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The association between data intermediaries and bond rating classification model prediction accuracy

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THE ASSOCIATION BETWEEN DATA INTERMEDIARIES AND BOND RATING CLASSIFICATION MODEL PREDICTION ACCURACY

by

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ABSTRACT

Kamstra et al. (2001) developed a bond rating classification model that was based on a similar model developed by Ederington (1985). While both studies use Moody's bond ratings as dependent variables, the studies differ with respect to the independent variable data source, that is, Kamstra et al. (2001) use financial statement data extracted from Moody's Industrial Manual (now known as Mergent) while Ederington (1985) uses financial statement data extracted from Compustat. Given this, and given the divergent results of the two studies, the following question must be addressed: Do different data sources yield models that differ considerably with respect to overall performance of bond rating classification?

New bond issues for the period January 2004 to June 2006 that are common to both the Moody's bond rating database and the Standard and Poor's (S&P) bond rating database are included in the analysis. The most recent annual financial statement data reported prior to the issuance of each issue were extracted from both the Mergent database and the Compustat database. Using ordered logit models, I determine the predicted probabilities of the bond ratings, as well as the correct classification rates using the Kamstra et al. (2001) bond rating model for each of the following four data source combinations: Moody's/Mergent; Moody's/Compustat; S&P/Compustat; and, S&P/Mergent.

The results of the Wilk's Lambda test show data source dependency while the results of McNemar test did not show data source dependency. The difference in test results may relate to the level of precision of the tests, that is, the Wilk's Lambda test focuses on the predicted probabilities of the bond rating while the McNemar test focuses on the bond rating categories. Since the predicted probabilities of the bond ratings represent compositional data, I transformed the data in order to avoid spurious interpretations. The need to transform compositional data was not an issue in the previous literature since that research focused on bond ratings and not the predicted probabilities of the bond ratings.

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DEDICATION

I dedicate this dissertation to my wonderful family. Specifically, I would like to dedicate this dissertation to my understanding and patient husband, Madhu, who has endured the numerous years of my dissertation research, and to our precious daughter Aditi, who is the joy of our lives. Additionally, I dedicate this dissertation to my parents, Narayana Tallapally and Sheela Tallapally, for giving me the strong academic as well as moral foundation necessary to complete my dissertation.

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CHAPTER 1

INTRODUCTION

Data intermediaries such as Compustat (www.compustat.com), Mergent (www.mergent.com) and Value Line (www.valueline.com) serve the needs of financial professionals and academic researchers by providing accounting and market data. Research (Miguel, 1977; Kinney and Swanson, 1993; Kern and Morris 1994; and, Yang et al, 2003) shows that accounting data provided by some intermediaries differs from data provided in annual financial statements. These studies show that, to some degree, accounting data is source-dependent.

Kamstra et al. (2001) developed a bond rating classification model using Moody's bond ratings as the dependent variable and financial statement data for the independent variables. The financial statement data was extracted from Moody's Industrial Manual currently known as Mergent Industrial Manual. The above bond rating classification model is similar to the model developed by Ederington (1985), which also uses Moody's bond ratings as the dependent variable and financial statement data for the independent variables. However, in contrast to Kamstra et al. (2001), the financial statement data used by Ederington (1985) was extracted from Compustat. Ederington (1985) reported a 70.3% correct classification rate while Kamstra et al. (2001) reported a 47.5% correct classification rate. In view of the similarity of these studies, the difference in the reported correct classification rates is substantial (that is, the correct classification rates reported in Ederington (1985) are approximately one and one half times greater than the classification rates reported by Kamstra et al. (2001)). Given that the primary difference between the two studies is the source of financial statement data for the independent variables, the following question must be addressed: Do different data sources yield models that differ considerably with respect to overall performance of bond rating classification?

While Moody's bond ratings were used in both Kamstra et al. (2001) and Ederington (1985), neither of these studies used S&P bond ratings. I use S&P (Standard and Poor's) and Moody's bond ratings with Mergent and Compustat financial statement data to extend the above study on bond rating classification models. Based on this, I derive a relationship between the data sources used and the overall performance of the bond rating classification models.

Background

Mergent, Value Line, and Compustat are leading providers of accounting data. Mergent, Inc., formerly a division of Moody's Investors Service, has been collecting financial data since 1900. Mergent data is available both online and as printed text. The print version, Mergent Industrial Manual (formerly known as Moody's Industrial Manual), provides the following description of its database product:

> For substance and accuracy, no other resource matches the Industrial Manual for coverage of 2,000 top industrial corporations listed on the New York Stock Exchange, the American Stock Exchange, and regional U.S. exchanges. This two-volume set provides in-depth text descriptions and "as-reported" financials. Whether you're researching potential investments or acquisitions, targeting new customers or competitors, or

> evaluating credit-worthiness or capital strength, Mergent's Industrial Manual gives complete, factual details.

Mergent Industrial Manual provides up to seven years of "as-reported" figures from income statements and unaltered figures from balance sheets of over 2,500 NASDAQ National Market industrial companies.

The online application, Mergent Online (Mergent), provides users with a wealth of historical financial information. It allows users to create and customize data searches, company reports, comparison analyses, and charts and graphs. This financial statement data is available in both "as reported" and "restated" forms. For each company in the database, a variety of financial information is maintained including annual income statement, balance sheet, and cash flow statement information. Mergent website (www.mergent.com) provides the following description of its database product:

> Mergent Online provides rich textual company business descriptions and histories on more than 25,000 global publicly traded companies and up to 15 years of detailed as-reported and generated company financial statements including income statement, balance sheet and cash flow statements. It also provides in-depth capital stock information on stock splits and dividend payments and historical long-term debt information on bond issue terms and conditions.

In contrast to Mergent, Value Line does not provide "restated" financial statement data. A description of the Value Line database product follows:

> DataFile contains fundamental data (both current and historical) on approximately 8000 publicly traded companies that follow US GAAP. The Value Line DataFile provides annual data from 1955, quarterly from 1963, and full 10-Q data from 1985. It includes hundreds of items on each company, with balance-sheet and income-statement data, risk measure, rates of return, and analytic ratios.
>
> Value Line's treatment of data for DataFile is on an 'as reported' basis, which does not restate prior period adjustments such as mergers, acquisitions and spin-offs.

Compustat (in contrast to both Mergent as well as Value Line) edits the "as reported" financial statement data of a company by using a proprietary data standardization process. This process is described below:

> Our internal research team rigorously examines original company sources by carefully extracting financial information, removing reporting biases and reconciling data discrepancies. After collecting data from diverse sources, we standardize it by financial statement and by specific data item definition, preparing information that is comparable across companies, industries, time periods and sectors. This standardized presentation makes it easier to identify companies with similar characteristics, such as capital structure and operating performance and is designed to complement how the data [are] used. Additionally we analyze financial statement notes to provide detailed breakouts to gain additional insight overlooked by other companies.

In essence, Compustat transforms data extracted from 10-K's or annual financial statements by using a proprietary data standardization process that may be summarized in the following manner:

- Compustat, similar to Mergent and Value Line, extracts financial data from company sources.
- Unlike Mergent, Compustat standardizes data by using specific data item definitions. These proprietary data item definitions are fully disclosed on Compustat's website. The definitions relevant to this study are found in Appendix A.

Compustat data can be obtained from Compustat North America - Wharton Research Data Services (http://wrds.wharton.upenn.edu). Compustat North America is a database that contains financial statement data including annual and quarterly income statements, balance sheets and cash flow statements for more than 24,000 companies.

Wharton Data Services website provides the following description of the Compustat North America database:

> Compustat North America is a database of U.S. and Canadian fundamental and market information on more than 24,000 active and inactive publicly held companies. It provides more than 300 annual and 100 quarterly Income Statement, Balance Sheet, Statement of Cash Flows, and supplemental data items. Standard & Poor's offers a selection of Compustat North America files that are available in both annual and quarterly formats. The industrial annual formats offer both historical and restated data. The industrial quarterly formats offer restated data as reported by the company. The restated data allows analysts to compare current and prior years' results on a comparable basis and determine financial trends and growth rates. For most companies, annual and quarterly data are available for a maximum of 20 years and 48 quarters.

In summary, Mergent revises its database for subsequent changes in financial statement data, and therefore represents a proxy for Electronic Data Gathering, Analysis, and Retrieval (EDGAR provides annual financial statements, 10–Ks, of publicly-held companies). In contrast, Value Line does not restate prior period adjustments such as mergers, acquisitions, and spin-offs and is not proxy for EDGAR. Additionally, Compustat provides "standardized" financial statement data, and therefore does not represent a proxy for EDGAR.

Motivation and Objectives

There are two motivations for this study. First, Kern and Morris (1994) indicate that "[a]nalysts and researchers need to exercise great care when selecting databases and variables from those databases. These choices can affect the results of and the inferences drawn from empirical research in ways more than is anticipated by researchers." While the thoughts of Kern and Morris (1994) are based on the results of individual financial statement measures, no research of which I am aware employs multivariate measures of financial statements to support (or refute) the thoughts of Kern and Morris (1994). Thus I am motivated to employ a multivariate model when comparing financial statement data sources.

Second, Compustat customers are apparently satisfied with standardized data or they would not continue to purchase this data. However, no research of which I am aware has explored the value that Compustat's proprietary data standardization process provides to Compustat users. Thus I am motivated to provide evidence to support (or refute) the assumption that Compustat's data is superior to "as reported" data.

Given these two motivations, the purpose of this study is to gain additional insight into the conclusions of Kern and Morris (1994) as well as the value of Compustat's proprietary data standardization process. The primary objective of this study is to analyze the relationship between financial statement data sources and the correct classification rates of bond rating models. This includes exploring differences in the bond rating model predictions associated with the various data source combinations, that is, the various combinations of different bond rating data sources and different financial statement data sources. Additionally, this includes evaluating the extent to which certain industries are associated with a specific pattern of differences in bond rating predictions.

Methodology

The Kamstra et al. (2001) bond rating classification model is the primary component of the methodology used in this study. This model utilizes five independent variables (interest coverage ratio, debt ratio, return on assets ratio, total assets, and subordination status) from data sources mentioned below.

1. Mergent: a proxy for EDGAR, that is, a provider of "as reported" financial statement data
2. Compustat: a provider of standardized financial statement data

Mergent data are obtained from Mergent Online, while Compustat data are obtained from Compustat North America - Wharton Research Data Services.

The model uses bond ratings as the dependent variable. Moody's bond ratings are obtained from Mergent Online, while S&P bond ratings are obtained from the S&P website. New bonds issued from January 2004 through June 2006 that are common to both the Moody's bond rating database and the S&P bond rating database are included in the analysis. The list of new bond issues is obtained from Mergent BondViewer (http://bv.mergent.com). Only bond issues for which relevant data is present in both S&P and Moody's bond rating databases are included in the analysis. The most recent annual financial statement data reported prior to the issuance of each bond issue is extracted from the Compustat (http://wrds.wharton.upenn.edu) and Mergent (www.latech.edu/library) databases.

I analyze the relationship between the financial statement data sources and the prediction accuracy of the bond rating models using the following methodology. First, I develop a bond rating model using Moody's bond ratings for the dependent variable and Mergent data for the independent variables. I then develop another bond rating model using Moody's bond ratings for the dependent variable and Compustat data for the independent variables. Thereafter, I determine the overall correct classification rates achieved by an ordered logit model (predicted vs. actual bond ratings) utilizing both of these data source combinations. For the bond ratings of the above two models, I evaluate if there are any differences between the vector of predicted probabilities associated with bond ratings using Wilks Lambda. Additionally, I investigate if there are any differences in the number of correct predictions generated by these same two models using McNemar's test. Both the Wilk's Lambda and the McNemar test are performed again by substituting the S&P bond ratings for the Moody's bond ratings. Additionally, I examine the relationship between the bond rating sources (bond agencies ratings) and the number of correct predictions from the bond rating models using the McNemar test. Finally, I perform a cluster analysis to identify the industries, if any, associated with the patterns of differences in the predicted bond rating probabilities.

Possible Results and Implications

If the classification models produce bond ratings that are substantially different:

1. The concerns of Kern and Morris (1994) are supported; that is, "analysts and researchers need to exercise great care when selecting databases and variables from those databases." Stated otherwise, such results would suggest that an association exists between data intermediaries and bond rating classification model prediction accuracy.
2. Compustat users should consider the implications of using Compustat's proprietary standardized data. Similarly, Mergent users (as well as EDGAR and Value Line users) should consider the implications of using "as reported" data. Both user groups need to evaluate the merits of the alternative data provider. Stated otherwise, inconsistent predictions of bond ratings do not imply one data source is better than another, it merely implies that results are data source dependent.

If the classification models produce bond ratings that are not substantially different:

1. The concerns of Kern and Morris (1994) are not supported with respect to differences among databases.
2. Compustat's proprietary data standardization process does not add value, and Compustat users should not pay additionally for Compustat's proprietary data standardization process.

The remainder of this dissertation is organized as follows. An overview of the research on data intermediaries is provided in Chapter 2. The methodology of the study is explained and justified in Chapter 3. The results of the study are presented and interpreted in Chapter 4. Thereafter, the implications of the study are discussed and the limitations of the study (and opportunities for further research) are identified in Chapter 5.

CHAPTER 2

REVIEW OF RELEVANT LITERATURE

In this chapter I summarize and discuss relevant scholarly research in data intermediaries. In addition, I provide an overview of research on bond rating models. This chapter is divided into two sections. Section I contains a summary of relevant research comparing data from Compustat with data from annual financial statements, Value Line, and U.S. tax return data. In Section II I discuss research related to bond rating models and the research related to comparing bond ratings from different agencies.

Literature Related to Data Intermediary (Compustat)

Empirical accounting research has greatly benefited by the presence of computerized databases such as Compustat, Mergent, and Value Line. However, researchers must be aware that prior studies provide evidence that errors exist in the databases. Miguel (1977) and Kinney and Swanson (1993) compare data from a data intermediary (Compustat) with annual financial statement data; Kern and Morris (1994) and Yang et al. (2003) compare data from a data intermediary (Compustat) with data from another data intermediary (Value Line); while Mills et al. (2003) compare data from a data intermediary (Compustat) with U.S tax return data. An overview of each of these studies follows.

