the performance of the two-group discriminant model. The performance of both models is measured in terms of classification accuracy and predictive accuracy of each model. Regarding the classification accuracy of the two models, the data in Table XXII show that the linear probability model outperforms the two-group discriminant model in the classification of the changed ratings (72.2% versus 66.67%). However, the two-group discriminant model outperforms the linear probability model...
in the classification of the nonchanged ratings (58.1% versus 51.60%). The results for the sample as a whole show that the two models have almost the same classification accuracy (62.68% for each model).

The prediction accuracy for the two models is also shown in Table XXII. These results suggest that the linear probability model has a higher predictive accuracy than the two-group discriminant model in the prediction of the "changed" ratings group (58.33% versus 48.61%). However, in the prediction of the "nonchange" ratings group, the two-group discriminant model outperforms the linear probability model (58.1% versus 48.4%). For the entire sample, the results indicate that the linear probability model has a predictive accuracy that is slightly above the predictive accuracy of the two-group discriminant model. Again, the poor performance of the linear probability model may be due to the fact that the nonchanged group used in the study is a heterogeneous group that may have some fast-growing firms with large information values conveyed by their higher decomposition measures but with no real possibility of a rating change.

To determine if there is a significant difference between the performance of the two models, a chi-square test was performed. Using the .05 level of significance, the chi-square test was repeated several times to make all the possible comparisons on the results in Table XXIII. The
results of the chi-square test show that there is no significant difference between the performance of the two models.

Finally, the performance of the linear probability model was compared with the performance of the three-group discriminant analysis. Table XXIII presents the data for this comparison.

TABLE XXIII

COMPARISON BETWEEN THE THREE-GROUP MULTIPLE DISCRIMINANT ANALYSIS AND THE MULTIVARIATE DECOMPOSITION ANALYSIS (classifications and predictions)

<table>
<thead>
<tr>
<th></th>
<th>Performance on Change Sample (72)</th>
<th>Performance on Nochange Sample (62)</th>
<th>Performance on Whole Sample (134)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Classification</td>
<td>CODE</td>
<td>CODE</td>
<td>CODE</td>
</tr>
<tr>
<td>N</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>%</td>
<td>38</td>
<td>32</td>
<td>70</td>
</tr>
<tr>
<td></td>
<td>52.78</td>
<td>51.61</td>
<td>52.24</td>
</tr>
</tbody>
</table>

| Prediction       | N                     |                       |                       |                       |
| N                |                       |                       |                       |                       |
| %                | 35                    | 29                    | 64                    | 72                    |
|                  | 48.61                 | 46.78                 | 47.70                 | 53.73                 |

The data in Table XXIII suggest that the accuracy of the linear probability model in classifying the "change" ratings group is well above the classification accuracy of the three-group discriminant model (72.22% versus 52.78%). Regarding the "nonchange" ratings group, the results show that both models have the same classification accuracy (51.6% for each model). However, the results for the entire sample indicate
that the linear probability model has a higher classification accuracy than the three-group discriminant model (62.68% versus 52.24%).

The predictive accuracy of the two models is shown in Table XXIII. Based on the reported results, the linear probability model has a higher predictive accuracy than the three-group discriminant model. The superiority of the linear probability model over the three-group discriminant model exists in the predictions of the change ratings group and the nonchange ratings group as well. As a result, the predictive accuracy of the linear probability model is higher than the predictive accuracy of the three-group discriminant analysis (53.73% versus 47.77%).

To test if there is a significant difference between the performance of the linear probability model and the performance of the three-group discriminant model, a chi-square test was performed. Using .05 as the significant level, the results of the chi-square test indicate that there is no significant difference between the performance of the linear probability model and the performance of the three-group discriminant analysis.

Based on the results of the univariate analysis—size attribute—shown in Table II, the first null hypothesis is accepted. Hypothesis one predicts that the decomposition measures for companies that experienced bond rating changes
are larger than the decomposition measures for companies that did not experience bond rating changes. In addition, the results of the univariate analysis—stability attribute, as shown in Table IV, indicate that the second null hypothesis is accepted. Hypothesis two predicts that the decomposition measures for companies that had experienced bond rating changes are more unstable than the decomposition measures for companies that did not experience bond rating changes.

