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THE EX-ANTE AND EX-POST RELATIONSHIPS BETWEEN BOND RATINGS AND SFAS 33 MEASURES[*]

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THE EX-ANTE AND EX-POST RELATIONSHIPS BETWEEN BOND RATINGS AND SFAS 33 MEASURES

ABSTRACT

This study examines the association between SFAS 33 accounting information and bond ratings to assess (1) whether SFAS 33 accounting information have incremental value (to historical cost variable models) for predicting bond ratings, (2) whether SFAS 33 accounting information available subsequent to the bond ratings reflects the economic conditions that induce the ratings, and (3) whether bond raters use SFAS 33 accounting information in the rating process.

The results indicate that (1) SFAS 33 disclosures provide incremental value for investors for predicting bond ratings, (2) SFAS 33 disclosures reflect certain economic conditions considered by bond raters, but not measured by traditional financial disclosures, and (3) although professional market participants (bond raters) may have already adjusted for inflation based on a broad information set, the SFAS 33 disclosure requirement may reduce the aggregate cost of generating restated data.

THE EX-ANTE AND EX-POST RELATIONSHIPS

BETWEEN BOND RATINGS AND SFAS 33 MEASURES

1. INTRODUCTION

In September 1979, the Financial Accounting Standards Board (FASB) issued Statement No. 33 (SFAS 33), *Financial Reporting and Changing Prices*, which requires disclosure of constant dollar (CD) and current cost (CC) information. The Board labeled the disclosures experimental and stated that it would "study the extent to which the information is used, the types of people to whom it is useful, and the purposes for which it is used." [SFAS 33, p. 6] Early research studies [for example, Beaver & Landsman (1983), Beaver & Ryan (1985)] indicated no incremental information content for SFAS 33 disclosures in market association tests as well as very limited usage by security analysts [Berliner, 1983]. In response to these early findings the Board eliminated its CD requirement and amended a new set of CC requirements (SFAS 82). In 1986, the FASB issued SFAS 89, which encourages, but no longer requires, the disclosure of supplementary information on the effects of changing prices. Bublitz, Frecka & McKeown [BFM] (1985), Thorne (1991) and Eichenseher, Lobo & Tung [ELT] (1991) used different research approaches and observed evidence of information content in SFAS 33 disclosures.

These conflicting results concerning the incremental value of SFAS 33 data suggest the need for further research. Bond ratings are usually a direct reflection of information usage. The impact of SFAS 33 accounting information on bond rating decisions provides such an opportunity. Unlike securities price research using market return model to examine the incremental value of SFAS 33 data, this study provides additional evidence by examining the ex-ante and ex-post relationships between SFAS 33 disclosures and bond ratings. Three main questions are addressed in this research:

1. Does SFAS 33 accounting information, available prior to a bond rating, have incremental value to historical cost [HC] variable models for predicting the bond rating?

2. Does SFAS 33 accounting information, available subsequent to the bond rating, reflect the economic conditions that induced the ratings?
3. Do bond raters use SFAS 33 accounting information in the rating process?

The results of this study provide additional evidence on the usefulness of SFAS 33 accounting information as well as empirical insight into the bond rating process. The results indicate significant association between SFAS 33 information and bond ratings in line with the "optimistic results" reported by BFM (1985) and Thorne (1991).

The next section summarizes the previous studies relevant to this research. Section 3 discusses the ex-ante and ex-post relationships between SFAS 33 data and bond ratings. That discussion leads to two hypotheses and three resulting scenarios. Section 4 presents the research design including: methods, models, sample selection criteria and variables. Section 5 reports the empirical results of the multivariant discriminant and N-chotomous PROBIT analyses. Section 6 provides some concluding remarks in terms of the study's objectives.

2. PREVIOUS RESEARCH FINDINGS

The traditional price level literature has been surveyed extensively [Vasarhelyi and Pearson (1979), Frishkoff (1982)]. More recently, with the advent of the SFAS 33 tapes [Vasarhelyi et al, (1984)], and the FASB's interest in the evaluation of SFAS 33 disclosures, a new set of studies emerged.

1. Surveys have not provided definitive conclusions concerning the usefulness of SFAS 33 disclosure. Financial analysts tend to favor the CC method [Berliner, 1983], while preparers and controllers [Arthur Young (1981), and Flesher & Soroosh (1983)] tend to support the CD method. Most groups stated that SFAS 33 was not an integral part of their analysis, but it was found to be usable and desirable on a supplementary basis.
2. Security price studies include Beaver and Landsman (1983) and Beaver & Ryan (1985), who concluded that SFAS 33 disclosures were either useless -- the information was already impounded in stock prices -- or misunderstood.

However, other studies [Haw & Lustgarten (1988), BFM (1985), Thorne (1991), and ELT (1991)], showed that the SFAS 33 disclosures have incremental explanatory power.

3. Dharan's (1988) findings suggest that CC data have no incremental explanatory power over dividend decisions. Brown (1983) concluded that changing prices adjusted earnings are not useful to analysts for the purpose of revising estimates of future HC earnings, dividends or cash flow. However, Lobo & Song (1989) has found there is incremental information in cash flow over that conveyed by alternative measures of operating income. Brown, Huefner & Sanders (1994) found the CC disclosures provide reliable estimates of the market value of property, plant and equipment in the representational faithfulness sense of Statement of Financial Concepts No. 2.
4. Predictive ability studies assess the predictive ability of SFAS 33 data, Bartley and Boardman (1990) concluded that classificatory models for takeover targets may be developed by combining HC, CD and CC data. Walter (1994) also reported that the CC data required by Statement 33 were useful to investors for identifying future takeover targets and earning above-average stock returns.

In summary, these conflicting results underscore the need for further research on SFAS 33 disclosures. This paper provides additional evidence by focusing upon the relationships between SFAS 33 data and bond ratings.

Given that bond ratings have a significant influence on yields [Katz (1974), Grier & Katz (1976), and Griffin & SanVicente (1982)], a number of studies[1] have developed statistical models that explain and predict ratings of a large cross section of corporate industrial bonds. In general, those models use HC financial data to correctly classify 60%-70% of the bonds. Since changing prices may affect a firms operations, prediction accuracy might be increased by including inflation-adjusted financial data.