Miguel (1977) and Kinney and Swanson (1993) suggest that Compustat provides accounting data that differs from accounting data provided in annual financial statements.Miguel (1977) compares 1972 research and development expenditures reported by Compustat to the related amounts reported in the Form 10-K for a sample of 256 companies. Differences are reported for 78 of 256 companies (30%). No additional analyses are reported.

Kinney and Swanson (1993) examine the accuracy of the following nineteen tax field amounts reported by Compustat over the period 1985-1988:

- deferred income taxes
- investment tax credit
- deferred taxes and ITC
- tax payable
- tax refund
- total tax expense
- deferred income taxes
- change in accrues taxes
- taxes paid
- total deferred taxes
- deferred federal taxes
- deferred foreign taxes
- deferred state taxes
- current federal taxes
- current foreign taxes

- current state taxes
- other current taxes
- investment tax credit
- NOL carryforward.

A sample of one-hundred companies is randomly selected from the fiscal year 1985 Compustat database. The authors report the following results. First, error rates are generally higher for items reported in footnotes than for items reported on income statements or balance sheets. Second, error rates are higher i) for utilities and ii) when special items are reported on the income statement, e.g., net operating loss (NOL) carryforward, discontinued operations, cumulative adjustments, and extraordinary items. Finally, Kinney and Swanson (1993, p. 121) suggest that "…researchers should be aware of Compustat's coding policies."

Kern and Morris (1994) and Yang et al. (2003) suggest that Compustat provides accounting data that differs from accounting data provided by Value Line. Kern and Morris (1994) compare Compustat and Value Line on the basis of sales and total assets. Data are examined over a twenty-one year period (1971-1990) for an unspecified number (sample) of firms common to both the 1991 Compustat and Value Line databases. For total assets, the mean difference between the data reported in the two databases is not statistically significant at the 0.05 level of significance for any of the twenty-one years examined. For sales, the mean difference between the data reported in the two databases increased over time and the mean difference is significant at the 0.05 level from 1978 through 1987 and at the 0.01 level from 1988 through 1990. In order to determine the source of these differences, data from Value Line and Compustat are compared to the corresponding annual report data for the years 1985 through 1990. For total assets, Kern and Morris (1994, p. 279) indicate that "[t]he largest source of material differences for total assets was Value Line's practice of reporting a foreign firm's financial data in its foreign currency. Compustat restates the data in U.S dollars." For sales, the authors (p. 279) also indicate that "[t]he largest source of material differences in reported sales was because Value Line reported information for certain lines of business, while Compustat reported for the entire consolidated entity."

In order to demonstrate how differences in the two databases can materially affect inferences about the population of firms, Kern and Morris (1994) replicate a study examining the relation between firm size (sales) and a single effective tax rate measure (Porcano, 1986) using each database (Compustat and Value Line). The effective tax rate measure is calculated as current U.S. federal income taxes divided by adjusted net income before taxes (with adjusted net income before taxes defined as the sum of net income before extraordinary items, extraordinary items, current federal income taxes, minority interest less equity in earnings of unconsolidated subsidiaries). The computed effective tax rate measure of a firm is allocated to a quartile based on the firm's sales. With respect to measures based on both Compustat and Value Line data, the highest quartile has the lowest effective tax rate throughout the entire period. However, on an overall basis, the computed effective tax rate measure is higher using Value Line database than using Compustat database, and the difference is significant at the 0.05 level.

Yang et al. (2003) compare Compustat and Value Line with respect to the following seven variables of interest: assets; sales; inventory; net income before extraordinary items; current liabilities; depreciation, depletion and amortization, and gross plant. Data are from 1971 through 1981 are examined for 1,479 companies. The authors (p. 205) define the discrepancy rate as "…the total of discrepancy numbers, greater than 0.01, including missing values, divided by the number of companies." Their analysis yields the following discrepancy rates between the two databases:

- 3.3% for assets
- 10.0% for sales
- 14.7% for inventory
- 23.2% for net income before extraordinary items
- 39.5% for current liabilities
- 11.8% for depreciation, depletion and amortization
- 19.5% for gross plant.

In order to determine the source of these data discrepancies, data from a common sample of two-hundred companies is drawn from both Compustat and Value Line and compared to the corresponding data from the original financial statements for 1981. Yang et al. (2003, p. 204) indicate that "…most of the differences were attributable to definitional discrepancies (foreign currency differences, industry factors, definitional factors) and others to direct measurement errors (non-disclosed coding rules)."

These authors also compare Compustat and Value Line with respect to the following ten financial ratios:

- current assets/sales
- quick assets/sales

- working capital/sales
- current assets/current liabilities
- quick assets/current liabilities
- current assets/total assets
- quick assets/total assets
- working capital/total assets
- net income/total assets
- total debt/total assets.

The authors evaluate the first four moments (mean, variance, skewness, and kurtosis) of each of these ratios. They find the moments for the following ratios to be very similar for Compustat and Value Line: working capital/sales; current assets/current liabilities; current assets/total assets; working capital/total assets; and total debt/total assets. In contrast, they state that the moments for the following ratios are significantly different (although the level of significance was not provided in the paper): current assets/sales; and quick assets/sales. None of the ten financial ratios extracted from Compustat or Value Line is compared with similar information found in the related annual financial statements.

Mills et al. (2003) suggest that Compustat provides accounting data that differs from accounting data available in U.S tax return data. Mills et al. (2003) compares Compustat data with U.S tax return data on the basis of NOL carryforward status. Data for a sample of 219 firms during 1981 – 1995 are examined. A frequency analysis shows that 9.4 percent of the sample is classified as having a Compustat NOL carryforward when no NOL carryforward is indicated in the related U.S tax return.

Conversely, 3.3 percent of the sample is classified as having no Compustat NOL carryforward when an NOL carryforward is indicated in the related U.S tax return.

Several studies address differences in databases developed by data intermediaries relating to non-financial statement data such as market/price data. Rosenberg and Houglet (1974) find that differences exist in the monthly price relatives between Compustat and CRSP. Bennin (1980) suggests that differences between Compustat and CRSP drop remarkably after 1970. A study by Wood (2000) compares the book-to-market ratio for Compustat and Non-Compustat firms and finds little evidence of any differences. On the other hand, Elton et al. (2001) reports differences in mutual fund returns between Compustat and Morningstar. Additionally, Courtney and Keller (1994) find differences in the prices for stock distributions between CRSP and Moody's Dividend Record. The authors also find differences in the prices for stock distributions between CRSP and the financial statements of certain companies. Sarig and Warga (1989) note differences in government bond price data between CRSP and Shearson Lehman Brothers Bond Data.

Prior studies also provide evidence of differences in analysts forecast data provided by Value Line, Institutional Brokers Estimate System (IBES) and/or Compustat. Using the matched pair t-test and the Wilcoxon sign ranked test, Philbrick and Ricks (1991) find that Compustat data produces significantly larger absolute forecast errors than Value Line or IBES data. Using IBES and Value Line data, Skantz and Pierce (1997) present evidence that quarterly earnings forecasts and the associated "actual" earnings numbers reported by these databases are inconsistent in the treatment of special gains and losses.

Finally, prior studies also provide evidence of differences in SIC Codes and ownership data. Guenther and Rosman (1994) as well as Kahle and Walkling (1996) find differences between SIC Codes assigned to companies by Compustat and CRSP. Guenther and Rosman state that large differences are observed at two-, three-, and four-digit levels. Anderson and Lee (1997a, 1997b) report differences in the ownership data reported by Compact Disclosure, Value Line, and Spectrum.

In contrast to the studies noted above, this study employs both Mergent as well as Compustat financial statement data. Additionally, while prior studies indentify differences in data provided by various intermediaries, they do not focus on the consequences of such differences in terms of decision making. Fortunately, the bond rating literature provides a mechanism ("black box") to gain insights into this issue.

Literature Related to Bond Rating Models

Several areas of research in the bond rating models area have been investigated. One area focuses on attempting to determine how rating agencies arrive at their assigned rating for a particular issue. This involves a statistical model (using ordinary least squares (OLS) regression, multinomial discriminant analysis (MDA), ordered or unordered logistic regression (logit), or ordered probit regression (probit)) with bond rating categories as the dependent variable and various firm characteristics as the independent variables. Pogue and Soldofsky (1969), Pinches and Mingo (1973), West (1970), Kaplan and Urwitz (1979), Belkaoui (1980), Ederington (1985), Gentry et al. (1988), and Kamstra et al. (2001) are examples of this branch of the literature.

Using OLS regression analysis to predict bond ratings, Pogue and Soldofsky (1969) find that the significant independent variables are long-term debt to total capital, net income to total assets, coefficient of variation of net income to total assets, net total assets, net income, and interest coverage. Their model predicts Moody's bond ratings for eight out of ten bonds in the hold-out sample. West (1970) uses earnings variability (coefficient of variation for previous 9 years of earnings), period of solvency (number of years without loss to creditors), equity to debt ratio and bonds outstanding as independent variables, and accurately predicts 62% of Moody's ratings using OLS regression analysis.

Pinches and Mingo (1973, 1975) use MDA to classify bonds into bond rating categories. They include the following independent variables in their model: subordination, issue size, income and interest to interest ratio, years of consecutive dividends, long-term debt to total assets, and net income to total assets. In their first article, their model accurately predicts approximately 65% of the Moody's ratings for the holdout sample. The second article uses separate MDA models for subordinated and non subordinated bonds and the correct predictions increase to 70%. Both studies suggest that the OLS method is inappropriate to estimate bond ratings since bond ratings represent categorical variables.

Kaplan and Urwitz (1979), as well as Belkaoui (1980) and Gentry et al. (1988), use probit analyses to predict bond ratings. Each of these studies suggests that MDA is inappropriate to estimate bond ratings because MDA ignores the ordinal nature of bond ratings. Kaplan and Urwitz (1979) use long-term debt to total assets, long-term debt to net worth, net income to total assets, total assets, coefficient of variation of total assets, and subordination status and the model predicts 69% of the Moody's ratings. Belkaoui (1980) uses the following independent variables: total debt, long-term debt as a percentage of total invested capital, short term debt as a percentage of total invested capital, current ratio, fixed charge coverage ratio, stock price as a percentage of book value, and subordination status. The model correctly predicts 62.8% of the S&P ratings. Gentry et al. (1988) use operations, accounts receivable, inventory, other current assets, accounts payable, other current liabilities, interest and lease payments, capital expenditures, dividends, other assets and liability flows, and the change in cash and marketable securities as independent variables, and their model correctly predicts 47.6 % of the Moody's ratings.

Ederington (1985) estimates a bond rating model using four different statistical methods (OLS, ordered probit, MDA, and unordered logit) to estimate bond ratings. Data for the independent variables (interest coverage ratio, debt ratio, and total assets) are collected from Compustat. The results (overall correct classification rates) indicate that the logit (73%) and probit (78%) models produce higher classification rates for the Moody's bond ratings than the MDA (69%) and linear regression (65%) models.

The Kamstra et al. (2001) bond rating classification model is the most recent bond rating model that primarily uses accounting variables. Similar to Ederington (1985), the following accounting variables are included in the Kamstra et al. (2001) model: interest coverage ratio, debt ratio, and total assets. In addition to the independent variables employed by Ederington (1985), Kamstra et al. (2001) also includes return on assets as well as the non-accounting variable subordination status in their model. Data for the dependent variable and independent variables are obtained from Moody's. Two models are developed using ordered logit; one model is developed using data from industrial companies and the other is developed using data from transportation companies. The industrial data set is comprised solely of new industrial bonds issued in 1993, and the sample size consists of 265 observations. In contrast, the transportation data set is comprised solely of eighty-nine new transportation bonds issued between 1989 and 1992. The model generates a higher classification rate using the transportation data (58.4%) versus the industrial data set (34.5%). I use the Kamstra et al. (2001) bond rating classification model since it is the most recent bond rating model that primarily uses accounting variables. However, in contrast to Kamstra et al. (2001), I use both industrial as well as transportation data in my study to maximize the sample size.

As previously indicated, Ederington (1985) reported a 70.3% correct classification rate while Kamstra et al. (2001) reported a 47.5% correct classification rate. In view of the similarity of these studies (discussed next), the difference in the reported correct classification rates is substantial. Kamstra et al. (2001) developed a bond rating classification model using Moody's bond ratings as the dependent variable and financial statement data for the independent variables. The financial statement data was extracted from Moody's Industrial Manual (currently known as Mergent Industrial Manual). The Kamstra et al. (2001) bond rating classification model is similar to the model developed by Ederington (1985), which also uses Moody's bond ratings as the dependent variable and financial statement data for the independent variables. However, in contrast to Kamstra et al. (2001), the financial statement data used by Ederington (1985) was extracted from Compustat. Given that the primary difference between the two studies related to the sources of the financial statement data, this suggested to me that I should further investigate the association between data sources and overall bond rating model performance.

Another area of literature focuses on comparisons of ratings from different bond rating agencies. Most bonds issued in the U.S. are rated by one or both of the two prominent rating agencies – Moody's and S & P. When ratings issued by the two agencies are in disagreement, a split rating is said to occur.

Research findings to date are inconclusive. For example, a study of municipal bond ratings by Morton (1975) suggests that Moody's ratings are more conservative (lower) than S&P. In contrast, Cate's (1977) study of bank holding companies finds that ratings assigned by S&P are more conservative than Moody's. Altman (1980) finds that bond ratings differ among rating agencies approximately twenty percent of the time. While these studies primarily focus on the direct comparison of split ratings, other studies employ prediction models in addition to directly comparing split ratings,

When directly compared, Horrigan (1966) suggests that Moody's ratings tend to be lower (more conservative) that S&P. Additionally, he performs the first study using accounting data to estimate and predict bond ratings. The following independent variables for his model (based on their high correlation with the bond ratings): total assets, net worth to total debt (book values), net operating profit to sales, working capital to sales (industry adjusted), subordination status, and sales to net worth (industry adjusted). Horrigan's OLS model accurately predicts 58% of Moody's ratings and 52% of S&P ratings.

Perry (1985) evaluates differences between the Moody's bond ratings and S&P bond ratings. Bond ratings are obtained for March and May 1982 from both the Moody's Bond Record and the S&P Bond Guide. A direct comparison of 218 bond ratings indicates that 77.06% of the bond ratings agree in March while only 41.74% of the ratings agree in May of 1982. Using Compustat data as the source of values for the independent variables, Perry develops separate "best models" (the set of variables that result in highest classification rate) for both the Moody's bond ratings and the S&P bond ratings (i.e., the dependent variables); both models were developed using MDA. Numerous independent variables are used including interest coverage ratio, debt ratio, return on assets ratio, and assets. Perry indicates that "...models developed using Moody's bond ratings classify S&P ratings better than vice versa."