The results of the multivariate decomposition analysis, as shown in Table VIII, indicate that the third null hypothesis is accepted. Hypothesis three predicts that the company's bond rating change can be predicted on the basis of an index or score that incorporates the size and stability of that company's decomposition measures. In addition, the results of multiple discriminant analyses, as shown in Tables XI through XVI and XIX, indicate that the fourth null hypothesis is rejected. Hypothesis four predicts that there will be no significant difference among the means of the three groups of bond ratings that were upgraded, unchanged or downgraded. In other words, the results show that discriminant analysis can be used in the prediction and duplication of bond rating changes.

Finally, the results of the comparison between decomposition analysis and discriminant analysis, as shown in Tables XX through XXIII, indicate that the fifth null
hypothesis can be accepted. Hypothesis five predicts that both statistical decomposition analysis and multiple discriminant analysis can achieve the same performance in duplicating and predicting bond rating changes.

Summary

This chapter presented data analyses and study results. A univariate decomposition analysis revealed that the individual decomposition measures are capable of signaling the bond rating change. These decompositions were found to have different attributes for the firms that experienced a rating change and those firms that did not experience a rating change during the 1977-1981 period. Specifically, the decomposition measures were found to be larger and more unstable for firms that experienced a rating change than for the firms that did not experience a bond rating change during the 1977-1981 period.

The multivariate decomposition analysis showed that the incorporation of more than one decomposition measure and its instability attribute in a single index can lead to more accurate predictions of bond rating changes. However, the multivariate decomposition model did not perform as well in the prediction of the nonchanged ratings as it did in the prediction of the rating changes. The poor performance of the model in the case of the nonchanged ratings raises serious
questions about the composition of the nonchanged ratings group and about the adequacy of the bond rating revisions by rating agencies.

A multiple discriminant analysis was also performed on the same sample. Two discriminant models were performed: a two-group discriminant model and a three-group discriminant model. In each case, two sets of independent variables were tried. In the case of two-group discriminant analysis, the four-variable model performed better than the ten-variable model. However, in the case of three-group discriminant analysis, the ten-variable model performed better than the four-variable model. Comparison of the performance of the two-group discriminant analysis and the performance of the three-group analysis showed that the two-group discriminant model outperformed the three-group discriminant model. The poor performance of the three-group model relative to the two-group model is due to the fact that when the dependent variable—rating change—is represented by three groups instead of two groups, the groups are expected to be less distinct; therefore, the accuracy of the three-group model is expected to be less than the accuracy of the two-group model. In addition, the poor performance of the three-group model raises questions about a rating agency’s ability to keep the ratings current or updated.
Finally, a comparison between the performance of the discriminant analysis and the performance of the decomposition analysis was made. Chi-square tests indicate that there was no significant difference between the performance of two techniques.


CHAPTER V

SUMMARY AND CONCLUSIONS

This chapter includes a summary of the main research aspects and the conclusions of the study. In addition, several suggestions for future research on rating changes are made.

Summary

Chapter 1 presented the purpose of the study which is the investigation of the usefulness of statistical decomposition measures in the predictions of bond rating changes. A comparison between the performance of statistical decomposition analysis and the performance of another leading statistical technique—discriminant analysis—was considered a means of evaluating the usefulness of decomposition analysis in the prediction of industrial bond rating changes.

A bond rating is a measure of default risk, and as such it affects the investment decisions of both institutions and individuals. It is also important to borrowers because it affects the interest costs they pay on bonds. Because of the special importance of bond ratings to investors and the borrowers, a decision to change the rating of an outstanding bond is expected to have an impact on these investors and borrowers.
Given the importance of bond ratings to both investors and borrowers, and considering the fact that decomposition analysis has been applied in the prediction of corporate events on a limited basis, this study is significant for several reasons. First, the study demonstrates that industrial bond rating changes can be predicted. Second, the study provides some insights into financial statement changes that can be used in the prediction of certain corporate events. Third, the study represents an extension of the use of statistical decomposition analysis into a new area—the prediction of bond rating changes.

Chapter II presented a review of the related literature. Previous bond rating and rating change studies provided a basis for the selection of the variables in the discriminant model. Studies on the use of statistical decomposition analysis in the prediction of corporate failure assisted in structuring the research design for the application of the statistical decomposition analysis into the prediction of bond changes.