Baran, Lakonishok & Ofer [BLO] (1980) used general price level adjusted data to predict bond ratings. They employed discriminant analysis model and 38 variables which included: HC data, general price-level [GPL] data and a

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1 For a summary, see Kaplan & Urwitz (1979) and Belkaoui (1983).

combination of the two. Their sample of 202 corporations was taken from the 1974 Standard & Poor's *Bond Guide*. A "small improvement" was found when comparing GPL (61.9%) with historical cost (57.4%); a greater improvement when combined data (65.8%) were used. Their results show that estimate GPL data, obtained by using the Parker (1977) estimation model,[2] improve predictions. However, Walther (1982) has warned that the reliability of conclusions reached in studies by using an estimation model depend on the accuracy of the surrogate data produced by the model. Smith's (1984) findings confirm that perceived relative corporate profitability is very dependent on the estimation method used to generate inflation-adjusted measures and that the differences between traditional measures and inflation-adjusted measures may not be predictable from traditional historical cost data sources. A limitation of the BLO (1980) study is the usage of an estimation procedure to generate the CD data rather than working with firm's CD disclosures. This study expands the bond rating literature by (1) using SFAS 33 information for bond rate prediction and (2) examining whether bond raters use SFAS 33 information (or a surrogate) in the rating process.[3]

3. SFAS 33 INFORMATION AND BOND RATINGS

A bond rating is primarily a judgment of the investment quality of a long-term obligation of a firm. It reflects the raters' estimates of the relevant characteristics of the quality of the investment. Although each rating agency has defined the meaning of its ratings, the agencies have not explicitly specified the process they use to arrive at ratings. Prior studies show that a significant relationship exists between historical measures of a company's performance and the ratings assigned to its bonds. Hence, one would expect SFAS 33 information to be related to bond ratings for the same reason that historical cost variables are related. If SFAS 33 data contain relevant information, bond raters are likely to use it in their rating process.

3.1 Predictive Ability and the Incremental Value of SFAS 33

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2 Davidson and Weil (1975) provide a detailed description of an adjustment procedure based upon publicly available financial statements. Parker (1977) outlines in detail an adjustment procedure based upon Compustat data that contains a more restricted set of financial data.

3 Bond raters may already adjust for inflation based on adjusted data leading to obtaining no incremental information from SFAS 33.

The predictive ability criterion [Elam (1975), Monahan and Barenbaum (1983), and Mensah (1983)] is employed as a means to examine the effect of SFAS 33 information on the prediction of bond ratings. A signal (X) from a particular information system is said to have information content if the distribution of outcomes (Y), conditional on this signal, differs from the unconditional outcomes distribution. [$F(Y/X) \neq F(Y)$]. The concept of information content is similar to the one proposed by Beaver (1968).[4] If the realization of these signals alters bond raters' beliefs about the attributes that cause bonds to be of value, then they adjust bond ratings accordingly. The relation between bond ratings and a given signal is defined as the information content of that signal, and is measured by the ability of the signal to predict bond ratings. Hence, let

H_t = information content based on the signal of the reported historical cost accounting numbers at time t,

I_t = information content based on the signal of the reported SFAS 33 accounting numbers at time t,

B_t = bond rating assigned by bond raters at time t.

Given the above definitions, a number of scenarios related to the incremental information content[5] of SFAS 33 can be developed.

SCENARIO 1: SFAS 33 accounting numbers available prior to a bond rating are useful for predicting the bond rating.

Given the historical cost information prior to a bond rating, the accuracy of bond rating prediction will be improved with additional SFAS 33 information. Information content of SFAS 33 accounting numbers (I_{t-1}) is not a subset of information content of historical cost accounting numbers (H_{t-1}).

4 Beaver (1968) defines information as a change in expectations about the outcome of an event.

5 This concept is similar to Granger's (1969) definition of "causality". The definition of causality given by Granger is: X2 "causes" X1 if and only if X1 is better predicted by using the past history of X2 than by not doing so with the past of X1 being used in either case.

SCENARIO 2: SFAS 33 accounting numbers available prior to a bond rating are not useful for predicting the bond rating.

Given the historical cost information prior to a bond rating, the accuracy of bond rating prediction will not be improved with additional SFAS 33 information. Information content of SFAS 33 accounting numbers (I_{t-1}) is a subset of information content of historical cost accounting numbers (H_{t-1}).

One hypothesis follows from the above discussion:

HYPOTHESIS A: SFAS 33 accounting measures available prior to a bond rating have no incremental value for predicting bond ratings.

FASB's **Statement of Financial Accounting Concepts No. 1** (1978) states: "Financial reporting should provide information that is useful to present and potential investors, creditors, and other users in making rational investment, credit and similar decisions." (para. 34) and "--- financial reporting should provide information that can be used by all - *nonprofessionals as well as professionals* - who are willing to learn to use it properly. --- financial reporting should not exclude relevant information merely because it is difficult for some to understand or because some investors or creditors choose not to use it." (para. 36, emphasis added.) Hypothesis A (H_A) is mainly designed to address this type of non-professional investors.

3.2 Rational Expectations and the Use of SFAS 33 Accounting Information

If bond raters perceive SFAS 33 data to be useless or unreliable, we should not observe a relationship between SFAS 33 data and bond ratings. There are two reasons why we might find such a relationship exists: (1) bond raters do not consider SFAS 33 information in their rating process because they perceive SFAS 33 data to be useless, or (2) SFAS 33 information provide no information to bond raters who have adjusted for inflation based on other sources containing similar and more timely information and SFAS 33 data is a surrogate of those more timely information.

One of the major implications of market efficiency is that expected inflation equals actual inflation and, in general, all expectations are realized. From this perspective, the merits of SFAS 33 disclosures rest on an assumption that a material portion of price changes (either general or specific) is unanticipated.

Evidence in the finance and economics literature (Begg, 1982) suggests that the stock market reacts rationally to indications of inflation. Those studies, however, have not investigated the case of accounting disclosures. Because bond raters are experienced and professional participants in the bond market, it is hypothesized that bond raters are rational and have already adjusted for inflation in the rating process. Therefore, two more scenarios can be derived:

> **SCENARIO 3**: SFAS 33 accounting numbers available subsequent to the rating reflect some of the economic conditions which are considered by bond raters, but are not measured by traditional financial disclosures.

Given the historical cost information subsequent to a bond rating, the accuracy of bond rating classification will be improved with additional SFAS 33 information subsequent to a bond rating.

> **SCENARIO 4**: SFAS 33 accounting numbers available subsequent to the bond rating reflect none of the economic conditions which are considered by bond raters except those reflected by traditional financial disclosures.

Given the historical cost information subsequent to a bond rating, the accuracy of bond rating classification will not be improved with additional SFAS 33 information subsequent to a bond rating.

Consideration of Scenarios 3 & 4 gives rise to hypothesis B (H_B):

> **HYPOTHESIS B**: SFAS 33 accounting measures released subsequent to the bond rating reflect none of the economic conditions considered by bond raters except those reflected by traditional financial disclosures.

A number of scenarios related to the usage of SFAS 33 information can be derived by examining the results of testing hypotheses H_A and H_B:

SCENARIO 5: SFAS 33 disclosures provide no information to bond raters since they have already adjusted for inflation based on a broad and more timely information set [see Freeman (1983) and Seed (1982, p. 20)] --- for example, bond raters are likely to adjust historical cost data to reflect price level changes by estimation models, such as the Parker (1977) or the Davidson, Stickney and Weil (1976) models. (If Scenario 5 is valid, then both H_A and H_B will be rejected.)