Ederington (1986) uses a sample of 493 industrial bonds, 63 of which had split ratings to develop an ordered probit model. Moody's bond ratings and S&P bond ratings are used as dependent variables; the independent variables used are leverage, coverage forecast, profitability forecast, profitability forecast error, coverage forecast error, cash flow forecast, and cash flow forecast error. Bond ratings (i.e., data for the dependent variables) are obtained for January 1975 to December 1980 from Moody's Bond Survey and the S&P Bond Guide. Data for the independent variables are collected from Compustat. The results of the ordered probit model estimations suggest the overall correct classification rate for the Moody's bond rating model is higher than the overall classification rate for the S&P bond rating model.

The above studies examine ratings assigned by two major rating agencies, i.e., Moody's and S&P. Some recent studies have examined ratings assigned by the other rating agencies such as Duff and Phelps; Fitch IBCA; and McCarthy, Crisanti, and Maffei, Inc. (MCM). Examples of this research include Cantor and Packer (1995, 1996), Jewell and Livingston (1999), and Feinberg et al. (2004). The two Cantor and Packer studies show a higher average rating of the "other" rating agencies compared to the two major agencies. Jewell and Livingston findings show that Moody's and S&P ratings are higher for firms with publicly available Fitch IBCA ratings than for firms without Fitch IBCA ratings. Feinberg et al. indicate that the ratings assigned by Moody's and S&P are consistently lower than those assigned by Duff and Phelps or Fitch IBCA, and are consistently higher than those assigned by MCM. While Moody's and S&P generally downgrade bond ratings sooner than Duff and Phelps or Fitch IBCA, the two major agencies upgrade at the same time.

While the above studies evaluate bond ratings, the following studies evaluate bond ratings as a determinant of bond yields. Billingsley et al. (1985) examine a sample of 258 industrial bonds issued between January 1977 and June 1983, and rated Ba and above. Of the 258 bonds, only 33 received split ratings. The authors regressed "off-Treasury yields" against four bond rating dummy variables, four split bond rating dummy variables, and several control variables. As expected, the results suggest that as bond ratings increase (indicating higher quality or less risk), yields decrease (i.e., become lower).

Ederington et al. (1987) evaluate the association between bond yields and both financial accounting ratios as well as agency bond ratings. Using a non-linear OLS model, they analyze a sample of 176 bonds issued in 1979 and a sample of 180 bonds issued in 1981. Ederington et al. (1987) conclude that both agency ratings and financial accounting data are used by market participants in evaluating bond creditworthiness. Additionally, they conclude that the market essentially views both Moody's ratings and S&P ratings as identical in terms of information content.

Perry et al. (1988) also addresses the impact of bond ratings on bond yields. They use a sample of 269 non-financial corporation bonds obtained from two separate periods: March and May 1982. The authors select these months because they immediately precede and follow the month in which Moody's began using modified ratings (S&P began using modified ratings in 1975). The effect of split Moody's and S&P credit ratings is assessed by comparing the average yield premium for bonds with split ratings with the average yield premium for bonds with equal Moody's and S&P ratings. In March 1982, using unmodified ratings, split rated bond yields were significantly different from bond yield associated with identical Moody's and S&P ratings. In contrast, the results indicate no significant differences in the yields for May 1982 using modified ratings. The authors state that a possible explanation for the difference in results is the use of modified ratings. In addition, they explain that "...in the modified rating system, a rating would have to differ by three classes before it would signify the same difference in quality as a one class split in the unmodified system." Only 3.3 percent of the bonds in the modified rating system differ by three rating classes. Therefore, a split rating of one category under the unmodified rating system should have a greater impact on interest yields than a split rating of one category under the modified system.

Summary

As stated previously, Kern and Morris (1994) and Yang et al. (2003) suggest that data provided by Compustat differs from data provided by Value Line. Notably, no research has analyzed annual financial statement data provided by Compustat versus annual financial statement data provided by Mergent. Additionally, no research has employed a multivariate model when comparing annual financial statement data sources. Additionally, Yang et al. (2003) and Kern and Morris (1994) compared individual measures of financial statement data. Also, a direct comparison of the overall performance of bond rating classification models using the four data source combinations previously specified in Chapter 1 has not appeared in the literature.

As indicated in Chapter 1, the Kamstra et al. (2001) bond rating model is used to analyze both the Mergent and Compustat databases. I use the Kamstra et al. (2001) bond rating model because it is the most recent bond rating model using accounting variables and because the model includes all of the variables employed by Ederington (1985); thus enhancing the comparability of my results with previous results. Additionally, the research related to bond ratings indicate rating differences between Moody's and S&P, therefore both ratings will be used in this study.

CHAPTER 3

METHODOLOGY

This chapter states the research question and describes the methodologies employed in analyzing the relationship between the different data source combinations and the accuracy of the resulting bond rating classification model predictions. Section 3.1 defines the research problem, Section 3.2 provides an overview of the data collection and the methodology followed to generate a sample of bond ratings that will be used for the study and Sections 3.3 and 3.4 discuss the bond rating classification model and the statistical tools used in the analysis.

Research Question

As previously stated in Chapter 1, the following question needs to be addressed. Do different data sources yield bond rating models that differ considerably with respect to overall performance of bond rating classification? To address this question I first develop several bond rating models using different data source combinations. Thereafter, I use various statistical techniques to analyze differences in overall bond rating performance.

Additionally, while Kamstra et al. (2001) and Ederington (1985) use Moody's bond ratings, neither use S&P bond ratings. Given this, and given that prior research shows that Moody's bond ratings do not agree with the S&P bond ratings, I use both

S&P and Moody's bond ratings to extend this branch of literature. While Perry (1985) use both Moody's and S&P bond ratings to measure the dependent variable in his study, he use Compustat data as the data source for independent variables. Thus I expand on Perry (1985) by employing both Mergent and Compustat data to measure my independent variables.

Data Collection

This section talks about the data source used for extracting data pertaining to bond issues. A list of new bond issues for the period of study (January 2004 – June 2006) is obtained. An overview of sampling methods is presented and the methodology followed for generating the sample of bond issues to be used in the study is described. A Chi-Square Goodness of Fit Test is then performed to ascertain if this sample represents the population of new bond issues with respect to SIC (Standard Industrial Classification) codes for period January 2004 – June 2006.

Mergent BondViewer (http://bv.mergent.com) is a database that contains bond related data for U.S. taxable bonds, municipal bonds and retail notes. Mergent provides the following description of their BondViewer database:

> Mergent BondViewer offers on-demand access to a wide-range of bond data including both issuer and issue level terms and conditions and end of day evaluated prices for U.S. taxable bonds, municipal bonds and retail notes. From a bond's issuance to its redemption and maturity, Mergent BondViewer's integrated fixed income database allows clients to improve their bond data management with efficiency and convenience.

Mergent BondViewer listed 2,292 new bond issues for the period January 2004 - June 2006 (Table 3.3).

An overview of traditional sampling methods can be classified into two broad categories: probability sampling and non-probability sampling. Probability sampling methods incorporate the premise that each element of the population has a known probability of being selected. When conducted properly, probability sampling methods ensure that the sample is representative of the census under investigation. On the other hand, a non-probability sampling is a judgment sampling, in which selection is based on the judgment of researcher or based on the availability of the data. The consequence is that a portion of the population is conveniently excluded. One of the most common types of non-probability sample is called a convenience sample where members of the population are chosen based on the availability of data or relative ease of access. Because some members of the population have no chance of being sampled, the extent to which a convenience sample actually represents the entire population is sometimes questionable. In this study, I generate a convenience sample and perform a Chi-Square Goodness of Fit Test to determine whether the sample represents the population of all companies with new bond issues for the period January 2004 to June 2006.

As described earlier in this section, a list of all new bond issues for the period of January 2004 – June 2006 was extracted from Mergent BondViewer (Table 3.3). Consistent with Kamstra et al. (2001), only data associated with new bond issues will be included in the analysis. Specifically, 2,292 new active (frequently traded) issues—for the period January 2004 to June 2006—are identified using Mergent BondViewer. Of the 2,292 new issues, 772 are single issues (i.e., are related to companies having only one new bond issue for a particular year). The remaining 1,520 bonds were issued by 324 companies. Similar to Ederington (1987), data for only one issue per year for each company with multiple issues is included in the analyses. Thus 1,196 issues are excluded (on a net basis) from the analyses. Table 3.1 shows a summary of this data.

Table 3.1
New Bond Issues – Total Sample 333

PANEL 1: Sample Selection	
Total Active New Bond Issues	2,292
Minus: Multiple Issues	1,520
Add: Companies With Multiple Issues	324
Net Exclusions Due to Multiple Issues	1,196
Subtotal	1,096
Minus: Convertible Issues	244*
Subtotal	852
Minus: Issues Not Rated by Moody's And/or S&P	245
Subtotal	607
Minus: Issues with Missing Financial Statement Information in Mergent and/or Compustat	274
Total Sample	333

* Convertible bond issues were not included in the Kamstra et al. (2001) model.

PANEL 2: Subordinated vs. Non-Subordinated Issues	
Subordinated Issues	64**
Non-Subordinated Issues	269
Total Sample—New Bond Issues	333

** Subordinated bond issues were included in the Kamstra et al. (2001) model.

Similar to Kamstra et al. (2001), bond issues that are convertible are not included in the analyses in order to enhance the comparability of my results with the results of the previous literature; this results in the exclusion of 244 bond issues from the analyses. All relevant data must also be available in each database for a bond issue to be included in the analysis. In this study, 245 bond issues are excluded because they are not rated either by Moody's or S&P. Additionally, a bond issue is excluded from the analyses if the most recent annual financial statement data reported prior to the issuance of each issue are missing in either the Mergent or Compustat database. In this study, 247 issues are excluded because the relevant financial data is not available from the Mergent or Compustat database. After all incomplete observations have been excluded, the final sample consists of 333 issues; 64 of these remaining issues have subordination status. Consistent with Kamstra et al. (2001), subordination status is employed as a binary independent variable in the analyses. The sample of companies (and related new bond issues for 2004, 2005, and 2006) is provided in Appendix B.

As stated earlier, the sample used for this study is a convenience sample. Therefore, a Chi-Square Goodness of Fit Test is performed using SIC Code distribution of companies to determine whether this sample represents the population of companies that issued new bonds between January 2004 and June 2006. SIC Codes are obtained from Mergent BondViewer; these represent the primary activity of the business establishments included in the sample data. There are ten SIC divisions: Division A (agriculture, forestry and fishing); Division B (mining); Division C (construction); Division D (manufacturing); Division E (transportation, communications, electric, gas, and sanitary services); Division F (wholesale trade); Division G (retail trade); Division H (finance, insurance, and real estate); Division I (services); and Division J (public administration). The SIC Code distribution of the sample is presented in Table 3.2 and the SIC Code distribution for the entire population of companies for the period of study is presented in Table 3.3. The first column in these tables is the SIC Code Division, the second column (gross) represents the total number of bond issues from all companies that fall under each SIC Code Division, the third and fourth columns (two issues and three issues) represent the number of companies under each division that had two or three issues respectively during the period January 2004 – June 2006, the fifth column (net) represents the number of companies that fall under each division and the sixth column (proportion of total) represents the proportion of companies in each division with respect to total number of companies.

The goodness of fit test evaluates the consistency of the distribution of SIC Code Divisions for the sample of 275 companies with the distribution of SIC Code Divisions for the population of companies from which this sample is extracted. The null and alternative hypotheses are:

H_0: The SIC Code distribution of sample data follow the SIC Code distribution of population;

H_a: The SIC Code distribution of sample data do not follow the SIC Code distribution of population.

The following test statistic helps ascertain if any difference in the SIC Code Division distributions is statistically significant.

$$\chi^2 = \sum_{i=1}^{k} \frac{(f_i - e_i)^2}{e_i},$$

where f_i = Observed number of companies for category i,
e_i = Expected number of companies for category i based on the assumption that H_0 is true, and
k = Number of categories.

In this case, the sample includes only one company each under Division A (Agriculture, Forestry, and Fishing) and Division J (Public Administration). Considering that Divisions A and B both relate to natural resources and Divisions I and J are service oriented, it is logical to merge Division A with B and Division I with J, then carry out the analysis on the resulting eight divisions. The goodness of fit test is based on the differences between the observed number of companies under each division in the sample (Column 5 in Table 3.2) and the number of companies under each division that would be expected in the sample given the distribution of code division classifications in the population.

Table 3.2
Sample Distribution by SIC Code Division –
333 Issues (Gross); 275 Companies (Net)

Division	Gross	Two issues	Three issues	Net	Proportion of Total
A: Agriculture, Forestry, and Fishing	2	1	0	1	0.36%
B: Mining	10	1	0	9	3.27%
C: Construction	17	1	3	10	3.64%
D: Manufacturing	160	15	3	139	50.55%
E: Transportation, Communications, Electric, Gas, and Sanitary Services	25	4	0	21	7.64%
F: Wholesale Trade	17	2	0	15	5.45%
G: Retail Trade	30	1	2	25	9.09%
H: Finance, Insurance, and Real Estate	12	2	1	8	2.91%
I: Services	59	11	1	46	16.73%
J: Public Administration	1	0	0	1	0.36%
Totals	333	38	10	275	100.00%

Source (SIC Code Divisions): SIC Manual www.osha.gov/pls/imis/sic_manual.html.

The expected number of companies under each division in the sample is calculated by multiplying proportion of companies in each division of the population (Column 6 in Table 3.3) with the total number of companies in the sample (275). The resulting chi-square value is 1.473 with an associated p-value of 0.98323; thus, the SIC

Code Division distribution of the sample does not significantly differ from the SIC Code Division distribution of the population.