Chapter III presented the research design used in this study. Decomposition measures were computed for each firm using the set of equations presented in that chapter. Computed decomposition measures were used in univariate decomposition analysis and as independent variables in the multivariate decomposition model (linear probability model). In addition, the rating change groups—as well as the list
of independent variables used in the discriminant analysis—were also described and justified. Also discussed were types of discriminant analyses and the validation procedures. Finally, the chapter presented the structure of the comparison between the performance of decomposition analysis and the performance of discriminant analysis.

Chapter IV presented the data analyses and results of the study. The univariate decomposition analysis indicates that decomposition measures for firms that had experienced bond rating changes were larger than their respective industry average decomposition measure. However, individual decomposition measures did not perform as well in the predictions of the nonchange ratings as they did in the prediction of the changed ratings. The heterogeneous nature of the nonchanged ratings group, and the inadequacy of the bond rating revisions carried by the rating agencies were cited as reasons for the poor performance of univariate decomposition analysis in the predictions of unchanged ratings. In addition, individual decomposition measures for the firms that experienced bond rating changes were found to be more unstable than were decomposition measures for the firms that did not experience bond rating changes during the 1977-1981 period.

To evaluate the performance of the individual decomposition measures in the prediction of bond rating changes, the misclassification rates for each of the decomposition measures
were compared to the misclassification rates produced by a chance model. The results show the individual decomposition measures, as well as their instability measures, produce fewer classification errors than would be expected by random assignment.

A multivariate decomposition model, a linear probability model, was also used in the prediction of bond rating changes. Results show that the multivariate decomposition model predicted 72.2 percent of the industrial bond rating changes that took place during the 1977-1981 period. Although the multivariate decomposition model performed exceedingly well in the case of the changed ratings, the model performed poorly in the case of the unchanged ratings. The heterogeneous nature of the unchanged ratings group, as well as the inadequacy of rating revisions by rating changes, may be reasons for the poor performance of the multivariate decomposition model in the case of the unchanged ratings.

A multiple discriminant analysis was also performed in this study. Two discriminant models were derived: a two-group discriminant model and a three-group discriminant model. Ten independent variables were used in each model. However, because of the special nature of the dependent variable under investigation—rating changes—and based on results of two previous studies (1, 2), four independent variables out of the original list were also used in each model. The
results show that in the case of the two-group discriminant model, the list of four independent variables led to higher correct classifications and predictions than the list of ten independent variables. However, in the case of the three-group model, the list of ten independent variables produced higher correct classifications and predictions than the list of four independent variables. A comparison between the performance of the two-group discriminant analysis and the performance of the three-group discriminant analysis shows that the two-group discriminant model outperforms the three-group model in classification and prediction of bond rating changes.

Finally, a comparison was made between the performance of the decomposition analysis and the discriminant models. The comparison showed that there were some differences between the classification and prediction accuracy of the two techniques. These differences show that decomposition measures when used in a multivariate model outperform both the two-group and three-group discriminant models in the prediction of changed ratings. However, the comparison shows that the discriminant models outperform decomposition analysis in the classification and prediction of unchanged bond ratings. Reasons for the poor performance of decomposition analysis on the unchanged ratings group may include the heterogeneous
nature of the unchanged ratings group and the inadequacy of the rating revisions carried by Moody's agency.

To determine if there was a significant difference between the performance of the two techniques, a .05 significance level was selected and chi-square tests were performed. The results show that there is no significant difference between the performance of decomposition analysis and the performance of the discriminant model in the classification and prediction of industrial bond rating changes.

Conclusions

Based on the results of this study, several conclusions can be made. First, the study shows that decomposition measures for firms that experienced bond rating changes are larger and more unstable than decomposition measures for the firms that did not experience bond rating changes. Second, the incorporation of more than one decomposition measure in a multivariate decomposition model achieves a better accuracy in the prediction of industrial bond rating changes. Third, the study shows that decomposition analysis can perform as well as discriminant analysis in duplicating and predicting industrial bond rating changes. Fourth, since decomposition analysis has less restrictive assumptions than discriminant analysis, decomposition analysis can be recommended for use by rating agencies as a screening device in detecting potential bond rating changes. As shown in this study, although
decomposition analysis is useful in signaling a rating change, it does not provide any information about the type of change: upgrading or downgrading. This does not and should not represent a limitation on the use of decomposition analysis by rating agencies since these agencies can use certain financial ratios, or the trends in those ratios, to make decisions regarding the direction of a bond rating change. In this study, the trends in fixed charges coverage, current ratio, debt ratio, and the instability of the firms' earnings proved to be important variables in the prediction of bond rating changes. Fifth, the poor performance of decomposition analysis in the prediction of unchanged ratings raises a serious question about the inability of the agencies to keep ratings current. The poor performance of the three-group discriminant analysis raises the same question about the inadequacy of bond rating revisions made by rating agencies.