One potential reason for the lack of use of SFAS 33 information is the perception that the information is redundant. This view is consistent with the efficient market hypothesis, which asserts that the market as a whole is efficient in processing publicly-available information. The questionnaire survey by Berliner (1983, p. 67) reports that a significant number of analysts consider the SFAS 33 information redundant; the information they need is already available elsewhere. Arthur Young & Co.'s (1981, p. 10) study suggests that 80 percent of 201 financial officers use some type of inflation-adjusted data, whether SFAS 33 data or otherwise.

SCENARIO 6: SFAS 33 disclosures provide information to bond raters which is not available prior to its disclosures, and SFAS 33 disclosures are considered in the rating process. (If Scenario 6 is valid then H_A will be rejected and H_B will be accepted.)

This scenario recognizes that in view of the cost of generating SFAS 33 data and the inside information required to do so, capital market agents (investors and financial analysts) will not be able to fully and correctly estimate the SFAS 33 data on a firm-by-firm basis. Accordingly, the disclosures probably could contain new information not anticipated by the market. This view is consistent with the normative models that suggest that investors, in order to make optimal portfolio decisions, are interested in information which aids in formulating expectations about future returns and associated risks of competing investment opportunities. Empirical studies so far have not produced consensus on the market's efficiency regarding inside information, i.e., the strong form of market efficiency. Thus, assuming that current cost data is theoretically relevant information for investors, and that these data are not available elsewhere, SFAS 33 should be instrumental in conveying relevant information to bond ratings agencies.

SCENARIO 7: Bond raters do not use SFAS 33 information in their rating process because they perceive that the quality of disclosures is either unreliable or useless. (If Scenario 7 is valid, then both H_A and H_B will not be rejected.)

A variety of reasons for not using the SFAS 33 information can be found in the literature [see Arthur Young (1981), Berliner (1983) and Flesher and Soroosh (1983)]:

a. Users reject the data, perceiving them as simply a garbled or noisy version of information already available in the historical cost statement -- garbled in the sense that such numbers have less predictive or diagnostic ability.

b. The "noncomparability" of SFAS 33 information is a problem. It allows companies an unusual amount of discretion in selecting procedures for calculating the required information.

c. The information lacks relevance and reliability.

d. The information is not audited, is unduly complex and difficult to be understood.

Table 1 summarizes the discussion in this section. If hypothesis H_B is rejected, then the scenario that SFAS 33 disclosures available subsequent to the rating reflect the economic conditions which are considered by bond raters, but are not measured by traditional financial disclosures is supported. Because this SFAS 33 information is not available when bond ratings are assigned, bond raters must have already adjusted for inflation based on a broad and more timely information set. Following this discussion, since bond raters consider this surrogate information when bond ratings are assigned, it is unlikely that hypothesis H_A be supported.

TABLE 1. Two-by-two Contingency Table

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">Hypothesis H_B</td></tr>
<tr><td>Accepted (Scenario 4)</td><td>Rejected (Scenario 3)</td></tr>
<tr><td rowspan="2">Hypothesis H_A</td><td>Accepted (Scenario 2)</td><td>Scenario 7</td><td>cannot happen</td></tr>
<tr><td>Rejected (Scenario 1)</td><td>Scenario 6</td><td>Scenario 5</td></tr>
</table>

4. RESEARCH DESIGN

This section consists of three subsections: (1) sample selection, (2) independent variables, and (3) statistical analysis.

4.1 Sample Selection

This study started with SFAS 33 database's sample and excluded utilities[6] and banks[7], thereby focusing on the industrial sector of the corporate bond market. All Bond ratings were limited to those by Standard and Poor's, Inc.[8] Parents and subsidiaries were treated as separate entities as long as they had individual bond ratings assigned to them. This was necessary since a subsidiary could have its bond rating changed without affecting the parent's rating. The sample was limited to AAA, AA, A, BBB, BB and B bonds.

The sample was drawn from those firms issuing new bonds in 1980, 1981, 1982 and 1983 Standard & Poor's *Bond Guide*. Note that by restricting the sample to only newly issued industrial bonds, the problem posed by any lag in revising the existing bond ratings can be avoided [Foster (1978), p. 436]. Issues that met the following criteria were selected for use in the study:

1. The issue must have a rating assigned by Standard and Poor's of AAA, AA, A, BBB, BB or B.
2. The company must be listed in *FASB 33 Data Bank Users Manual*.[9]
3. The company should not have one of the following Standard & Poor's industry codes: 10, 26, 35, 61, 72, 73, 74, 75.[10]
4. The company should not have ratings occurring within one month subsequent to the respective fiscal year-end.
5. The company has SFAS 33 data and historical cost data for the independent variables used for this study.

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[6] Regulatory commissions predominantly base rate structures on historical costs. The role of current cost and constant dollar accounting in these settings is unclear.

[7] The effect of inflation on financial institutions is different from the effect on industrial companies. Property, plant, and equipment or total expenses constitute a relatively small proportion of the total assets. Consequently, financial institutions (banks, bank holding companies and insurance companies) were omitted.

[8] Standard & Poor's was selected, because Hettenhouse and Sartoris (1976) indicated that (1) investors place more reliance on the Standard & Poor's ratings than on Moody's ratings as an indicator of bond quality, (2) Standard & Poor's relies more heavily on those characteristics that investors are using in the assessment of bond quality and, (3) Standard & Poor's is more prompt in revising bond ratings.

[9] The Statement 33 Data Bank includes 1,172 nonfinancial and 265 financial companies that reported the effects of changing prices under SFAS 33. The full details of the data base are reported in the *FASB Statement 33 Data Bank Users Manual* (Vasarhelyi, et al., 1984).

[10] 10: Banking, 26: Finance, 35: Insurance, 61: Securities, 72: Utilities-Electric, 73: Utilities-Gas, 74: utilities-Water, 75: Utilities-Water.

Based on these criteria, 268 and 241 companies were chosen for prior-year models and subsequent-year models (see below), respectively. Since SFAS 33 applies only to certain large companies, the sample is likely to reflect a bias in favor of older and larger firms. Table 2 provides information on sample sizes broken down by ratings.

TABLE 2. Sample Broken Down by Ratings

Rating	Prior-year Models		Subsequent-year Models	
	No.	%	No.	%
AAA	14	5.2	11	4.5
AA	57	21.2	59	24.5
A	113	42.2	98	40.7
BBB	31	11.6	26	10.8
BB	30	11.2	27	11.2
B	23	8.6	20	8.3
Total	268	100.0	241	100.0

4.2 Independent Variables

Comments from bond rating agencies are difficult to elicit and shed little light on the specific techniques and formulas used in rating bonds. The agencies create the impression that bond ratings are part ratio analysis and part judgment (Ross, 1976). In the absence of more complete normative statements, research efforts on default risk must be guided by factors which theory and empirical research suggest are important in determining default risk.