Table 3.3
Population Distribution by SIC Code Division –
1,096 Issues (Gross); 912 Companies (Net)

Division	Gross	Two issues	Three issues	Net	Proportion of Total
A: Agriculture, Forestry, and Fishing	9	1	0	8	0.88%
B: Mining	36	5	1	29	3.18%
C: Construction	46	5	7	27	2.96%
D: Manufacturing	545	62	8	467	51.21%
E: Transportation, Communications, Electric, Gas, and Sanitary Services	89	14	3	69	7.57%
F: Wholesale Trade	65	4	3	55	6.03%
G: Retail Trade	81	7	2	70	7.68%
H: Finance, Insurance, and Real Estate	36	5	2	27	2.96%
I: Services	188	23	3	159	17.43%
J: Public Administration	1	0	0	1	0.11%
Totals	1096	126	29	912	100.00%

Source (SIC Code Divisions): SIC Manual: www.osha.gov/pls/imis/sic_manual.html.

Bond Rating Model and Variables

To analyze whether different data sources yield different results, the Kamstra et al. (2001) bond rating classification model is used in this study. I use the Kamstra et al. (2001) bond rating model because the model includes all of the variables employed by Ederington (1985); thus enhancing the comparability of my results with previous results.

$$BR = f\,(IC, DR, ROA, ASSETS, SUBORD)$$

where

BR	=	Bond Ratings
IC	=	Interest Coverage Ratio
DR	=	Debt Ratio
ROA	=	Return on Assets Ratio
ASSETS	=	Total Assets
SUBORD	=	Subordination Status

The data for the dependent variable (Bond ratings) are obtained from two different bond rating agencies: Moody's and Standard and Poor's (S&P). Moody's ratings and S&P ratings represent the opinions of Moody's Investors Service and Standard & Poor's, respectively, as to the relative creditworthiness of securities. Moody's ratings include the nineteen symbols shown in Table 3.4 to designate credit risk ranging from least credit risk (Aaa) to greatest credit risk (Caa3). All Moody's ratings except for Aaa are modified by the addition of a 1, 2, or 3 to show relative standing within the category, where the highest within the rating is 1 and the lowest is 3. The symbols used by S&P to designate its borrower ratings are also provided in Table 3.4.

Table 3.4
Bond Rating Categories

Moody's Ratings	S&P Ratings	Moody's Ratings	S&P Ratings
Aaa	AAA	Ba1	BB+
Aa1	AA+	Ba2	BB
Aa2	AA	Ba3	BB-
Aa3	AA-	B1	B+
A1	A+	B2	B
A2	A	B3	B-
A3	A-	Caa1	CCC+
Baa1	BBB+	Caa2	CCC
Baa2	BBB	Caa3	CCC-
Baa3	BBB-		

Moody's bond ratings are collected from Mergent Online (Long Term Debt Section) and S&P bond ratings are collected from the Credit Ratings Search Section of S&P website (www.standardandpoors.com).

The sample includes nineteen bond rating categories for both Moody's and S&P bond ratings as indicated in Table 3.5. Hollander and Wolfe (1999) suggest that the expected frequency of observations in each category should be at least five observations.

Table 3.5
Bond Rating Initial (Non-Collapsed) Distribution – 333 Issues

Moody's Ratings	Number of Issues	S&P Ratings	Number of Issues
Aaa	3	AAA	3
Aa1	0	AA+	0
Aa2	4	AA	9
Aa3	10	AA-	8
A1	13	A+	13
A2	18	A	21
A3	15	A-	21
Baa1	20	BBB+	21
Baa2	35	BBB	30
Baa3	28	BBB-	26
Ba1	15	BB+	18
Ba2	27	BB	18
Ba3	28	BB-	23
B1	32	B+	34
B2	29	B	44
B3	39	B-	25
Caa1	14	CCC+	13
Caa2	2	CCC	6
Caa3	1	CCC-	0
Total	333	Total	333

Since Aaa, Aa1, and Aa2 in Moody's ratings each have fewer than five observations, the observations in these categories are grouped into a single category identified as "Aa2 and above" as shown in Table 3.8. Also, Caa1, Caa2 and Caa3 are grouped and identified as "Caa1 and below". Similar aggregation is done for categories with less than five observations in S&P ratings. AAA, AA+ and AA are grouped and identified as "AA and above" and CCC+, CCC and CCC- are grouped into a category represented as "CCC+ and below". As a result of this aggregation, fifteen bond rating categories remain for both Moody's and S&P as shown in Table 3.6.

Table 3.6
Bond Rating Collapsed Distribution – 333 Issues

Moody's Ratings	Number of Issues	S&P Ratings	Number of Issues
Aa2 and Above	7	AA and Above	12
Aa3	10	AA-	8
A1	13	A+	13
A2	18	A	21
A3	15	A-	21
Baa1	20	BBB+	21
Baa2	35	BBB	30
Baa3	28	BBB-	26
Ba1	15	BB+	18
Ba2	27	BB	18
Ba3	28	BB-	23
B1	32	B+	34
B2	29	B	44
B3	39	B-	25
Caa1 and Below	17	CCC+ and Below	19
Total	333	Total	333

These fifteen bond rating categories are measured as follows. Bond ratings of Caa1 and below or CCC+ and below are assigned a value of 0; B3 or B- a value of 1; B2 or B a value of 2; B1 or B+ a value of 3; Ba3 or BB- a value of 4; Ba2 or BB a value of 5; Ba1 or BB+ a value of 6; Baa3 or BBB- a value of 7; Baa2 or BBB a value of 8; Baa1 or BBB+ a value of 9; A3 or A- a value of 10; A2 or Aa value of 11; A1 or A+ a value of 12; Aa3 or AA- a value of 13; Aa2 and above or AA and above a value of 14.

The five independent variables (interest coverage ratio, debt ratio, return on assets ratio, total assets, and subordination status) used in this study are obtained from following two data sources: Mergent Online and Compustat NorthAmerica – Wharton Research Data Services. The data related to net income, interest expense, total debt, and total assets are collected from both Mergent online and Compustat. The ratios for the independent variables are calculated using variable definitions as described in Table 3.7.

Table 3.7
Variable Definitions

Interest Coverage (ICR): net income plus interest expense, divided by interest expense
Debt Ratio (DR): total debt divided by total assets
Return on Assets (ROA): net income divided by total assets
Assets: total assets
Subordination Status (SUBORD): 1 if the debt issue has seniority and 0 otherwise.

Analysis Procedures

Given two competing data sources for both dependent and independent variables, four data source combinations will be evaluated (Table 3.8). Four different sets of decision outcomes (that is, four different sets of overall correct bond classification rates) will be generated using ordered logit analysis.

Table 3.8
Four Data Source Combinations

	Dependent Variable Data Source	Independent Variable Data Source	Mnemonic Name
1	Moody's Ratings	Mergent Financial Statement Information	MM
2	S&P Ratings	Compustat Financial Statement Information	SC
3	S&P Ratings	Mergent Financial Statement Information	SM
4	Moody's Ratings	Compustat Financial Statement Information	MC

Logistic Regression

Logistic regression is used to model the relationship between a binary or ordinal response variable and one or more explanatory variables. Since the dependent variable (bond rating) is measured on the ordinal scale, differences in successive categories of bond ratings are not equal or fixed, and so applying OLS regression will produce biased results (Greene, 1990). In addition, Kaplan and Urwitz (1979), Belkaoui (1980), and Gentry et al. (1988) suggest that MDA is also inappropriate to estimate bond ratings because it ignores the ordinal nature of bond ratings. In contrast, either probit or logit could be employed in this study since both statistical methods address the ordinal nature of bond rating. While the results of probit and logit are highly similar (Amemiya, 1981 and Greene, 1990), the rationale for selecting either procedure is related to study design. In probit analysis, errors are assumed to follow a normal distribution function, and therefore this method is appropriate when the study design is experimental (Rahman, 2004). On the other hand, logit analysis assumes a logistic distribution function and is appropriate when the study design is observational (Rahman, 2004). I use the logit model because this study involves observational data.

In the ordered logit model, maximum likelihood methods are used to find the regression coefficients that provide the best predictions for the logit-transformed probability that the observation belongs to a particular category; the estimates are called maximum likelihood estimators because the parameters are chosen to maximize the probability that the data are observed in the bond rating categories. The algorithm first selects initial estimates of the parameters. Given the parameter estimates, the algorithm then computes the likelihood of the data, calculates derivatives and changes the parameter values in terms of the direction of these derivatives (i.e., parameter values increase when the derivative is positive and decrease when the derivative is negative), and recalculates the likelihood of the data. The algorithm repeats the above process until the change in the likelihood is negligible or within the tolerance specified, or a prespecified maximum number of iterations has been executed.

The ordered logit model (described below) assumes that there is a continuous latent variable D with m-1 threshold points (where m is the number of categories in the ordinal dependent variable). Since there are fifteen categories in the dependent variable, I have fourteen threshold points $\delta_1, \delta_2 \ldots \delta_{14}$. The value in the dependent variable bond ratings depends on the D scores vis-à-vis $\delta_1, \delta_2 \ldots \delta_{14}$. Hence,

Bond Ratings j = 1 if $D_i \le \delta_1$

Bond Ratings j = 2 if $\delta_1 < D_i \le \delta_2$

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Bond Ratings j = 15 if $D_i > \delta_{14}$

The latent variable D_i is estimated by $\hat{Z}_i$, where $\hat{Z}_i$ is the combines the parameter estimates and the k independent variables (i.e., Interest Coverage Ratio, Debt Ratio, Return on Assets Ratio, Total Assets and Subordination Status).

$$\hat{Z}_i = \sum_{k=1}^{k} \hat{\beta}_k X_k$$

In the ordered logit model, the probability of bond ratings is expressed as follows:

$$P_{(\text{bond ratings}=1)} = \frac{1}{1+\exp(Z_i - \delta_1)}$$

$$P_{(\text{bond ratings}=2)} = \frac{1}{1+\exp(Z_i - \delta_2)} - \frac{1}{1+\exp(Z_i - \delta_1)}$$

$$\vdots$$

$$P_{(\text{bond ratings}=15)} = 1 - \frac{1}{1+\exp(Z_i - \delta_{14})}$$

In summary, the ordered logit model will generate fifteen predicted bond rating probabilities for each bond issue (with the sum of these probabilities equaling one). Thereafter, Wilk's Lambda will be used to test the equality of the mean vector of the predicted probabilities for each of the bond ratings.

<u>Wilk's Lambda</u>

Wilk's Lambda is a test statistic used to assess the equality of mean vectors across different level groups of subjects on a combination of dependent variables. Wilk's Lambda is the ratio of the within-groups variance (SS_{within}) to the total variance

(SS_{total}). Total variance is a sum of within-groups variance and between-groups variance. A Wilk's Lambda value closest to zero implies that the source of total variance is from the between-groups variance instead of from the within-groups variance. Conversely, a large Wilk's Lambda value implies that there is no difference between within-groups averages. The Wilk's Lambda statistic can be transformed to a statistic that has approximately an F distribution, which simplifies calculating the P-value. There are a number of alternative statistics that are equivalent to Wilk's Lambda, such as Pillai's trace criterion and Roy's GCR criterion. However, Wilk's Lambda is the most widely used test statistic to compare the similarity of two group profiles or to compare the equality of two mean vectors. Therefore, I use Wilk's Lambda to assess the equality of the vector of predicted probabilities associated with each bond rating generated by the various ordered logit models.

I use the Wilk's Lambda test in my study for the following reasons. First, while the sign test is appropriate for one-sided tests, it is not appropriate for two-sided tests. For example, Perry (1985) used a sign test to test whether Moody's bond ratings were more conservative (lower) that the S&P bond ratings. The sign test was appropriate in this situation since the hypothesis was one-sided. Since I test for differences between predicted probabilities of bond ratings, the hypothesis is two sided and a sign test is inappropriate. Second, since the t-test statistically assesses the difference between two group means, the results of the t-test relate to aggregate differences--not individual differences. For example, the results of a t-test would relate to the difference between the mean of a group of Moody's bond ratings and the mean of a group of S&P bond ratings. At the aggregate level, a "one over" and a "one under" would offset each other and, in turn, suggest that no difference at the aggregate level exists even though two differences at the individual level do exist. Third, I lose less information by using the predicted probabilities of bond ratings rather than just the bond ratings themselves and the Wilk's Lambda test allows me to consider the vector of predicted probabilities as well as test at the individual (bond rating) level.

As previously indicated, the ordered logit model will generate fifteen predicted bond rating probabilities for each bond issue. Since each set of probabilities represents a vector, and since the fifteen probabilities in each vector sum to one, this suggests that the data represents compositional data. Compositional data consist of vectors of observations whose components are nonnegative and sum to one. Compositional data with n observations of an m-part composition are of the form

$$x_{ij}, \qquad i = 1,...n, \quad j = 1,...,m,$$

where

$$0 \le x_{ij} \le 1 \qquad \forall i, j$$

and

$$\sum_j x_{ij} = 1 \qquad \forall i$$

are the constraints induced by being a composition.

A multivariate analysis of raw compositional data may lead to misinterpretations as such analyses ignore the inherent constrained nature of these observations.. Aitchison (1986) reports that Pearson (1897) notes that compositional data will result in spurious correlations and such spurious correlations cannot be analyzed in any "standard" way. As a result, interpretations based on such spurious correlations must be different from those correlations derived from unconstrained data. Aitchison (1986) introduced a range of statistical techniques to handle the special problems and questions of inference in analyzing compositional data. The three transformations discussed by Aitchison are the additive log ratio (ALR), the multiplicative log ratio, and the box-cox transformations. The log ratio transformation principle was based on the fact that there is a one-to-one correspondence between compositional vectors and associated log ratio vectors, so that any statement about compositions can be reformulated in terms of log ratios, and vice versa. The additive log ratio transformation is defined as $alr(x) = [\log(x_1 / x_D)\log(x_2 / x_D),...\log(x_{D-1} / x_D)]$. The multiplicative logistic transformation is the transformation of y_i such as $y_i = \log\{x_i /(1 - x_1 - ... - x_i)\}$ where $(i = 1,2,...d)$. The Box-Cox transformation has the advantage of including the ALR transformation as a special case. Aguilar et al. (2007) state that they are only aware of one application of this approach and that this single application is presented in Bhaumik, Dey and Ravishanker (2003).

The additive transformation differs from the multiplicative transformation mainly in that the multiplicative transformation assumes an underlying order in the data whereas the additive transformation ignores any ordering in the data. Since the bond ratings are ordinal in nature, I use the multiplicative logistic transformation.