Suggestions for Future Research

This study examines and evaluates the usefulness of decomposition analysis in duplicating and predicting industrial rating changes. It provides evidence that decomposition measures can be used in duplicating and predicting bond rating changes. Based on the findings of this study, several recommendations can be made.
First, the study shows that decomposition analysis performs poorly on the unchanged ratings group. The heterogeneous nature of this group is cited as a possible reason for this poor performance. Therefore, one important recommendation for future research in this area would be to use homogeneous unchanged ratings, such as for electric utilities, in order to get more accurate results from the use of the decomposition analysis.

Second, the multivariate decomposition model performed well in the prediction of rating changes and poorly in the prediction of unchanged ratings. It is therefore recommended that the incorporation of some additional independent variables, such as the changes in key financial ratios over time, be included to improve the prediction accuracy of the model.

Third, since the study used only three decomposition measures (ADM, LPM, and BSDM), it is possible that decomposition measures based on financial statements other than the balance sheet (like the income statement) may add more predictive power to the decomposition analysis. Fourth, the multivariate decomposition model used in this study is recommended for use in studying other corporate events such as corporate failure and merger.

APPENDIX A

STATISTICAL DECOMPOSITION ANALYSIS

Statistical decomposition analysis has its roots in the information theory that was developed in the context of communication engineering. Information theory was the basis for Shannon and Weaver's (8) model that was developed in 1948. In that model, Shannon and Weaver were interested in the measurement of the amount of information transmitted over a channel for communication purposes and in the reduction of effects of the undesirable information.

Measurement of the Amount of Information: Entropy

The information theory concepts—namely, the measurement of the amount of information concept and the concept of noise or undesirable information—were applied to different areas in the social sciences (1, 2, 3, 4, 5, 9, 10, 11). A central theme in those applications was the concept of entropy, which is a measure of uncertainty. For example, if there is an event that is expected to take place and that will result in one of several possible outcomes, there is some uncertainty as to which of the possible outcomes of the event will occur. If it is assumed that every possible outcome \(X_i\) can be assigned a probability of occurrence \(P\) and that there are a number \(N\) of possible outcomes, then the degree of
uncertainty or entropy \((H)\) can be measured by the following formula:

\[
H = \sum_{i=1}^{n} P_i \log \frac{1}{P_i}
\]

where \(P_i > 0\) and \(\sum_{i=1}^{n} P_i = 1\).

Based on the mathematical fact that the logarithm of a fraction is equal in size, but opposite in sign to the logarithm of the reciprocal of the fraction, the entropy \((H)\) can be expressed as follows (6):

\[
H = -\sum_{i=1}^{n} P_i \log P_i
\]

This formula can be referred to as "the expected information of the message" (11, p. 438).

To gain information about the outcome of an event, the value of a definite message must be closely related to the degree of uncertainty about the event that existed before the receipt of this message. For example, if the \(P_i\) for a certain outcome is low, then it will be surprising if this outcome takes place; the message in this case is more informative than it would have been in \(P_i\) for \(X_i\) was high.

The minimum value of an entropy \((H)\) will be 0. That value may exist in a situation where one \(P_i\) is equal to 1 and all other \(P_i\)s are equal to 0. On the other hand, the maximum value of an entropy \((H)\) will be \(\log n\). Such a value will exist in a situation where all \(P_i\)s are equal to \(1/n\). In
this situation, more information is expected from the message about which event happened than in any other case (8).

Following are several characteristics of the entropy (H), according to Hamer (1, p. 5).

1. The amount of information, H, is dependent only on the probability of the events;

2. The amount of information is additive; if a particular set of events can be divided into two or more subsets the original amount of information in the set will be the weighted sum of the amount of information in the subsets;

3. The amount of information, H, is a continuous function of the event probability;

4. The amount of information, H, is a monotonically increasing function of the number of events when the probabilities of occurrence for the events are equal (7, pp. 48-53).