Since model specification based on extant theory is limited, the present study used variables found in the bond ratings prediction and the traditional financial statement analysis literatures. For convenience, the variables were grouped into four categories: (1) profitability, (2) debt-paying ability and risk, (3) efficiency, and (4) others. Tested independent variables were: (1) profitability ratios: earnings per common share (X1), return on total assets (X2), payout ratio (X3), profit-margin ratio (X4), return on net assets (X5), and P/E ratio (X6), (2) debt-paying ability and risk ratios: equity ratio (X8), times-charges-earned ratio (X9), income tax ratio (X10) and cash flow ratios (X11 and X12), (3) efficiency ratios: total asset turnover ratio (X13) and accounts receivable turnover ratio (X14), and (4) others: investor's expectation (X15), issue amount of bonds (X16), subordinated status (X17) and convertible status (X18).

The variable list was expanded to include current cost (C1 - C15) and constant dollar (D1 - D15) variations of the historical cost (H1 - H15) variables. Appendix 1 presents the independent variables in each category and summarizes the variables' components. Two multivariate statistical methods, (1) multiple discriminant analysis (MDA) and (2) N-chotomous PROBIT analysis (NPA), were employed to derive the ex ante prediction and the ex post classification results.

Eight multiple discriminant and PROBIT models were constructed: four to test whether SFAS 33 accounting numbers available prior to a rating have incremental value for predicting the rating and four to test whether SFAS 33 accounting numbers available subsequent to a rating reflect the economic conditions that initiated the rating.

The eight discriminant and PROBIT analyses used ratios from two different time periods (relative to the date of the rating). Prior-year models used accounting ratios for fiscal years ending prior to the dates of the ratings; that is, ratios for fiscal year 1979 or 1980 or 1981 with ratings occurring within 12 months subsequent to the respective fiscal year-end. Subsequent-year models used accounting ratios for fiscal years ending after the dates of the ratings; namely, ratios for fiscal year 1980 or 1981 or 1982 with ratings occurring within 12 months prior to the respective fiscal year-ends.

Models 1 through 8 are described by the following linear relationships:

Prior-Year Models:

$$Model\ 1:\quad Z_j = \sum_{i=1}^{15} P_i H_{ij} + \sum_{i=16}^{18} S_i X_{ij}$$

$$Model\ 2:\quad Z_j = \sum_{i=1}^{15} P_i H_{ij} + \sum_{i=1}^{15} Q_i D_{ij} + \sum_{i=16}^{18} S_i X_{ij}$$

$$Model\ 3:\quad Z_j = \sum_{i=1}^{15} P_i H_{ij} + \sum_{i=1}^{15} R_i C_{ij} + \sum_{i=16}^{18} S_i X_{ij}$$

$$Model\ 4:\quad Z_j = \sum_{i=1}^{15} P_i H_{ij} + \sum_{i=1}^{15} Q_i D_{ij} + \sum_{i=16}^{18} S_i X_{ij}$$

where:

Z_j = bond rating assigned during years from 1980 to 1982 for the j^{th} company;

P_i, Q_i, R_i, S_i = coefficients of the corresponding independent variable;

H_{ij}, D_{ij}, C_{ij} = independent variable X_i measured in historical cost, constant dollar, and current cost respectively for Company j for year 1979 or 1980 or 1981 with ratings occurring within 12 months subsequent to the respective fiscal year-end;

Subsequent-Year Models:

$$Model\ 5:\quad Z_j = \sum_{i=1}^{15} P_i H_{ij} + \sum_{i=16}^{18} S_i X_{ij}$$

$$Model\ 6:\quad Z_j = \sum_{i=1}^{15} P_i H_{ij} + \sum_{i=1}^{15} Q_i D_{ij} + \sum_{i=16}^{18} S_i X_{ij}$$

$$Model\ 7:\quad Z_j = \sum_{i=1}^{15} P_i H_{ij} + \sum_{i=1}^{15} R_i C_{ij} + \sum_{i=16}^{18} S_i X_{ij}$$

$$Model\ 8:\quad Z_j = \sum_{i=1}^{15} P_i H_{ij} + \sum_{i=1}^{15} Q_i D_{ij} + \sum_{i=1}^{15} R_i C_{ij} + \sum_{i=16}^{18} S_i X_{ij}$$

where:

Z_j = bond rating assigned during years from 1979 to 1981 for the j^{th} company;

P_i, Q_i, R_i, S_i = coefficients of the corresponding independent variable;

H_{ij}, D_{ij}, C_{ij} = independent variable X_i measured in historical cost, constant dollar, and current cost respectively for Company j for year 1980 or 1981 or 1982 with ratings occurring within 12 months subsequent to the respective fiscal year-end;

In Models 1 and 5, bond ratings are a function of only historical cost accounting variables. The effect of constant dollar accounting variables is introduced into Models 2 and 6. The effect of current cost accounting variables is introduced into Models 3 and 7. In Models 4 and 8, bond ratings are a function of both historical cost, constant dollar and current cost accounting variables. The MDA and PROBIT models will be estimated and evaluated separately for each set of independent variables.

4.3 Statistical Analysis

MDA and NPA were used to determine SFAS 33 information's impact on the ex-ante and ex-post prediction results:

4.3.1 MULTIPLE DISCRIMINANT ANALYSIS

4.3.1.1 Approach 1: Full Discriminant Models Under this approach, all independent variables were regarded as eligible to enter the model simultaneously if they contributed to the tolerance criterion. (The tolerance level[11] is 0.001.) SPSSX's DIRECT method of DISCRIMINANT was applied. Using such a large number of independent variables (48) can pose difficulty in that the variables may be highly correlated with one another. Since the purpose of the study is to determine the discriminating or classifying ability of the MDA model as a whole, and not that of the individual variables, the high intercorrelation or multicollinearity is not a problem.[12]

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[11] The tolerance of a variable is the proportion of its within-groups variance not accounted for by other variables in the analysis.

[12] Prediction can sometimes be improved when some degree of multicollinearity exits (Eisenbeis, 1977; Mason, Gunst and Webster, 1975; Haitovsky, 1969).

4.3.1.2 Approach 2: Reduced Collinearity Models Although such an approach is not necessary to the concerns of this study, a stepwise procedure was still employed to reduce the original set of variables to a smaller group of explanatory variables.

4.3.1.3 Approach 3: Jackknife Procedures The above predictive results may be biased upward because the same observations being classified by the MDA model were used to generate the model. To verify the model, the Lachenbruch jackknife procedure[13] was employed.