In addition to testing for differences in the predicted probabilities of bond ratings, I also test for differences in the correctly predicted bond ratings. While previous research has identified the extent of correct predictions, no studies of which I am aware test for significant differences in correct predictions among different models or the use of the McNemar test to consider such differences.

McNemar's Test

McNemar's test will be used to compare the proportions of correct predictions from the data source combination models. The sample in the data source combination models represents the same bond issues. Both McNemar's test and Z test can be used to compare two proportions. McNemar's test assesses the significance of the difference between two correlated proportions, where the two proportions are based on the same sample of subjects or on matched-pair samples. The Z test assesses the significance of the difference between two proportions based on independent random samples. In this study, I compare the proportions of correct predictions associated with two different models with each model generated using a different data source combination. The observations (bond issues) employed to generate the two different models are the same, but the data sources are different. Since the proportions of correct predictions of MM and MC (as well as SC and SM) are based on same sample of subjects, the samples are matched pairs; therefore, the McNemar test is used. Because of the matching, the samples are statistically dependent. Methods that treat the two sets of observations as independent samples are inappropriate because when the observations are matched the precision obtained from not pooling is less than precision obtained by matching analysis. Therefore, the Z test for two proportions, which is a test to compare two independent proportions, cannot be used in this situation. The McNemar's test statistic is chi-squared and is provided below:

$$\chi^2 = \frac{(n_{21} - n_{12})^2}{(n_{21} + n_{12})}$$

Where n_{12} = number of matched pairs exhibiting dissimilar results (outcome 1 for Model A and outcome 2 for Model B)

n_{21} = number of matched pairs exhibiting dissimilar results (outcome 2 for Model A and outcome 1 for Model B)

Cluster Analysis

Finally, a cluster analysis will be performed in order to group objects based on the differences in the predicted probabilities from two models. I will gauge whether the derived clusters appear to be homogenous within and heterogeneous between SIC Code Divisions. Researchers face a trade-off when determining the number of clusters: fewer clusters versus less homogeneity within a cluster, i.e., as the number of clusters decreases, the homogeneity within the clusters necessarily decreases. I have ten SIC Code Divisions in the sample, a cluster solution of ten or fewer will be sought for each of the two data source combinations. The number of clusters is determined by considering the usefulness of interpretation.

Cluster analysis is used to categorize a set of observations into groups or clusters that have similar characteristics. Cluster analysis groups objects so that each object is very similar to other observations in the cluster and different from observations in other clusters with respect to some predetermined selection criterion. The resulting clusters should then exhibit high internal (within-cluster) homogeneity and high external (between-cluster) heterogeneity. A majority of clustering techniques begin with the calculation of similarities or distances between entities. Similarity among objects can be measured in various ways that can be classified into three primary methods: correlation measures, distance measures, and association measures. Selection of a measure type is determined by data type. For metric data, the distance measure of similarity is applied, while association measures are used for nonmetric data.

In correlation measures, I invert the objects X variables matrix so that the columns represent the objects and the rows represent the variables. Thus, the correlation coefficient between the two columns of numbers is the correlation (or similarity) between the profiles of the two objects. High correlations (negative as well as positive) indicate similarity and low correlations denote a lack of it . Distance measures of similarity, which represent similarity as the proximity of observations to one another across the variables in the cluster, are the similarity measure most often used and therefore currently used in this study. A distance measure is actually a measure of dissimilarity with larger values denoting smaller similarity. Distance is converted into a similarity measure using an inverse relationship. Association measures of similarity are used to compare objects whose characteristics are measured only in non-metric terms. An association measure could assess the degree of agreement or matching between each pair of respondents.

There are two classes of cluster analysis: hierarchical clustering and non-hierarchical clustering. Hierarchical procedures are stepwise clustering procedures involving a combination (or division) of the objects into clusters. The clusters may be formed using either the agglomerative approach or divisive approach. In the agglomerative approach, each observation is initially viewed as a unique cluster. Thereafter similar clusters are joined (iteratively) until a single cluster is ultimately formed. A divisive approach is essentially the opposite of agglomerative in that all observations are initially viewed as belonging to a single cluster, and the most dissimilar clusters break off (iteratively) to form small clusters. While both these approaches are impractical, one never selects either of these solutions as the final set of clusters.

Nonhierarchical procedures, or iterative partitioning methods, are generally preferred to hierarchical clustering techniques when the sample size is large. In some nonhierarchical procedures, each observation is placed into the cluster with nearest centroid. The centroids are recalculated after all observations are assigned to a cluster, and clusters are reassigned based on their distances from the new centroids. In other nonhierarchical procedures, the centroids are recalculated after each observation is assigned to a cluster. In both cases, the clustering procedure continues until the specified number of iterations has been performed. Hair et al. (1998) stated that when the seed points are selected based on practical, objective, or theoretical rationales, non-hierarchical methods are better for large data sets and have advantages over hierarchical techniques. Considering the total sample of 333 bond issues, the non-hierarchical method seems to be more suitable for the cluster analysis in this study.

One of the more popular nonhierarchical procedures is k-means method. Punj and Steward (1983) indicate that when the initial seeds are specified nonrandomly and the number of clusters is correctly specified, the K-means algorithm demonstrates superior performance when compared to the hierarchical clustering procedure. They recommend a two stage clustering technique where a hierarchical clustering technique supplies the number of clusters and the initial seeds to a nonhierarchical clustering technique. In this study, a two-stage approach will be used, whereby an initial agglomerative (hierarchical) cluster analysis is conducted to determine the seeds as inputs into a non-hierarchical (K-means) analysis (Punj and Stewart, 1983 and Lertwacharwa, 2003).

In hierarchical cluster analysis, the first step is to identify which observations are similar by constructing a proximity/similarity matrix of all observations. Some of the distance measures are squared Euclidean, Euclidean, Chebychev, block, Mahalanobis, size difference, pattern difference, variance, simple matching, dice, Czekanowski, Sorensen, Lance and Williams, Bray-Curtis nonmetric coefficient, Nei & Lei's genetic distance, Yule coefficient. Mahalonobis distance is an appropriate measure in that it adjusts for covariances according to the following equation for p variables:

$$d_{ij}^2 = \left(\underset{\sim}{x_i} - \underset{\sim}{x_j} \right)' \underset{\sim}{S}^{-1} \left(\underset{\sim}{x_i} - \underset{\sim}{x_j} \right)$$

Where

$\underset{\sim}{S} =$ the population covariance matrix X

$\underset{\sim}{x}$ = the p*1 vector of coordinates.

Mimmack et al. (2000) report that Jollife (1986) states "...[i]f all principal components are retained and the principal component scores are standardized, Euclidean distances calculated from the principal components are the same as Mahalanobis distances calculated from original data". I therefore use Euclidean distances derived from the principal component scores to calculate the Mahalanobis distances.

In a hierarchical cluster analysis, the next step is to identify the method of linkage. The method of linkage defines the distance between groups. There are several methods of linkage including centroid, average, unweighted pair-groups method, median, complete/maximum or furthest-neighbor, single/minimum or nearest-neighbor, within groups or Ward's. I use Ward's method of linkage as this method is a hierarchical precursor to nonhierarchical clustering methods. Ward (1963) proposed a clustering procedure that seeks to form the partitions in a manner that minimizes the variance within clusters. This hierarchical procedure serves to facilitate the results of the non-hierarchical clustering methods.

Summary

The difference between the Kamstra et al. (2001) and Ederington (1985) studies is the source of the financial statement data for independent variables. This study attempts to explain whether different data sources yield models that differ considerably with respect to overall performance of bond rating classification. Also, previous research has compared data from Compustat and Value Line. However, no research has attempted to compare data from Compustat and Mergent. This study fills a void by providing such research. Chapter 3 discusses the approach by which this data is compared. Specifically, the sample is presented, bond rating model and variables identified, the coding scheme for the bond rating variable is presented and appropriate statistical tools are discussed. Results of the analyses are presented in Chapter 4.

CHAPTER 4

RESULTS

Chapter 4 presents the results of the data analysis. Section 4.1 presents the descriptive statistics of the sample. Section 4.2 and Section 4.3 provide the results of the ordered logit model for the four different data source combinations and their related classification rates. In Section 4.2, Moody's and S&P modified bond ratings are used while unmodified bond ratings are used in the Section 4.3. Section 4.4 describes the results of cluster analysis to explore the pattern of differences in predictions generated from bond rating models developed utilizing different sources of financial statement data.

Dataset

Of the 2,292 new bond issues for the period January 2004 to June 2006, 333 issues are included in the analyses after all incomplete observations have been excluded (described in Chapter 3). These bonds are rated by both Moody's as well as S&P. Table 4.1 summarizes how these bonds are rated by Moody's and by S&P. One hundred and seventy two ratings (52%) fall on the diagonal (the cells that contain the bonds for which Moody's and S&P agree on the ratings). Moody's and S&P do not assign the same rating for one hundred and sixty one bonds; these are referred to as split ratings. One hundred and four bonds (31%) are rated lower by Moody's than by S&P, whereas

Table 4.1
Cross Tabulation of Bond Ratings by S&P and Moody's

			S	&	P		A	c	t	u	a	L		R	a	T	i	n	g	s	
M		AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC+	CCC	CCC-	Total
o	Aaa	**3**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
o	Aa1	0	**0**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
d	Aa2	0	0	**3**	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4
y'	Aa3	0	0	4	**5**	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10
s	A1	0	0	2	2	**9**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13
	A2	0	0	0	0	3	**13**	2	0	0	0	0	0	0	0	0	0	0	0	0	18
A	A3	0	0	0	0	0	3	**10**	2	0	0	0	0	0	0	0	0	0	0	0	15
c	Baa1	0	0	0	0	0	6	6	**8**	0	0	0	0	0	0	0	0	0	0	0	20
t	Baa2	0	0	0	0	0	0	2	8	**20**	5	0	0	0	0	0	0	0	0	0	35
u	Baa3	0	0	0	0	0	0	0	3	9	**15**	0	0	0	0	0	0	0	0	0	27
a	Ba1	0	0	0	0	0	0	0	0	1	4	**8**	1	1	0	0	0	0	0	0	15
l	Ba2	0	0	0	0	0	0	0	0	0	2	8	**12**	4	1	0	0	0	0	0	27
	Ba3	0	0	0	0	0	0	0	0	0	0	1	2	**11**	12	3	0	0	0	0	29
R	B1	0	0	0	0	0	0	0	0	0	0	0	3	7	**14**	9	0	0	0	0	33
a	B2	0	0	0	0	0	0	0	0	0	0	0	0	1	6	**16**	5	0	0	0	28
t	B3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13	**18**	6	2	0	39
i	Caa1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	3	2	**6**	2	0	14
n	Caa2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	**1**	0	2
g	Caa3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	**0**	1
s	Total	3	0	9	8	13	22	20	21	30	26	17	18	24	34	44	25	13	6	0	**333**

fifty-seven bonds (17%) are rated lower by S&P than by Moody's. Therefore, for this sample, Moody's is more likely to assign a lower rating. Of the 333 bond issues in the sample, the rating that occurs most frequently in Moody's is "B3" (12%) followed by "Baa2" (11%). In contrast, the rating that occurs most frequently in S&P ratings in the sample is "B" (13%) followed by "B+" (10%). Note that Moody's bond rating "B3" is equivalent to the S&P bond rating "B-" and that the S&P bond ratings "B" is equivalent to the Moody's bond rating "B2".

The summary statistics for the explanatory variables over the entire sample are reported in Table 4.2. The sample ranges in asset size from $114 million to $448 billion for both Compustat and Mergent dataset. The most notable difference between the two databases is the interest coverage ratio - Mergent reports a higher interest coverage ratio than Compustat. Table 4.3 provides the summary statistics of explanatory variables for each bond rating category.

Table 4.2
Summary Statistics for Explanatory Variables

Variable	Database	Mean	Standard Deviation	Minimum	Maximum
Bond Rating	Mergent	5.76	3.83	0	14
	Compustat	5.97	3.97	0	14
Interest Coverage Ratio	Mergent	11.82	88.78	-50.22	1559.62
	Compustat	4.12	10.84	-40.58	107.06
Debt Ratio	Mergent	0.33	0.21	0.00014	1.5
	Compustat	0.33	0.21	0.00014	1.5
Return on Assets Ratio	Mergent	0.04	0.06	-0.23	0.34
	Compustat	0.04	0.08	-0.26	1.08
Total Assets	Mergent	1.25E+10	3.1E+10	1.1E+08	4.5E+11
	Compustat	1.2711E+10	3.15E+10	1.14E+08	4.5E+11
Subordination Status	Mergent	0.18	0.39	0	1
	Compustat	0.18	0.39	0	1

Table 4.3
Summary Statistics for Explanatory Variables –for Each Bond Rating Category