Of special importance is the additivity characteristic of the entropy. This property allows the users to disaggregate the total entropy by subsets and within subsets; therefore, it allows users to isolate the relative contribution of each subset to the total entropy.

The Expected Amount of Information in a Change of Probability Distribution

The entropy concept can also be applied to messages that are not completely definite. For example, there are situations where the probability of certain outcome, P_i, can
be changed or revised to become $q_i$. In such situations, $P_i$ can be referred to as prior probability and $q_i$ as posterior probability. However, the transformation of the probability $P_i$ to $q_i$ will not give an answer as to whether or not the event will occur (9). In such situations, the expected information of the message, which transforms prior probabilities, $P_1, \ldots, P_n$, to posterior probabilities, $q_1, \ldots, q_n$, can be stated as follows (10):

$$I (q:P) = \sum_{i=1}^{n} q_i \log \frac{q_i}{P_i}.$$  

The expected information given in the above equation is called the information inaccuracy (1). The information inaccuracy or $I (q:P)$ is always positive when the prior and the posterior probabilities are not pairwise equal ($P_i \neq q_i$ for some $i$). However, if $P_i = q_i$ for all $i$, then the information inaccuracy, $I (q:P)$, will be at its minimum value. If this is the case, the message does not produce a change in any of the probabilities, therefore no information is conveyed and the information inaccuracy will be zero. Information inaccuracy increases as the difference between the prior probabilities and the posterior probabilities increases. Information inaccuracy will take its maximum value when $q_i = 0$ for some event, given that $P_i = 0$ for that event. In this case an event which was previously considered impossible becomes possible; as a result, information inaccuracy will be $\infty$ (1).
APPENDIX BIBLIOGRAPHY


APPENDIX B

BASIC ASSUMPTIONS OF THE DISCRIMINANT ANALYSIS

There are several assumptions that need to be met for the application of discriminant analysis (2, 3, 4, 5, 6, 7). These assumptions are:

1. There must be two or more groups: $g \geq 2$;
2. There must be at least two cases in each group: $n_i \geq 2$;
3. There may be any number independent variables, provided that the number is less than the total number of cases minus two: $0 < p < (n - 2)$;
4. The covariance matrices for each group must be (approximately) equal, unless special formulas are used;
5. Each group has been drawn from a population with a multivariate normal distribution on the independent (discriminating) variables;
6. The set of independent variables does not include any variable which is a linear combination of other independent variables.

Derivation of the Discriminant Functions

A discriminant function is a linear equation that has several discriminating variables which are formed to satisfy certain conditions (1, 3). A discriminant function can be
stated as  \[ F_{km} = U_0 + U_1 X_{1km} + U_2 X_{2km} + \cdots + U_p X_{pkm} \]

where:

- \( F_{km} \) = the value (score) on the discriminant function for the case \( m \) in the group \( k \);
- \( X_{ikm} \) = the value on discriminating variable \( X_i \) for case \( m \) in group \( k \);
- \( U_i \) = coefficients that produce the desired characteristics in the function.

In the derivation of the coefficients (the \( U_i \)), the group means on the function are to be as different as possible. The maximum number of discriminant functions that can be derived is equal to the number of groups minus one, or the number of the discriminating variables, whichever is fewer (1).

For the development of a discriminant function, the differences among the data cases need to be measured. A table of group means and standard deviations is inadequate, because it will not include the interrelations among the variables. The most appropriate way to measure the differences among the data cases is the matrix of total sums of squares and cross products, \( T \). The following equation is the basis for the development of the matrix \( T \).

\[
t_{ij} = \sum_{k=1}^{g} \sum_{m=1}^{n_k} (X_{ikm} - X_{i..}) (X_{jkm} - X_{j..})
\]

where:

- \( g \) = number of groups;
\[ n_k = \text{number of cases in group } k; \]
\[ n = \text{the total number of cases over all groups; } \]
\[ x_{ikm} = \text{the value of variable } i \text{ for case } m \text{ in group } k; \]
\[ x_{ik} = \text{mean value of variable } i \text{ for the cases in group } k; \]
\[ x_i = \text{mean value of variable } i \text{ for all cases (grand or total mean). } \]

In the foregoing equation, the terms in parentheses measure the amount by which the value of a particular case deviates from the grand mean for that variable. If \( i = j \), then the two terms in the parentheses will be the same, and the deviation is squared. If \( i \neq j \), then the sum of a deviation on one variable is multiplied by the deviation on the other. The entire matrix constitutes a summary of how much the cases (points) are spread out around the total space by all variables. This will indicate the dispersion among the cases for all the variables.