4.3.2 N-CHOTOMOUS PROBIT ANALYSIS

In addition to MDA tests, PROBIT analysis was also performed. Kaplan and Urwitz (1979) criticized previous researchers treated bond rating as it were on an interval scale. To exploit the ordinal nature of bond ratings, they used the multivariate PROBIT analysis proposed by McKelvey and Zavoina (1975).[14]

5. EMPIRICAL RESULTS

This section presents major findings of statistical analyses, and consists of two subsections: (1) results of multiple discriminant analysis, and (2) results of PROBIT analysis.

5.1 Results of Discriminant Analysis

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13 Another estimation procedure is the "holdout" method. The limitation of this method is the large sample size required. In fact, Lachenbruch and Mickey (1968) conclude that the holdout method has no clear superiority over the jackknife procedure, and they specifically recommend the jackknife procedure when normality is questionable and the sample size is small relative to the number of variables.

14 The N-chotomous multivariate PROBIT Program developed in the California Institute of Technology was used in this study.

The results[15] of the multiple discriminant analysis (MDA) using the three approaches described in the previous section are presented in Table 3.

[15] Equal priors were used in calculating the discriminant functions. This assumption is based on the belief that the distribution of bonds in the population is either unstable or unknown. Bond raters do not predetermine that a proportion of bonds must be categorized into a particular rating group. A test of equality of the covariance matrix for the estimation sample failed because of the small number of observations in the AAA and B categories. The linear, rather than the quadratic model, was utilized in part because of the limited sample size. Sample size is a critical factor in the selection of discriminant model form (Wahl and Kronmal, 1977). Without large samples the classification results for the quadratic form are poorer than for linear models, even with unequal dispersion matrices due to the large number of parameters to be estimated. Monte Carlo studies by Marks and Dunn (1974) also suggest that there may be efficiency tradeoffs between use of linear and quadratic procedures and sample sizes. When samples are small and the number of variable relatively large, linear procedures may give more efficient estimates of the[15] expected error rates than quadratic procedures even when the population dispersions are unequal.

TABLE 3. Results of Discriminant Analysis

	Approaches		
	Full Discriminant Model	Reduced Collinearity Model	Jackknife Procedure
Prior-Year Models			
Model 1	61.2%(164/268)	60.8%(163/268)	53.4%(143/268)
Model 2	70.2%(188/268)	64.6%(173/268)	57.8%(155/268)
Model 3	70.2%(188/268)	68.7%(184/268)	59.0%(158/268)
Model 4	72.4%(194/268)	67.9%(182/268)	60.8%(163/268)
Subsequent-Year Models			
Model 5	63.5%(153/241)	64.3%(155/241)	56.8(%(137/241)
Model 6	73.4%(177/241)	66.8%(161/268)	56.0%(135/268)
Model 7	73.9%(178/268)	72.6%(175/268)	58.1%(140/268)
Model 8	77.6%(187/268)	73.0%(176/268)	63.1%(152/268)

5.1.1 FULL DISCRIMINANT MODEL

5.1.1.1 Prior-Year Models The MDA model was estimated first by employing all variables derived from historical cost data. The model estimated was then used to classify the original sample. Model 1 correctly rated 164 out of 268 bonds, a success rate of 61.2%. The HC model (Model 1) is critical to test the incremental value of CD and CC variables in predicting bond ratings. Next, the classification ability of Model 2 estimated on the basis of variables derived from historical cost and constant dollar data was examined. Model 2 correctly rated 188 bonds out of 268, a success rate of 70.2% compared with a success rate of 61.2% when only historical cost data were utilized. Model 3 utilized historical cost and current cost variables, correctly rating 188 bonds out of 268. Using Model 3, the prediction accuracy rate achieved is 70.2%, the same as Model 2. In other words, the results show some improvement in classification accuracy when CD or CC data are used.

Finally, Model 4 was tested on a combined data base that included variables derived from historical cost, CD and CC data. It shows that the MDA classified correctly 72.4% (194/268) of the bonds. The model performs better than the previous three models. The results presented above show some improvement in the classification accuracy of the MDA model when CD or CC data are used instead of historical cost data only. A greater improvement is achieved when a combined data set, including historical cost, CD and CC data (Model 4), is employed.

One method of measuring the discriminatory power of these models is to compare the classification accuracy obtained with the accuracy obtained from using a proportional chance criterion,[16] which randomly assigns entities to groups based on probabilities equal to group frequencies. Frank et al. (1965) suggest the following test of significance:

$$t = \frac{(Q - P)}{\sqrt{P(1 - P)/N}}$$

where

Q is the proportion of sample observations correctly classified by the discriminant analysis;

P is the proportion one expects by chance; and

N is the number of bonds.

The accuracy of prediction of bond ratings in Models 1 through 4 is 61.2%, 70.2%, 70.2% and 72.4% respectively (see Table 3). The results are significantly[17] better than the results expected due to chance,[18] indicating that these models

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16 The proportional chance criterion [see Pinches (1980, p.443)] is appropriate for establishing the number of correct classifications expected by chance when the focus is on the percentage correctly classified over all groups simultaneously. Under this criterion, the expected probability of correct classifications over all groups is equal to $(P_1)^2 + (P_2)^2 + \ldots + (P_n)^2$, where P_1 equals the prior probability in the population of an observation belonging to the first group, P_2 is the prior probability of an observation belonging to the second group, etc.

17 All models are significant beyond the 0.01 level. For example, t value is 13.19 for Model 1.

$$13.19 = (61.2 - 25.9)/\sqrt{(25.9)(74.1)/268}$$ **Error! Main Document Only.**

18 For the sample of 268 bonds in these prior-year models, the percentage correct classification expected due to chance equals 25.92 percent. $25.92\% = (5.2\%)^2 + (21.2\%)^2 + (42.2\%)^2 + (11.6\%)^2 + (11.2\%)^2 + (8.6\%)^2$

have discriminatory power. The evidence clearly does not support the hypothesis that SFAS 33 accounting information available prior to a bond rating has no incremental value for predicting bond ratings. Instead, these results support the contention that constant dollar and current cost disclosures required by SFAS 33 have information content relative to the HC financial data. SFAS 33 information can be used to improve bond ratings prediction. Hypothesis H_A is rejected.

5.1.1.2 Subsequent-Year Models Hypothesis H_B was also rejected. The accuracy of prediction of bond ratings in Models 5 through 8 is 63.5%, 73.4%, 73.9% and 77.6%, respectively. The results also show some improvement in the classification accuracy of the MDA model when constant dollar data or current cost data or both are used instead of traditional historical cost data only. The percentage correct classifications are also significantly better than the results expected due to chance.[19]

The results show that SFAS 33 disclosures available subsequent to the rating reflect certain economic conditions that are not measured by traditional financial disclosures, but that are considered by bond raters. Rejecting both hypotheses (Hypotheses H_A and H_B) supports Scenario 5. That is, the results suggest that SFAS 33 disclosures provide no information to bond raters, since these bond raters have already adjusted for inflation based on a broad information set. However, SFAS 33 disclosures have incremental value for non-professional market participants predicting bond ratings. This conclusion is consistent with Beaver (1979), who found that a nontrivial portion of inflation has been anticipated.