Variable	Data Source	Bond Rating Categories														
		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Interest	Mergent															
Coverage	Mean	-1.10	-0.44	-1.60	0.75	1.73	2.82	16.47	23.49	6.75	7.37	7.48	96.76	22.52	29.98	14.48
Ratio	Minimum	-6.96	-6.93	-50.22	-8.07	-2.17	-13.90	-4.18	-14.35	-1.38	0.08	-0.53	0.24	-0.63	7.70	9.99
	Maximum	1.84	2.42	4.98	8.97	18.38	28.85	120.45	287.79	46.54	33.96	31.57	1559.61	107.06	72.44	22.95
	Compustat															
	Mean	0.52	0.19	-1.30	1.13	0.07	1.59	4.14	3.96	4.82	6.53	9.97	6.49	19.67	11.47	16.83
	Minimum	-6.96	-2.44	-40.58	-13.90	-3.61	-1.33	-2.73	-12.28	-2.37	0.04	-0.30	0.49	3.05	-0.64	6.12
	Maximum	28.98	3.55	4.98	8.97	3.64	8.22	32.10	36.23	27.52	33.96	103.25	19.30	107.06	26.78	44.46
Debt Ratio	Mergent															
	Mean	0.64	0.49	0.42	0.36	0.35	0.30	0.23	0.31	0.26	0.19	0.23	0.25	0.31	0.15	0.12
	Minimum	0.31	0.16	0.00	0.06	0.03	0.05	0.00	0.10	0.02	0.06	0.02	0.10	0.04	0.02	0.05
	Maximum	1.31	1.51	0.79	0.70	0.71	0.60	0.39	0.68	0.67	0.33	0.61	0.90	0.70	0.36	0.20
	Compustat															
	Mean	0.62	0.42	0.45	0.38	0.36	0.31	0.27	0.28	0.27	0.20	0.20	0.23	0.23	0.21	0.13
	Minimum	0.25	0.18	0.00	0.12	0.06	0.11	0.05	0.00	0.03	0.06	0.02	0.02	0.04	0.06	0.05
	Maximum	1.31	0.94	1.49	0.70	0.68	0.60	0.44	0.68	0.59	0.44	0.46	0.90	0.51	0.52	0.22
Return	Mergent															
Assets	Mean	-0.03	0.00	0.01	0.02	0.03	0.04	0.07	0.06	0.06	0.05	0.07	0.07	0.09	0.12	0.07
	Minimum	-0.18	-0.18	-0.18	-0.16	-0.04	-0.11	-0.08	-0.23	-0.01	0.03	0.01	0.02	0.01	0.07	0.03
	Maximum	0.02	0.06	0.07	0.14	0.11	0.12	0.25	0.34	0.13	0.15	0.14	0.18	0.14	0.17	0.10
	Compustat															
	Mean	0.02	0.01	-0.01	0.03	0.02	0.04	0.06	0.06	0.06	0.07	0.06	0.06	0.10	0.11	0.09
	Minimum	-0.18	-0.09	-0.26	-0.11	-0.04	-0.01	-0.04	-0.22	-0.02	0.03	0.01	0.02	0.07	0.01	0.03
	Maximum	1.08	0.06	0.14	0.09	0.08	0.12	0.14	0.34	0.13	0.13	0.14	0.18	0.14	0.17	0.13

Table 4.3 (Continued)

Variable	Data Source	Bond Rating Categories 0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Assets	Mergent															
	Mean	3E+10	2E+09	2E+09	3E+09	4E+09	8E+09	6E+09	9E+09	1E+10	1E+10	2E+10	2.3E+10	3E+10	4E+10	1E+11
	Minimum	1E+08	1E+08	2E+08	2E+08	4E+08	6E+08	1E+09	6E+08	6E+08	2E+09	3E+09	2.4E+09	7E+09	9E+09	3E+10
	Maximum	4E+11	2E+10	1E+10	8E+09	3E+10	2E+10	1E+10	4E+10	3E+10	3E+10	1E+11	8.4E+10	1E+11	1E+11	1E+11
	Compustat															
	Mean	2E+09	2E+10	3E+09	2E+09	5E+09	6E+09	8E+09	8E+09	1E+10	1E+10	2E+10	1.9E+10	3E+10	4E+10	7E+10
	Minimum	1E+08	1E+08	2E+08	2E+08	2E+08	6E+08	1E+09	6E+08	1E+09	2E+09	6E+08	2.4E+09	4E+09	9E+09	2E+10
	Maximum	1E+10	4E+11	1E+10	1E+10	3E+10	2E+10	2E+10	3E+10	4E+10	1E+11	8E+10	8.4E+10	1E+11	6E+10	1E+11
Sub-ordination	Mergent															
Status	Mean	0.41	0.44	0.43	0.34	0.38	0.11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Minimum	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Maximum	1.00	1.00	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Compustat															
	Mean	0.37	0.40	0.49	0.47	0.13	0.00	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Minimum	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Maximum	1.00	1.00	1.00	1.00	1.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Results

Ordered logit analysis is used to analyze the association between the data sources and the bond ratings. The logit model predicts the probability of being in a lower category, i.e., receiving a lower bond rating. The predicted probability ranges from 0 to 1. The level of statistical significance associated with each of the estimated coefficients indicates whether that variable is significant in explaining the dependent variable (bond ratings). The significant positive (negative) coefficients of the continuous independent variables indicate that increasing the level of the explanatory variable will increase (decrease) the likelihood of bond to have a lower ratings, given that all the other explanatory variables are held constant. A significant positive (negative) coefficient on a dummy variable indicates that having the characteristic will increase (decrease) the likelihood that the bond will have a lower bond rating.

The odds ratio for each variable is equal to the exponential of the negative value of the estimated maximum likelihood coefficient (Nannyonga, 2000). The odds ratio measures the effect of an explanatory variable on the change in the odds of having a lower bond rating instead of a higher bond rating. If the odds ratio is equal to one, this implies that changing the continuous explanatory variable by one unit, keeping all other variables constant, will leave the odds of having a lower bond rating versus a higher bond rating unchanged. If the odds ratio is more (less) than 1, then increasing (decreasing) the continuous explanatory variable by one unit, holding all other variables constant, will increase (decrease) the odds of the bond being categorized as lower bond rating versus a higher bond rating. For the dummy variable, the odds ratio of more (less) than 1 indicates that the likelihood of lower bond ratings increases (decreases) by the magnitude of the odds ratio, if the bond possesses those characteristics (Agresti, 2002).

Higher total assets, return on assets, and interest coverage indicate lower credit risk, and therefore should lower the probability of having a lower bond rating. On the other hand, higher debt ratio indicates higher credit risk and therefore should increase the probability of having a lower bond rating. A subordinated debt ranks below other debt with regard to claim on assets or earnings, thereby indicating a higher credit risk that should correspond with a higher probability of having a lower bond rating. The analysis of four data source combinations is divided into phases; detailed discussions of each follow.

Phase 1 – Part A: Original Data Sources
Mergent Moody's Bond Ratings;
Substitute Data Source ; Compustat

Moody's bond ratings are used for the dependent variables throughout Phase 1 – Part A of the analyses. For the independent variables, the Mergent database is used in Phase 1 – Part A – Step 1 while the Compustat database is used in Phase 1 – Part A – Step 2 of the analyses.

Phase 1 – Part A – Step 1 (MM). I develop a model based on the Kamstra et al. (2001) bond rating classification ordered logit model using Moody's bond ratings as the data source for the dependent variables and the Mergent database as the data source for the independent variables. I use SAS PROC LOGISTIC to perform logit analysis. The parameter estimates for this model are reported in Table 4.4. The ordered logit results show that all the variables except the interest coverage variable are significant at the 0.01 level of significance. The significant coefficients indicate that debt ratio, return on assets, assets and subordination status are factors that determine the bond ratings. This is consistent with the results obtained by Kamstra et al. (2001). All the variables have expected signs; the positive coefficients associated with debt ratio and subordination status imply that the probability of a bond having lower ratings is directly related to debt ratio and subordination status. Similarly, the negative coefficients associated with interest coverage ratio, return on assets, and total assets imply that the probability of a bond having lower ratings is inversely related to interest coverage ratio, return on assets, and total assets.

Table 4.4
Logistic Regression Estimates for Bond Rating Model using Moody's Bond Ratings and Mergent Financial Statement Data

Parameter	DF	Estimate	Standard Error	Pr > ChiSq	Odds Ratio
Intercept 0	1	-4.8396	0.4274	<.0001	0.008
Intercept 1	1	-2.9743	0.3228	<.0001	0.051
Intercept 2	1	-2.1765	0.2953	<.0001	0.113
Intercept 3	1	-1.4019	0.2750	<.0001	0.246
Intercept 4	1	-0.7354	0.2634	0.0052	0.479
Intercept 5	1	-0.1268	0.2581	0.6232	0.881
Intercept 6	1	0.1965	0.2575	0.4454	1.217
Intercept 7	1	0.7839	0.2605	0.0026	2.190
Intercept 8	1	1.5666	0.2733	<.0001	4.791
Intercept 9	1	2.1153	0.2892	<.0001	8.292
Intercept 10	1	2.6385	0.3103	<.0001	13.992
Intercept 11	1	3.5027	0.3605	<.0001	33.205
Intercept 12	1	4.5944	0.4541	<.0001	98.930
Intercept 13	1	6.7342	0.7443	<.0001	840.688
ICR	1	-0.00093	0.00115	0.4210	0.999
DR	1	3.7927	0.5693	<.0001	44.374
ROA	1	-16.6186	1.9289	<.0001	0.000
ASSETS	1	-549E-13	7.08E-12	<.0001	1.000
SUB	1	1.4921	0.2834	<.0001	4.446

Note. Correct Classification Rate = 27.63%

The odds ratios for this model are also reported in Table 4.4. The odds ratio equal to one for the total assets implies that changing the total assets by one dollar, keeping all other variables constant, will leave unchanged the odds of having a lower bond rating versus a higher bond rating. The odds ratio more than 1 for debt ratio implies that increasing the debt ratio by one unit, holding all other variables constant, will increase the odds of the bond being categorized as lower bond rating versus a higher bond rating by 44.374. The odds ratio less than 1 for return on assets ratio implies that increasing the return on asset ratio by one unit, holding all other variables constant, will decrease the odds of the bond being categorized as lower bond rating versus a higher bond rating . For the subordination status, the odds ratio of more than 1 indicates that the likelihood of lower bond ratings increases by the 4.466, if the bond possesses has subordination status.

Using the parameter estimates (coefficients) from the ordered logit model, I calculate predicted probabilities and predicted bond ratings associated with each bond rating. The highest predicted probability determines the predicted bond rating. Thereafter, the predicted bond rating is compared with the actual bond rating for each observation. When predicted rating is the same as the actual rating, the bond is correctly classified by the model. The correct classification rate is calculated by summing all correct predictions and dividing this sum by the sample size (i.e., 333 observations). The correct classification rates resulting from the bond rating ordered logit model is 27.63% as reported in Table 4.4.

Phase 1 – Part A – Step 2 (MC). Using Moody's bond ratings as the data source for the dependent variables and the Compustat database as the data source for the independent variables, I develop an ordered logit model. The parameter estimates for this model are shown in Table 4.5. Similar to MM, the ordered logit results show that all the variables except the interest coverage variable are significant at the 0.01 level of significance. All the variables have expected signs. The positive coefficients, and odds ratio greater than 1, of debt ratio and subordination status imply that the probability of a bond having lower ratings is directly related to debt ratio and subordination status. Similarly, the negative coefficients, and odds ratio less than 1, of interest coverage ratio, return on assets, and total assets imply that the probability of a bond having lower ratings is inversely related to interest coverage ratio, return on assets, and total assets.

The odds ratios for this model are also reported in Table 4.5. The odds ratio equal to one for the total assets implies that changing the total assets by one dollar, keeping all other variables constant, will leave unchanged the odds of having a lower bond rating versus a higher bond rating. The odds ratio more than 1 for debt ratio implies that increasing the debt ratio by one unit, holding all other variables constant, will increase the odds of the bond being categorized as lower bond rating versus a higher bond rating by 76.059. The odds ratio less than 1 for return on assets ratio implies that increasing the return on asset ratio by one unit, holding all other variables constant, will decrease the odds of the bond being categorized as lower bond rating versus a higher bond rating . For the subordination status, the odds ratio of more than 1 indicates that the likelihood of lower bond ratings increases by the 4.853, if the bond possesses has subordination status.

Table 4.5
Logistic Regression Estimates for Bond Rating Model using Moody's Bond Ratings and Compustat Financial Statement Data

Parameter	DF	Standard Estimate	Error	Pr > ChiSq	Odds Ratio
Intercept 0	1	-5.2615	0.4408	<.0001	0.005
Intercept 1	1	-3.4599	0.3334	<.0001	0.031
Intercept 2	1	-2.6862	0.3031	<.0001	0.068
Intercept 3	1	-1.9425	0.2800	<.0001	0.143
Intercept 4	1	-1.3134	0.2660	<.0001	0.269
Intercept 5	1	-0.7386	0.2581	0.0042	0.478
Intercept 6	1	-0.4338	0.2560	0.0902	0.648
Intercept 7	1	0.1275	0.2562	0.6189	1.136
Intercept 8	1	0.8833	0.2657	0.0009	2.419
Intercept 9	1	1.3949	0.2789	<.0001	4.034
Intercept 10	1	1.8636	0.2965	<.0001	6.447
Intercept 11	1	2.6430	0.3386	<.0001	14.055
Intercept 12	1	3.5448	0.4076	<.0001	34.633
Intercept 13	1	5.1182	0.6045	<.0001	167.037
ICR	1	-0.0263	0.0112	0.0190	0.974
DR	1	4.3315	0.6015	<.0001	76.059
ROA	1	-10.1569	1.8541	<.0001	0.000
ASSETS	1	-281E-13	5.28E-12	<.0001	1.000
SUB	1	1.5796	0.2842	<.0001	4.853

Note. Correct Classification Rate = 25.53%

Using the parameter estimates (coefficients) from the ordered logit model, I calculate predicted probabilities and predicted bond ratings associated with each bond rating. Thereafter, the predicted bond rating is compared with the actual bond rating for each observation. The correct classification rate is 25.53% as reported in Table 4.5.

Phase 1- Part A- Step 3. I then compare the predicted probabilities determined in Step 2 with the predicted probabilities determined in Step 1 using Wilk's Lambda test. As discussed in Chapter 3, since the data is compositional, a multiplicative logistic transformation is performed prior to the analysis. The results of the Wilk's Lambda test (Wilk's Lambda value = 0.084) indicate that the predicted probabilities of the MM model are statistically different from the predicted probabilities of the MC model (p-value < 0.0001).

A 100(1-α) % confidence region for the difference mean vector $\underset{\sim}{\delta}$ is the ellipsoid determined by all the possible points $\underset{\sim}{\delta}$ that satisfy

$$\left(\bar{\underset{\sim}{d}}-\underset{\sim}{\delta}\right)' \underset{\sim}{S}_d^{-1}\left(\bar{\underset{\sim}{d}}-\underset{\sim}{\delta}\right) \leq \frac{(n-1)p}{n(n-p)} F_{p,n-p}(\alpha).$$

Since $\frac{(n-1)p}{n(n-p)} F_{p,n-p}(\alpha) = 7.26$, $\left(\bar{\underset{\sim}{d}}-\underset{\sim}{\delta}\right)' \underset{\sim}{S}_d^{-1}\left(\bar{\underset{\sim}{d}}-\underset{\sim}{\delta}\right) = 10.87$, and $10.87 > 7.26$, the point $\underset{\sim}{\delta} = 0$ falls outside the 95% confidence region for $\underset{\sim}{\delta}$. The results show that statistically significant differences exist between the predicted probabilities of the two models ($\alpha = 0.05$) and so suggest that the overall performance of the bond rating classification models reflect data source dependency.