The degree of distinction in the group locations will determine the extent to which the dispersion within the groups will vary from total dispersion. If the group centroids are not identical, then the dispersion within the groups will be less than the total dispersion. This is measured by matrix \( W \), which is referred to as the within groups sums of squares and cross products matrix. Matrix \( W \) is similar to matrix \( T \) in every way except that the deviations in matrix \( W \) are measured from the mean of the group and not the grand mean as
is the case in matrix T. Matrix W is computed using the following equation:

\[ W_{ij} = \sum_{k=1}^{g} \sum_{m=1}^{n_k} (X_{ikm} - \bar{X}_i) (X_{jkm} - \bar{X}_j). \]

In there are no differences among the group centroids (i.e., group centroids are identical) then all the elements of W will be equal to the corresponding elements of T since \( X_{ik} \) always equals \( X_i \). If, however, the group centroids are different, then the elements of W will be smaller than the corresponding elements of T. This difference can be measured by the matrix B, which is computed as follows:

\[ B = T - W \quad (i.e., b_{ij} = W_{ij}). \]

Matrix B is referred to as the between-groups sums of squares and cross products matrix.

The information provided by matrices B and W provides the basis for the derivation of the discriminant function. First, the researcher needs to obtain a vector of coefficients.

\[ \mathbf{v}_1 = (U_{i1}, U_{i2}, \ldots, U_{ip}) \]

which will maximize the discriminant criteria defined as:

\[ \lambda = \frac{\mathbf{v}^T B \mathbf{v}}{\mathbf{v}^T \mathbf{w} \mathbf{v}} \]

where:

\( \lambda \) = eigenvalue;

\( \mathbf{v} \) = eigen vector of the matrix \( W^{-1}B \).
The researcher can obtain a value for \( \mathbf{v} \) by solving the matrix equation

\[
(W^{-1}B - \lambda I) \mathbf{v} = 0.
\]

The \( b \)s and \( W \)s will be known quantities computed from the sample data. Based on those values and with the use of calculus and other mathematical techniques, the researcher can solve the above equation and obtain a vector of coefficients.

**Computational Method and Statistical Significance**

Two computational methods are used in discriminant analysis; these methods are the direct (simultaneous) method and the step-wise method. When the direct method is used, all independent variables are included in the computation at the same time. On the other hand, when the step-wise method is used, the independent variables will be entered into the analysis one at a time on the basis of their discriminating power. As more variables may be removed if the information they contain about the differences in the dependent variable exists in some combinations of other independent variables. For this study, the step-wise method is used because a large number of independent variables are used in the analysis.
In most of the empirical research that uses multiple discriminant analysis, a .05 level of significance is used. This study will also use the .05 level of significance in the evaluation of the discriminant function. Therefore, the derived discriminant function must be significant at the .05 level or beyond, otherwise there will be a little change that the function can classify more accurately than a chance model (1, 3).
APPENDIX BIBLIOGRAPHY