5.1.2 REDUCED COLLINEARITY MODEL

A stepwise procedure was used to develop the discriminant function. Variables were selected for inclusion in the model based on the maximum F-ratio to enter.[20] In addition, as shown in Table 5, the omission of two variables (C4 and C7) actually caused an increase in the approximate F-statistic. This is an indication that the discriminatory power and

[19] In this case of 241 bonds, the percentage correct classification expected due to chance equals 25.88 percent. $25.88\% = (4.5\%)^2 + (24.5\%)^2 + (40.7\%)^2 + (10.8\%)^2 + (11.2\%)^2 + (8.3\%)^2$. Models 5 through 8 are also significant beyond the 0.01 level.

[20] The F-to-enter is set to 1.0.

perhaps the classification accuracy of the model could be increased by eliminating some of these independent variables. Therefore, an attempt was made to maximize the separation between the groups (bond ratings) while minimizing the number of variables used, through backward discriminant analysis. Under this process, the variable that added the least to the separation of the groups was removed from the discriminant function. It was then possible to observe the impact of the elimination of each variable on both the approximation F-statistic and the classification accuracy.

Tables 4 through 7 list the variables that remained after the stepwise deletion process had removed variables not making a significant contribution to the overall discriminatory power of the model. The variables are presented in their order of importance in the discriminant models (based on their performance). The results generally indicate that historical cost variables are more important than either the constant dollar or current cost alternatives. However, the large number of constant dollar or current cost variables in the final models indicates the significant impact that inflation has on the rating decision.

Using the stepwise technique approach, the classification accuracy drops to 60.8%, 64.6%, 68.7% and 67.9% for Models 1 through 4 respectively. In subsequent-year models, the classification accuracy drops to 64.3%, 66.8%, 72.6% and 73% for models 5 through 8 respectively. Again, Models 1 through 8 are significantly better than the results expected due to chance beyond the 0.01 level. The results are in line with those reported in full discriminant models.

TABLE 4. Relative Ranking of Independent Variables in Reduced Collinearity Models -- Models 1 and 2

Prior-Year Models						
Rank	Model 1			Model 2		
	Variable Entered (Removed)	F Value to Enter (Remove)	Approximate F-statistic	Variable Entered (Removed)	F Value to Enter (Remove)	Approximate F-statistic
1	X17	54.8	54.80	X17	54.80	54.80
2	H7	12.37	30.84	H7	12.37	30.84
3	X18	9.26	23.24	X18	9.26	23.24
4	H3	7.31	19.20	H3	7.31	19.20
5	H15	4.63	16.24	H15	4.63	16.24
6	H1	4.32	14.28	H1	4.32	14.28
7	H9	3.43	12.75	H9	3.43	12.75
8	X16	3.31	11.61	X16	3.31	11.61
9	H11	2.23	10.58	D1	2.99	10.69
10	H2	2.40	9.78	D11	2.40	9.89
11	H5	1.78	9.06	D6	1.96	9.18
12	H8	2.09	8.50	D5	1.92	8.59
13	H13	1.98	8.02	D15	2.11	8.11
14	H14	2.65	7.67	D7	3.64	7.86
15	H4	1.83	7.30	H5	2.56	7.51
16				H11	3.63	7.34
17				H8	2.38	7.08
18				H2	2.50	6.86
19				H13	2.10	6.63
20				D14	2.37	6.45
21				H4	1.63	6.23
22				D4	2.85	6.12
23				H14	1.48	5.93

TABLE 5. Relative Ranking of Independent Variables in Reduced Collinearity Models -- Models 3 and 4

Prior-Year Models						
Rank	Model 3			Model 4		
	Variable Entered (Removed)	F Value to Enter (Remove)	Approximate F-statistic	Variable Entered (Removed)	F Value to Enter (Remove)	Approximate F-statistic
1	X17	54.80	54.80	X17	54.80	54.80
2	H7	12.37	30.84	H7	12.37	30.84
3	X18	9.26	23.24	X18	9.26	23.24
4	H3	7.31	19.20	H3	7.31	19.20
5	H15	4.63	16.24	H15	4.63	16.24
6	H1	4.32	14.28	H1	4.32	14.28
7	H9	3.43	12.75	H9	3.43	12.75
8	X16	3.31	11.61	X16	3.31	11.61
9	C9	2.49	10.62	D1	2.99	10.69
	C4	2.56	9.84			
10	H5	3.35	9.31	C9	2.42	9.89
11	C5	3.28	8.87	D5	2.82	9.29
	C7	3.29	8.50			
12	H11	3.92	8.25	D15	2.86	8.71
13	H8	3.06	7.95	C7	4.66	8.49
14	C15	3.29	7.72	C5	2.77	8.13
15	C2	3.96	7.57	H5	4.08	7.94
16	H13	1.91	7.28	H11	3.68	7.74
17	C14	1.83	7.10	C2	3.06	7.52
	(C4)	(0.93)	7.35			
18	C11	2.01	7.01	H8	4.03	7.40
19	H14	2.32	6.89	D8	2.95	7.21
20	C8	1.72	6.66	H13	2.17	6.99
21	C1	1.22	6.41	D13	2.04	6.78
22	H2	1.89	6.28	D6	1.24	6.53
	(C7)	(0.51)	6.51			
23	H4	1.15	6.24	H10	1.07	6.29
24	H12	1.02	6.06	D2	1.14	6.08

TABLE 6. Relative Ranking of Independent Variables in Reduced Collinearity Models -- Models 5 and 6

Subsequent-Year Models						
Rank	Model 5			Model 6		
	Variable Entered (Removed)	F Value to Enter (Remove)	Approximate F-statistic	Variable Entered (Removed)	F Value to Enter (Remove)	Approximate F-statistic
1	X17	30.23	30.23	X17	30.23	30.23
2	H7	19.58	24.65	H7	19.58	24.65
3	X18	10.57	19.87	X18	10.57	19.87
4	H15	5.10	16.04	D12	7.90	16.92
5	H15	4.80	13.80	H15	5.00	14.55
6	X16	3.84	12.16	X16	3.86	12.78
7	H1	3.38	10.94	H5	3.44	11.48
8	H4	4.29	10.19	H3	4.18	10.65
9	H2	5.25	9.77	H6	5.48	10.21
10	H3	3.55	9.21	H4	4.19	9.70
11	H6	4.32	8.86	H8	3.99	9.27
12	H8	2.86	8.40	H1	3.39	8.85
13	H9	2.57	8.00	H12	2.04	8.35
14	H13	2.39	7.63	D1	2.93	8.01
15	H14	2.02	7.28	D5	3.80	7.81
16	H5	1.50	6.93	D7	3.03	7.57
17	H10	1.35	6.61	D11	2.48	7.31
18	H11	1.30	6.32	D2	3.72	7.18
19				H2	2.08	6.94
20				H13	2.49	6.76
21				H9	2.26	6.58
22				H11	1.95	6.39
23				D14	1.95	6.22
24				H10	1.62	6.04
25				D15	1.57	5.88
26				D3	1.34	5.71
27				D6	2.32	5.62