Table 4.6 presents 2x2 classification table comparing predictions made by the MM and MC models. When the predicted bond rating of MM model is compared with the predicted bond rating of MC model for each observation, 78 bond ratings were correctly predicted by both models. Using the McNemar test, I compare the proportions of correct predictions determined in Step 2 with the proportion of correct predictions determined in Step 1 to determine if there are any significant differences.

Table 4.6
Cross Classification - Predictions of MM and MC Models

		MC		
		Correct	Incorrect	Total
MM	Correct	78	14	92
	Incorrect	7	234	241
	Total	85	248	333

Using the traditional .05 level of significance, the result of the McNemar test (chi square=2.333) provides little evidence of a difference between the proportion of correct predictions of the MM and MC models (p-value = 0.12663).Therefore, a change in the data source of the independent variable is not associated with the proportion of correct responses.

The difference in the test results (between the Wilk's Lambda and McNemar tests) may relate to the level of precision of the tests. While the Wilk's Lambda test focuses on the predicted probabilities of the bond rating (continuous data), the McNemar test focuses on the bond rating itself (categorical data). An additional analysis of predicted ratings is presented in Table 4.7. When the predicted bond rating is compared with the actual bond rating for each observation, the MM model has predicted 107 bond ratings higher than the actual bond ratings (over predicted) and 134 bond ratings lower than the actual bond ratings (under predicted) whereas the MC model has predicted 115 bond ratings higher than the actual bond ratings (over predicted) and 134 bond ratings lower than the actual bond ratings (under predicted).

Table 4.7
Analyses of Predicted Ratings from MM and MC Models

Model	Over Predicted	Under Predicted	Correctly Predicted	Percent Correct
MM	107	134	92	27.63
MC	115	134	85	25.53

Phase 1 – Part B: Original Data Sources: Compustat; S&P Bond Ratings; Substitute Data Source; Mergent

S&P bond ratings are used for the dependent variables throughout Phase 1 – Part B of the analyses. For the independent variables, the Compustat database is used in Phase 1 – Part B – Step 1 while the Mergent database is used in Phase 1 – Part B – Step 2 of the analyses.

Phase 1 – Part B – Step 1 (SC). I then develop a model based on Kamstra et al. (2001) bond rating classification model using S&P bond ratings as the data source for the dependent variables and the Compustat database as the data source for the independent variables. The parameter estimates for the model are shown in Table 4.8. Similar to MM and MC, the ordered logit results show that all the variables except the interest coverage variable are significant at the 0.01 level of significance. All the variables have expected signs. The positive coefficients, and odds ratio greater than 1, of debt ratio and subordination status imply that the probability of a bond having lower ratings is directly related to debt ratio and subordination status. Similarly, the negative coefficients, and odds ratio less than 1, of interest coverage ratio, return on assets, and total assets imply that the probability of a bond having lower ratings is inversely related to interest coverage ratio, return on assets, and total assets.

The odds ratios for this model are also reported in Table 4.8. The odds ratio equal to one for the total assets implies that changing the total assets by one dollar, keeping all other variables constant, will leave unchanged the odds of having a lower bond rating versus a higher bond rating. The odds ratio more than 1 for debt ratio implies that increasing the debt ratio by one unit, holding all other variables constant, will increase the odds of the bond being categorized as lower bond rating versus a higher bond rating by 58.784. The odds ratio less than 1 for return on assets ratio implies that increasing the return on asset ratio by one unit, holding all other variables constant, will decrease the odds of the bond being categorized as lower bond rating versus a higher bond rating . For the subordination status, the odds ratio of more than 1 indicates that the likelihood of lower bond ratings increases by the 5.340, if the bond possesses has subordination status.

Table 4.8
Logistic Regression Estimates for Bond Rating Model using S&P Bond Ratings and Compustat Financial Statement Data

Parameter	DF	Estimate	Standard Error	Pr > ChiSq	Odds Ratio
Intercept 0	1	-4.9889	0.4192	<.0001	0.007
Intercept 1	1	-3.8542	0.3517	<.0001	0.021
Intercept 2	1	-2.6636	0.3012	<.0001	0.070
Intercept 3	1	-1.8548	0.2764	<.0001	0.156
Intercept 4	1	-1.3113	0.2645	<.0001	0.269
Intercept 5	1	-0.9249	0.2587	0.0003	0.397
Intercept 6	1	-0.5580	0.2552	0.0288	0.572
Intercept 7	1	-0.0426	0.2541	0.8668	0.958
Intercept 8	1	0.5764	0.2590	0.0261	1.780
Intercept 9	1	1.0608	0.2682	<.0001	2.889
Intercept 10	1	1.6013	0.2849	<.0001	4.960
Intercept 11	1	2.4523	0.3263	<.0001	11.615
Intercept 12	1	3.2718	0.3848	<.0001	26.359
Intercept 13	1	4.1323	0.4697	<.0001	62.323
ICR	1	-0.0305	0.0115	0.0081	0.970
DR	1	4.0739	0.5930	<.0001	58.784
ROA	1	-9.0422	1.8331	<.0001	0.000
ASSETS	1	-255E-13	5.2E-12	<.0001	1.000
SUB	1	1.6752	0.2854	<.0001	5.340

Note. Correct Classification Rate = 24.32%

Using the parameter estimates (coefficients) from the ordered logit model, I calculate predicted probabilities and predicted bond ratings associated with each bond rating. Thereafter, the predicted bond rating is compared with the actual bond rating for each observation. The correct classification rate is 24.32% as reported in Table 4.8.

Phase I – Part B – Step 2 (SM). Using S&P bond ratings as the data source for the dependent variables and the Mergent database as the data source for the independent variables, I develop an ordered logit model. The parameter estimates for this model are shown in Table 4.9. Similar to MM, MC and SC, the ordered logit results show that all the variables except the interest coverage variable are significant at the 0.01 level of significance. All the variables have expected signs. The positive coefficients, and odds ratio greater than 1, of debt ratio and subordination status imply that the probability of a bond having lower ratings is directly related to debt ratio and subordination status. Similarly, the negative coefficients, and odds ratio less than 1, of interest coverage ratio, return on assets, and total assets imply that the probability of a bond having lower ratings is inversely related to interest coverage ratio, return on assets, and total assets.

The odds ratios for this model are also reported in Table 4.9. The odds ratio equal to one for the total assets implies that changing the total assets by one dollar, keeping all other variables constant, will leave unchanged the odds of having a lower bond rating versus a higher bond rating. The odds ratio more than 1 for debt ratio implies that increasing the debt ratio by one unit, holding all other variables constant, will increase the odds of the bond being categorized as lower bond rating versus a higher bond rating by 40.243. The odds ratio less than 1 for return on assets ratio implies that increasing the return on asset ratio by one unit, holding all other variables constant, will decrease the odds of the bond being categorized as lower bond rating versus a higher bond rating . For the subordination status, the odds ratio of more than 1 indicates that the likelihood of lower bond ratings increases by the 4.931, if the bond possesses has subordination status.

Table 4.9
Logistic Regression Estimates for Bond Rating Model using S&P Bond Ratings and Mergent Financial Statement Data

Parameter	DF	Estimate	Standard Error	Pr > ChiSq	Odds Ratio
Intercept 0	1	-4.6548	0.4101	<.0001	0.010
Intercept 1	1	-3.4585	0.3422	<.0001	0.031
Intercept 2	1	-2.2223	0.2951	<.0001	0.108
Intercept 3	1	-1.3848	0.2730	<.0001	0.250
Intercept 4	1	-0.8134	0.2630	0.0020	0.443
Intercept 5	1	-0.4004	0.2585	0.1214	0.670
Intercept 6	1	-0.00910	0.2565	0.9717	0.991
Intercept 7	1	0.5304	0.2576	0.0395	1.700
Intercept 8	1	1.1738	0.2651	<.0001	3.234
Intercept 9	1	1.6829	0.2762	<.0001	5.381
Intercept 10	1	2.2662	0.2956	<.0001	9.642
Intercept 11	1	3.2038	0.3442	<.0001	24.627
Intercept 12	1	4.1327	0.4159	<.0001	62.346
Intercept 13	1	5.1430	0.5239	<.0001	171.234
ICR	1	-0.00095	0.00115	0.4079	0.999
DR	1	3.6949	0.5668	<.0001	40.243
ROA	1	-15.8160	1.9082	<.0001	0.000
ASSETS	1	-495E-13	6.82E-12	<.0001	1.000
SUB	1	1.5956	0.2847	<.0001	4.931

Note. Correct Classification Rate = 21.92%

Using the parameter estimates (coefficients) from the ordered logit model, I calculate predicted probabilities and predicted bond ratings associated with each bond rating. Thereafter, the predicted bond rating is compared with the actual bond rating for each observation. The correct classification rate is 21.92% as reported in Table 4.9.

Phase I – Part B – Step 3. After the multiplicative logistic transformation, the results of the Wilk's Lambda test (Wilk's Lambda = 0.1156) indicate that the predicted probabilities of the SM model are statistically different from the predicted probabilities of the SC (p-value < 0.0001). For 15 Ratings, $\frac{(n-1)p}{n(n-p)}F_{p,n-p}(\alpha)$ = 7.26 and $\left(\underset{\sim}{\bar{d}}-\underset{\sim}{\delta}\right)' \underset{\sim}{S_d^{-1}}\left(\underset{\sim}{\bar{d}}-\underset{\sim}{\delta}\right)$ = 7.48, Therefore, the point $\underset{\sim}{\delta}$ = 0 falls outside the 95% confidence region for $\underset{\sim}{\delta}$. The results show that statistically significant differences exist between the predicted probabilities of the two models (□ = 0.05). Therefore, these results suggest that the overall performance of the bond rating classification models reflect data source dependency.

Table 4.10 presents a 2x2 classification table comparing the predictions of SC and SM models. When the predicted bond rating of SM model is compared with the predicted bond rating of SC model for each observation, both the models correctly predicted 67 bond ratings.

Table 4.10
Cross Classification - Predictions of SC and SM Models

		SM		
		Correct	Incorrect	Total
SC	Correct	67	14	81
	Incorrect	6	246	252
	Total	73	260	333

Using the traditional .05 level of significance, the result of the McNemar test (chi square = 3.2) provides little evidence for the difference between the proportion of correct responses of SC and SM models (p-value = 0.07). Therefore, a change in the data source of the independent variable is not associated with the proportion of correct responses. An additional analysis of predicted ratings is presented in Table 4.11. When the predicted bond rating is compared with the actual bond rating for each observation, the SM model has predicted 112 bond ratings higher than the actual bond ratings (over predicted) and 148 bond ratings lower than the actual bond ratings (under predicted). In contrast, the SC model has predicted 111 bond ratings higher than the actual bond ratings (over predicted) and 142 bond ratings lower than the actual bond ratings (under predicted).

Table 4.11
Analyses of Predicted Ratings from SM and SC Models

Models	Over Predicted	Under Predicted	Correctly Predicted	Percent Correct
SM	112	148	73	21.92
SC	111	142	81	24.32

<u>Phase 1 – Part B: Original Data Sources; Mergent; Moody's Bond Ratings; Substitute Data Source; Mergent</u>

Mergent/Moody's database is used as a data source for the independent variables throughout Phase 1 – Part B of the analyses. For the dependent variables, Moody's bond ratings and S&P bond ratings are used in the analyses.

Table 4.12 presents a 2x2 classification table comparing the predictions of MM and SM models. When the predicted bond rating of MM model is compared with the predicted bond rating of SM model for each observation, both the models correctly predicted 40 bond ratings. Using McNemar test, I compare the proportion of correct predictions determined in Phase 1 – Part A - Step 1 (MM) with the proportion of correct predictions determined in Phase 2 - Part B - Step 2 (SM) to determine if there are any significant differences.

Table 4.12
Cross Classification - Predictions of MM and SM Models

		SM		
		Correct	Incorrect	Total
MM	Correct	40	52	92
	Incorrect	33	208	241
	Total	73	260	333

Using the traditional .05 level of significance, the result of the McNemar test (chi square = 4.247) provides an evidence of a difference between the proportion of correct predictions of MM and SM models (p-value = 0.039). Therefore, a change in the data source of the independent variable is associated with differences in the proportion of correct responses.

<u>Phase 1 – Part B: Original Data Sources; Compustat; S&P Bond Ratings; Substitute Data Source; Moody's Bond Ratings</u>

Compustat database is used as a data source for the independent variables throughout Phase 1 – Part B of the analyses. For the dependent variables, Moody's bond ratings and S&P bond ratings are used in the analyses.

Table 4.13 presents a 2x2 classification table comparing the predictions of SC and MM models. When the predicted bond rating of MM model is compared with the predicted bond rating of SC model for each observation, both the models correctly predicted 41 bond ratings.

Table 4.13
Cross Classification - Predictions of SC and MM Models

		SC		
		Correct	Incorrect	Total
MM	Correct	41	44	85
	Incorrect	40	208	248
	Total	81	252	333

Using McNemar test, I compare the proportions of correct predictions determined in Phase 1 – Part A - Step 2 (MC) with the proportion of correct predictions determined in Phase 2 - Part B - Step 1 (SC) to determine if there are any significant differences. Using the traditional .05 level of significance, the result of the McNemar test (chi square = 0.190) provides little evidence of a difference between the proportion of correct predictions of MC and SC models (p-value = 0.66). Therefore, a change in the data source of the independent variable is associated with differences in the proportion of correct responses.

The results, in terms of the research question, are as follows. When Moody's ratings used as a dependent variable, the results suggest that the Compustat data do not produce the same predicted probabilities as the predicted probabilities produced by the Mergent data. However, the results also suggest that the correct predictions are not data source dependent. Similarly, when S&P rating is used as a dependent variable, the results suggest that the Compustat data do not produce the same predicted probabilities as the predicted probabilities produced by the Mergent data. However, the results also suggest that the correct predictions are not data source dependent. Therefore, the results suggest that that the predicted probabilities are data source dependent. When Mergent database is used as a data source for independent variable, the results suggest that the correct predictions are ratings source dependent. For the entire sample of 333 new bond issues, the correct classification rate for all the four data source combinations range from a low of 21.92 % (for SM model) to a high of 27.63 % (for MM model).