<table>
<thead>
<tr>
<th>This Study</th>
<th>Belkaoui (1)</th>
<th>Horrigan (3)</th>
<th>West (6)</th>
<th>Pinches and Mingo (5)</th>
<th>Kaplan and Urwitz (4)</th>
<th>Bhandari (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Total assets</td>
<td>Total assets</td>
<td>Total assets</td>
<td>Not used</td>
<td>Not used</td>
<td>Total assets</td>
<td>Total assets</td>
</tr>
<tr>
<td>2. Not used</td>
<td>Total debt</td>
<td>Not used</td>
<td>Bonds outstanding</td>
<td>Not used</td>
<td>Not used</td>
<td>Not used</td>
</tr>
<tr>
<td>3. Total debt</td>
<td>Long term as % of total assets</td>
<td>Net worth over total debt</td>
<td>Debt to equity ratio</td>
<td>Long-term debt over total assets</td>
<td>Long-term debt over total assets</td>
<td>Long-term debt as % of total assets</td>
</tr>
<tr>
<td>4. Not used</td>
<td>Short-term debt</td>
<td>Not used</td>
<td>Not used</td>
<td>Not used</td>
<td>Not used</td>
<td>Not used</td>
</tr>
<tr>
<td>5. Current ratio</td>
<td>Current ratio</td>
<td>Working capital over sales</td>
<td>Not used</td>
<td>Not used</td>
<td>Not used</td>
<td>Not used</td>
</tr>
<tr>
<td>This Study</td>
<td>Belkaoui (1)</td>
<td>Horrigan (3)</td>
<td>West (6)</td>
<td>Pinches and Mingo (5)</td>
<td>Kaplan and Urwitz (4)</td>
<td>Bhandari (2)</td>
</tr>
<tr>
<td>------------------------------------</td>
<td>--------------</td>
<td>--------------</td>
<td>----------</td>
<td>-----------------------</td>
<td>-----------------------</td>
<td>--------------</td>
</tr>
<tr>
<td>6. Fixed charged coverage</td>
<td>Not used</td>
<td>Not used</td>
<td>Not used</td>
<td>Not used</td>
<td>Not used</td>
<td>Fixed used coverage</td>
</tr>
<tr>
<td>7. Not used</td>
<td>Five-year cash flow as a % of five-year growth needs</td>
<td>Not used</td>
<td>Not used</td>
<td>Not used</td>
<td>Not used</td>
<td>Not used</td>
</tr>
<tr>
<td>8. Not used</td>
<td>Stock price as % of book value</td>
<td>Not used</td>
<td>Not used</td>
<td>Not used</td>
<td>Accounting and market betas</td>
<td>Not used</td>
</tr>
<tr>
<td>9. Not used</td>
<td>Subordination status</td>
<td>Subordination status</td>
<td>Not used</td>
<td>Subordination status</td>
<td>Not used</td>
<td>Subordination status</td>
</tr>
<tr>
<td>10. Total assets trend</td>
<td>Not used</td>
<td>Not used</td>
<td>Not used</td>
<td>Not used</td>
<td>Not used</td>
<td>Total assets trend</td>
</tr>
<tr>
<td>11. Current ratio trend</td>
<td>Not used</td>
<td>Net operating profit</td>
<td>Nine-year earnings</td>
<td>Net income over total assets</td>
<td>Coefficient of variations of total assets</td>
<td>Not used</td>
</tr>
<tr>
<td>This Study</td>
<td>Belkaoui (1)</td>
<td>Horrigan (3)</td>
<td>West (6)</td>
<td>Pinches and Mingo (5)</td>
<td>Kaplan and Urwitz (4)</td>
<td>Bhandari (2)</td>
</tr>
<tr>
<td>------------</td>
<td>-------------</td>
<td>-------------</td>
<td>----------</td>
<td>----------------------</td>
<td>----------------------</td>
<td>-------------</td>
</tr>
<tr>
<td>12. Fixed charges coverage trend</td>
<td>Not used</td>
<td>Not used</td>
<td>Not used</td>
<td>Not used</td>
<td>Not used</td>
<td>Fixed charges coverage trend</td>
</tr>
</tbody>
</table>

13. Residual standard deviation of ordinary least squares of the regression of net income after tax to total assets for each of the past five years.
APPENDIX BIBLIOGRAPHY


**Articles**


Bostwick, C. L., "The Use of Information Theory in Accounting," Management Accounting, 48 (June, 1968), 11-17.

Broy, Anthony, "How Good are the Bond Rating Agencies?" Financial World, 145 (September 1, 1976), 11-15.


"Lowering the Boom on Bond Ratings," Business Week, May 12, 1975, 70-71.


Ross, Irwin, "Higher Stakes in the Bond Rating Game," Fortune, 93 (April, 1976), 133-142.

Sherwood, Hugh C., "How They'll Rate Your Company's Bonds," Business Management, 29 (March, 1966), 38-42.


Reports


Publications of Learned Organizations


Schiff, Michael and George Sorter, editors, Proceedings of Conference on Topical Research in Accounting, New York, New York University, 1976.

Unpublished Materials