TABLE 7. Relative Ranking of Independent Variables in Reduced Collinearity Models -- Models 7 and 8

Subsequent-Year Models						
Rank	Model 7			Model 8		
	Variable Entered (Removed)	F Value to Enter (Remove)	Approximate F-statistic	Variable Entered (Removed)	F Value to Enter (Remove)	Approximate F-statistic
1	X17	30.23	30.23	X17	30.23	30.23
2	H7	19.58	24.65	H7	19.58	24.65
3	X18	10.57	19.87	X18	10.57	19.87
4	C12	7.96	16.94	C12	7.96	16.94
5	H15	5.00	14.56	H15	5.00	14.56
6	X16	3.85	12.79	X16	3.85	12.78
7	H1	3.36	11.48	H1	3.36	11.48
8	H4	4.35	10.67	H4	4.35	10.67
9	H2	5.32	10.21	H2	5.32	10.21
10	C11	5.09	9.82	C11	5.09	9.82
11	H3	3.30	9.29	H3	3.30	9.29
12	H6	4.88	9.04	H6	4.88	9.04
13	H8	2.71	8.60	H8	2.71	8.60
14	C8	2.72	8.23	C8	2.72	8.23
15	C7	3.15	7.95	C7	3.15	7.95
16	H11	2.68	7.67	H11	2.68	7.67
17	H13	2.78	7.43	H13	2.78	7.43
18	H12	2.12	7.16	H12	2.12	7.16
19	C14	2.07	6.92	C14	2.07	6.92
20	C1	2.12	6.71	C1	2.12	6.71
21	C5	2.02	6.51	D5	3.04	6.60
22	C15	2.60	6.38	C15	2.51	6.45
23	C2	2.14	6.22	D1	2.33	6.30
24	C10	1.34	6.02	C5	2.96	6.21
25	C3	2.55	5.92	C2	2.75	6.12
26	H9	1.17	5.74	D2	2.76	6.04
27	C9	3.63	5.73	D12	2.68	5.95
28	H5	1.05	5.56	H9	1.82	5.83

29				C3	1.34	5.68

5.1.3 JACKKNIFE PROCEDURE

Because the above results are an outcome of a reclassification of the original sample, the estimates of the classification errors might be overly optimistic. Therefore, the "jackknife" procedure was used to estimate the discriminant function and to classify the bonds. The jackknife procedure has been shown to be superior to a wide variety of validation methods [see Lachenbruch and Mickey (1968), and Efron (1979)]. The function performed as expected, with somewhat fewer successful classifications than the regular discriminant results (see Table 3).

The prior-year models correctly rated 141, 155, 158 and 163 of the 268 bonds (53.4%, 57.8%, 59% and 60.8%) for the Models 1, 2, 3 and 4 respectively. The subsequent-year models, Models 5, 6, 7 and 8 correctly rated 137, 135, 140 and 152 of the 241 bonds (56.8%, 56%, 58.1%, 63.1%). Although the classification error rate is higher when the jackknife procedure is used, the results generally are consistent with those reported in regular discriminant analysis. It is noteworthy to observe that Model 5 slightly outperforms Model 6. The implication is that CD disclosures provide information to bond raters which is not available prior to its disclosure.

5.2 Results of N-Chotomous PROBIT Analysis

Three measures of performance are used to summarize the explanatory power of each model. One is the estimated R^2 measure, described in McKelvey and Zavoina (1975, p. 111), which controls for the discrete and ordinal nature of bond ratings. The second measure of performance is the percentage of bonds correctly classified in the estimating sample. This statistics can be constructed by using the maximum likelihood predictions of the PROBIT model. The third measure is the Spearman rank order correlation, which can be used to determine the strength of association between predicted and actual values of the dependent variable (bond ratings). Thus, the higher the rank order correlation, the more accuracy the model achieves.

N-chotomous PROBIT analysis (NPA) results[21] for eight models are shown in Table 8. The PROBIT chi-square is used to compare the overall fit of the PROBIT model. The results from the eight models are all significant at the 0.01 level. The correct predictions achieved by these eight PROBIT models are all significantly better than the results expected due to chance at the 0.01 level.

Table 8 displays that the estimated R^2 is 0.70 for Model 1. When SFAS 33 variables are included, the results are improved to 0.75, 0.78 and 0.81 for Models 2, 3 and 4 respectively. Using Models 2, 3 and 4, the predictive accuracy rate achieved is 49%, 56% and 52%, respectively. Model 1 has a lower success rate, 47%. In addition, observe that Models 2, 3 and 4 all outperform Model 1 in terms of the rank order correlation measure. This suggests that the cost of misclassifying bond ratings may be less with the inclusion of SFAS 33 variables in the models. The results indicate some improvement of the PROBIT model when constant dollar data or current cost data or both are included. Hypothesis H_B is rejected.

TABLE 8. Results of PROBIT Analysis

Model	Percent Predicted Correctly	Estimated R^2	X^2	D. F.	Rank Order Correlation
Prior-Year Models					
Model 1	0.47	0.70	82.08	15	0.731
Model 2	0.49	0.75	141.41	23	0.735
Model 3	0.56	0.78	72.39	24	0.768
Model 4	0.52	0.81	48.65	24	0.742
Subsequent-Year Models					
Model 5	0.57	0.78	37.44	18	0.752
Model 6	0.61	0.78	218.59	27	0.801
Model 7	0.57	0.82	154.61	28	0.802
Model 8	0.62	0.81	188.54	29	0.805

[21] Since no more than 30 independent variables can be handled on each run by this computer program, only variables selected by stepwise discriminant analysis were used.

In subsequent-year models, Model 6 achieves a prediction success rate of 61% as compared with a success rate of 57% achieved when only historical cost data are utilized in Model 5. Using Model 6, though, the estimated R^2 achieved is 0.78 as high as Model 5. However, the rank order correlation of Model 6 is higher than in Model 5. Model 7 achieves a 57% success rate in predicting the bond rating, and this is as high as in Model 5. However, Model 7 has a higher estimated R^2 (0.82) and a higher rank order correlation (0.802) than Model 5. The results reported show some improvement of the PROBIT model when CD or CC data are used. A greater improvement is achieved when combined data, including HC, CD and CC data, are employed. Model 8 outperforms Model 5 in terms of every measure of performance, i.e., prediction accuracy rate, estimated R^2 and rank order correlation. These results generally conform to the results of MDA tests, and therefore Hypothesis H_B is rejected.

Overall, results from MDA and NPA indicate that both hypotheses (Hypotheses H_A and H_B) are rejected and Scenario 5 is supported.

6. CONCLUDING REMARKS

SFAS 33 represents one of the few attempts by the FASB to experiment in financial reporting. The FASB has expressed strong interest in sponsoring and supporting corporate and academic research regarding SFAS 33 issues. This study examined the ex-ante and ex-post relationships between SFAS 33 accounting information and bond ratings to assess:

1. whether SFAS 33 data have incremental value to historical cost variable model for predicting bond ratings, and
2. whether bond raters use SFAS 33 data in the rating process.

This assessment was performed through the examination of the ability of SFAS 33 data and historical cost data to explain bond ratings. The statistical techniques employed were multiple discriminant analysis (MDA) and N-chotomous PROBIT analysis (NPA).

While the relative cost/benefit question remains open, this study shows that the use of SFAS 33 data, can improve the classification accuracy of bond ratings. The disclosures of SFAS 33 data in annual reports will assist non-professional financial statement users and improve investment decision making. This result is consistent with BLO (1980) which found that price level adjusted data can be used to predict bond ratings more accurately. The results also support the contention that some sophisticated market participants -- for example, bond raters in this study -- have adjusted historical-cost data to reflect changes in the purchasing power of money in their rating process.

The above findings imply: Although SFAS 33 disclosures provide little information to professional analysts, it may help non-professional market participants to do investment analysis. Namely, though such information is redundant for the market as a whole, it may well serve a useful function for some market participants as a basis for assessing relative risk.

The findings of the study can be summarized as: (1) SFAS 33 disclosures provide incremental value for investors, to predict bond ratings, (2) although professional market participants, like bond raters, may have already adjusted for inflation based on a broad information set, SFAS 33 disclosure requirement would reduce the aggregate cost of generating restated data.

Another important factor to be considered by standard setters is the cost/benefit of generating of SFAS 33 information. When evaluating the pros and cons of SFAS 33, SFAS 82 and SFAS 89, the FASB will need to judge whether the benefits of constant dollar and current cost disclosures sufficiently outweigh the costs associated with producing the information. In making this judgment, the Board will need to evaluate SFAS 33, SFAS 82 and SFAS 89 information from many different perspectives. Among these prospectives, an important one, is the association of SFAS 33 to bond ratings.

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APPENDIX 1: Independent Variables

Profitability Ratios
X1: Earnings Per Common Share = (Income From Continuing Operations (NI) - Preferred Dividends) / Common Shares Outstanding H1: (VL28 - VL74) / Vl160 D1: (IFCOCD - VL74) / VL160 C1: (IFCOCC - VL74) / VL160 X2: Return on Assets = NI / Total Assets H2: VL28 / VL44 D2: IFCOCD / VL44 C2: IFCOCC / VL44 X3: Payout Ratio = Common Dividends / X1 H3: VL73 / H1 D3: VL73 / D1 C3: VL73 / C1 X4: Profit-margin Ratio = NI / Sales H4: VL28 / VL08 D4: IFCOCD / VL08 C4: IFCOCC / VL 08 X5: Return on Net Assets = NI / Net Assets H5: VL28 / (VL44 - VL 56) D5: IFCOCD / NACD C5: IFCOCC / NACC X6: P/E Ratio = Average of Weekly Prices / X1 H7: VL157 / H1 D7: VL157 / D1 C7: VL157 / C1

Debt-paying Ability and Risk Ratios

X7: Long-term Debt / Equity Ratio = Long-term Debt / Net Assets
- H7: VL53 / (VL44 - VL56)
- D7: VL53 / NACD
- C7: VL53 / NACC

X8: Debt / Equity Ratio = Total Debt / Net Assets
- H8: VL56 / (VL44 - VL56)
- D8: VL56 / NACD
- C8: VL56 / NACC

X9: Time-Charges-Earned
= Net Income Before Interest and Taxes / (Interest Charges + Preferred Dividends)
- H9: (VL28 + VL15 + VL17 + VL23) / (VL15 + VL17 + VL74)
- D9: (IFCOCD + VL15 + VL17 + VL23) / (VL15 + VL17 + VL74)
- C9: (IFCOCC + VL15 + VL17 +VL23) / (VL15 + VL17 + VL74)

X10: Income Tax Ratio = Total Taxes / NI
- H10: VL25 / VL28
- D10: VL25 /IFCOCD
- C10: VL 25 / IFCOCC

Cash Flow Ratios

X11: (NI + Depreciation Exp) / Sales
- H11: (VL28 + VL14) / VL08
- D11: (IFCOCD + DEPRCD) / VL08
- C11: (IFCOCC + DEPRCC) / VL08

X12: (NI + Depreciation Exp) / Long-term Debt
- H12: (VL28 + VL14) / VL53
- D12: (IFCOCD + VL14) / VL53
- C12: (IFCOCC + VL14) / VL53

Efficiency Ratios

X13: Asset Turnover Ratio = Net Sales / Total Assets
- H13: VL08 / VL44
- D13: SALECD / VL44
- C13: SALECC / VL44

X14: Accounts Receivable Turnover = Net Sales / Accounts Receivable
- H14: VL08 / VL33
- D14: SALECD / VL 33
- C14: SALECC / VL33

Other Ratios
X15: Investor's Expectation: = Average of Weekly Prices / Common Equity Per Share H16: VL157 / [(VL44 - VL56) / VL160] D16: VL157 / (NACD / VL160) C16: VL 157 / (NACC / VL160) X16: Subordinated Status of A Bond X17: Issue Amount of Bonds X18: Convertible Bond or not VL08: Net Sales VL14: Depreciation, Depletion, Amort. VL15: Total Interest VL17: Interest Charged to Construction VL23: Current Income Taxes VL25: Total Income Taxes VL28: Net Income Before Extraordinaries VL33: Accounts Receivable VL44: Total Assets VL53: Long-term Debt VL56: Total Liabilities VL73: Common Dividends VL74: Preferred Dividends VL157: Average of Weekly Prices VL160: No. of Common Shares Outstanding SALECD: Net Sales-Constant Dollar SALECC: Net Sales-Current Cost IFCOCD: Income from Continuing Operations - Constant Dollar IFCOCC: Income from Continuing Operations - Current Cost NACD: Net Assets - Constant Dollar NACC: Net Assets - Current Cost DEPRCD: Depreciation - Constant Dollar DEPRCC: Depreciation - Current Cost

* Data items initialed VL are historical cost information collected from Value Line data tapes. Subordinated status and convertible status of bonds, and issue amount of bonds were gathered from 1980 to 1983 Standard & Poor's *Bond Guide*. All current cost and constant dollar data described in this study were obtained from FASB Statement 33 Data Bank.