Supplemental Procedures – Six Ratings

As indicated in Section 4.2, the significance of the independent variables included in the various ordered logit models (reported in Table 4.) were consistent with Kamstra et al. (2001). However, the related correct classification rates were substantially less than the correct classification rate of 47.5 percent found by Kamstra et al. (2001). Since Kamstra et al. (2001) used six bond rating categories versus fifteen bond rating categories. I reanalyzed all of the four data source combinations using six bond rating categories.

Kamstra et al. (2001) use the following six bond rating categories—Aaa, Aa, A, Baa, Ba, and B. With the exception of category Aaa, the other five bond rating categories represent "collapsed categories" (e.g., B1, B2, and B3 were collapsed into category B). This collapsing procedure is typical of most bond rating studies. Additionally, bonds that were rated Caa1 or below were not included in Kamstra et al. (2001) because such bonds represented "less than investment grade" bonds.

Given the low frequency of bond ratings at the highest levels, these observations in this study were collapsed into a category specified as "Aa and above" or "AA and above" (as applicable). Also, in contrast to Kamstra et al. (2001), no observations were excluded based on actual or perceived investment grade quality.

The following six bond rating categories—and their respective assigned values—were employed in the supplemental analysis: Ratings of Caa1 and below or CCC+ and below were assigned a value of 0; B3 or B-, B2 or B, B1 or B+ a value of 1; Ba3 or BB-, Ba2 or BB, Ba1 or BB+ a value of 2; Baa3 or BBB-, Baa2 or BBB, Baa1 or BBB+ a value of 3; A3 or A-, A2 or A, A1 or A+ a value of 4; Aa3 or AA-, Aa2 and above or AA and above a value of 5.

Table 4.14 shows the parameter estimates for the ordered logit model of the four data source combinations using six bond rating categories. Consistent with Kamstra et al. (2001), the results indicate that all variables except the interest coverage variable are significant.

Table 4.14
Estimated Coefficients (with p-values) from Ordered Logit Model

Variable	MM	SC	SM	MC
Intercept 0	-4.8121	-5.2909	-5.0741	-5.2000
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Intercept 1	-1.3008	-1.7633	-1.4542	-1.8357
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Intercept 2	0.2361	-0.4421	-0.1174	-0.3977
	(0.3876)	(0.1052)	(0.6668)	(0.1408)
Intercept 3	2.1852	1.2779	1.6058	1.4046
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Intercept 4	4.6740	3.8032	3.9458	3.4594
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
ICR	-0.00135	-0.0272	-0.00127	-0.0245
	(0.2815)	(0.0273)	(0.3050)	(0.0445)
DR	3.5630	4.2622	3.8172	4.0454
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
ROA	-17.4926	-8.9521	-15.5265	-10.8268
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
ASSETS	-5E-11	-4.7E-11	-4.5E-11	-2.3E-11
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
SUBORD	1.5496	2.0155	2.0310	1.6757
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)

Table 4.15 presents the correct classification rates resulting from the bond rating ordered logit model using four data source combinations and with six bond rating categories. For the entire sample of 333 new bond issues, the correct classification rate for all the four data source combinations range from a low of 47.25% (for MC model) to a high of 51.35% (for MM model). After reducing the bond rating categories from fifteen to six, the resulting classification rate increased by approximately 25 percentage points (on average). The differences may be due to the following reasons. First, since the number of possible rating categories were decreased by almost one-third (15 to 6),there is a lower probability of incorrect classification. Second, while the ratings have been decreased by almost one-third, no similar adjustment was made to the predictor variables.

Table 4.15
Correct Classification Rates – Six Ratings and fifteen Ratings

Panel A: Correct Classification Rates – Six Ratings				
Asset Transformation	Moody's/ Mergent	S&P/ Compustat	S&P/ Mergent	Moody's/ Compustat
None	51.35	49.25	49.25	47.25

Panel B: Correct Classification Rates – fifteen Ratings				
Asset Transformation	Moody's/ Mergent	S&P/ Compustat	S&P/ Mergent	Moody's/ Compustat
None	27.63	24.32	21.92	25.53

Table 4.16 reports the results of the Wilk's Lambda test for the two model comparisons (MM-MC and SC-SM). The results indicate that the predicted probabilities associated with each of the two model comparisons were statistically different. Therefore, these results suggest that the overall performance of the bond rating classification models developed by using six bond rating categories do reflect data

source dependency. This is same as the results of the bond rating classification models developed using fifteen bond rating categories.

Table 4.16
Wilk's Lambda Test Comparing Differences in Mean Vector of Predicted Probabilities – Six Ratings

Model Comparisons	Wilk's Lambda[a]	p-Value
MM –MC	0.9928	0.7956
SM – SC	0.9767	0.1694

[a] SAS software generates Wilk's Lambda value

Table 4.17 reports the results of the McNemar test for the four model comparisons (MM-MC, SC-SM, MC-SC and MM-SM). The results indicate that the predicted probabilities associated with each of the four model comparisons were not statistically different. This is same as the results of the bond rating classification models developed using fifteen bond rating categories.

Table 4.17
McNemar Test

Model Comparisons	Chi-Square	p-Value
MM –MC	3.6	0.0578
SM – SC	0	1
MM-SM	0.65	0.4189
MC-SC	0.301	0.5831

An additional analysis of predicted ratings is presented in Table 4.18. When the predicted bond rating is compared with the actual bond rating for each observation, the MM model has predicted 75 bond ratings higher than the actual bond ratings (over predicted) and 87 bond ratings lower than the actual bond ratings (under predicted). The MC model has predicted 79 bond ratings higher than the actual bond ratings (over predicted) and 95 bond ratings lower than the actual bond ratings (under predicted). The SM model has predicted 77 bond ratings higher than the actual bond ratings (over predicted) and 92 bond ratings lower than the actual bond ratings (under predicted). The SC model has predicted 80 bond ratings higher than the actual bond ratings (over predicted) and 89 bond ratings lower than the actual bond ratings (under predicted).

Table 4.18
Analyses of Predicted Ratings for Four Data Combination Models – Six Ratings

Models	Over Predicted	Under Predicted	Correctly Predicted	Percent Correct
MM	75	87	171	51.35
MC	79	95	164	47.25
SM	77	92	164	49.25
SC	80	89	164	49.25

In summary, the results of the Wilk's Lambda test – for both the fifteen and six bond rating models--suggest that the predicted probabilities are data source dependent. In contrast, the results of McNemar test--for both the fifteen and six bond rating models – did not suggest data source dependency. As previously stated the difference in test results may relate to the level of precision of the tests. That is, the Wilk's Lambda test focuses on the predicted probabilities of the bond rating while the McNemar test focuses on the bond rating category.

Cluster Analysis

The cluster analysis for this study is performed to identify the pattern of differences in the predicted probabilities of bond ratings from the two models; this is done to look for SIC Code frequencies in the resulting clusters. Because there are ten SIC Code Divisions in the sample, a ten cluster solution is sought for each of the two data source combinations (MM-MC and SM-SC). Clustering is performed first for the data source combination of MM-MC. The initial ten cluster solutions are calculated using the differences in predicted probabilities from MM model and MC model shown in Table 4.19. The variables, d1diff through d6diff, are the differences in predicted probabilities from two models with respect to six bond ratings. Initial clustering is performed by using an agglomerative hierarchical approach and Ward's minimum variance method.

Table 4.19
Initial Cluster Means (Initial Seeds) of Variables

Cluster	d1diff	d2diff	d3diff	d4diff	d5diff	D6diff
1	0.001852	0.003015	-0.003290	-0.012270	0.002638	0.008053
2	0.001225	0.004752	0.0019020	-0.001300	-0.000550	-0.006020
3	0.000738	0.006032	7.67E-05	-0.012270	-0.003420	0.008843
4	0.000434	0.009145	-0.013590	0.000884	0.008599	-0.005470
5	-0.003820	0.017139	0.005018	-0.001830	-0.006870	-0.009640
6	0.025220	-0.03984	-0.001500	0.014193	0.004778	-0.002850
7	0.025307	-0.046900	0.005791	0.021634	0.001941	-0.007780
8	-0.047030	0.039203	0.037848	-0.009980	-0.014340	-0.005700
9	-0.000840	-0.005600	0.013881	0.023371	-0.013730	-0.017080
10	-0.004890	-0.064060	-0.007010	0.060066	0.019346	-0.003450

The centroids of the ten clusters are saved as a separate data set to serve as the inputs into the second stage of the cluster analysis; these centroids are then used as the seeds for the k-means algorithm. Table 4.20 shows the mean (i.e., the centroid) of each variable for final clusters.

Table 4.20
Final Cluster Means of Variables

Cluster	FREQ	d1diff	d2diff	d3diff	d4diff	d5diff	D6diff
1	116	-0.01111	0.018914	0.033509	-0.00818	-0.01745	-0.01568
2	126	0.006966	-0.00858	0.001282	0.00683	-0.01944	0.012943
3	38	-0.00348	-0.06178	-0.05106	0.069135	0.073083	-0.0259
4	24	-0.00154	-0.03005	-0.04811	-0.07806	0.097985	0.059767
5	29	0.033101	0.117232	-0.03479	-0.05829	-0.01891	-0.03835

Table 4.21 shows the SIC Code Divisions in each cluster. The table presents the number and percentage of observations for each SIC Code in the cluster. The percentage of observations is calculated by dividing the number of observations in each cell by the total number of observations in each cluster. SIC Code Division 4 is the major component in nine of ten clusters. Thus, there is no development of meaningful clusters with respect to SIC Code Divisions. Stated otherwise, the results indicate that the clusters do not appear to be homogenous within clusters and heterogeneous between clusters with respect to SIC Code Divisions.

This clustering process is then repeated for SM and SC models. Table 4.22 shows the means of each variable for initial clusters (i.e., the initial centroids or seeds) while Table 4.23 shows the mean of each variable for final clusters (i.e., the final centroids).

Table 4.21
Table of Cluster by SIC Code

	SIC CODE DIVISIONS										
Cluster	1	2	3	4	5	6	7	8	9	10	Total
1	2	2	3	52	10	9	7	6	25	0	116
	1.72%	1.72%	2.59%	44.83%	8.62%	7.76%	6.03%	5.17%	21.55%	0.00%	34.83%
2	0	5	7	64	6	6	14	2	21	1	126
	0.00%	3.97%	5.56%	50.79%	4.76%	4.76%	11.11%	1.59%	16.67%	0.79%	37.84%
3	0	0	6	12	7	2	4	1	6	0	38
	0.00%	0.00%	15.79%	31.58%	18.42%	5.26%	10.53%	2.63%	15.79%	0.00%	11.41%
4	0	2	1	15	1	0	4	1	0	0	24
	0.00%	8.33%	4.17%	62.50%	4.17%	0.00%	16.67%	4.17%	0.00%	0.00%	7.21%
5	0	1	0	17	1	0	1	2	7	0	29
	0.00%	3.45%	0.00%	58.62%	3.45%	0.00%	3.45%	6.90%	24.14%	0.00%	8.71%
	2	10	17	160	25	17	30	12	59	1	333
Total	0.60%	3.00%	5.11%	48.05%	7.51%	5.11%	9.01%	3.60%	17.72%	0.30%	100.00%

Table 4.22
Initial Cluster Means (Initial Seeds) of Variables

CLUSTER	d1diff	d2diff	d3diff	d4diff	D5diff	d6diff
1	-0.00106	-0.00448	0.002495	0.003193	0.001166	-0.00131
2	-3.2E-05	-0.0139	0.003917	0.003958	-0.01422	0.020282
3	4.89E-05	-0.0335	0.010271	0.013168	0.010621	-0.00061
4	0.004983	-0.00206	-0.00071	0.002949	-0.00121	-0.00395
5	-0.15603	0.129375	0.018667	0.006506	0.001394	8.57E-05
6	0.009057	-0.01194	0.002383	0.002395	-4E-05	-0.00185
7	-0.00075	0.022411	-0.01031	-0.00877	0.00054	-0.00313
8	0.029831	-0.07689	0.004543	0.030101	0.011705	0.000704
9	0.001053	0.017968	0.017244	-0.00675	-0.01996	-0.00956
10	0.000753	0.001716	-0.00255	-0.00039	0.003363	-0.00289

Table 4.23
Final Cluster Means of Variables

Cluster	FREQ	d1diff	d2diff	d3diff	d4diff	d5diff	d6diff
1	275	-0.00312	-0.00398	-0.00163	0.004227	0.009302	-0.0048
2	34	0.002152	0.048473	0.055901	0.007907	-0.08822	-0.02622
3	17	0.05534	-0.04676	-0.05032	-0.05496	-0.0104	0.107098
4	7	-0.078	-0.25893	0.04598	0.101178	0.049032	0.140737

Table 4.24 shows the SIC Code Divisions in each clusters. SIC Code Division 4 is the major component in seven of ten clusters. Thus, there is no development of meaningful clusters with respect to SIC Code Divisions. Stated otherwise, the results indicate that the clusters do not appear to be homogenous within clusters and heterogeneous between clusters with respect to SIC Code Divisions.

Table 4.24
Table of Cluster by SIC Code

	SIC CODE DIVISIONS										
Cluster	1	2	3	4	5	6	7	8	9	10	Total
1	2	8	8	137	24	14	24	8	49	1	275
	0.73%	2.91%	2.91%	49.82%	8.73%	5.09%	8.73%	2.91%	17.82%	0.36%	82.58%
2	0	2	9	10	0	3	6	1	3	0	34
	0.00%	5.88%	26.47%	29.41%	0.00%	8.82%	17.65%	2.94%	8.82%	0.00%	10.21%
3	0	0	0	10	1	0	0	1	5	0	17
	0.00%	0.00%	0.00%	58.82%	5.88%	0.00%	0.00%	5.88%	29.41%	0.00%	5.11%
4	0	0	0	3	0	0	0	2	2	0	7
	0.00%	0.00%	0.00%	42.86%	0.00%	0.00%	0.00%	28.57%	28.57%	0.00%	2.10%
Total	2	10	17	160	25	17	30	12	59	1	333
	0.60%	3.00%	5.11%	48.05%	7.51%	5.11%	9.01%	3.60%	17.72%	0.30%	100.00%

Results in Terms of the Research
Question

The results of the Wilk's Lambda test suggest that the predicted probabilities of the bond ratings are data source dependent, that is, the results suggest that Compustat data do not produce the predicted probabilities for each bond ratings similar to those produced by Mergent data. In contrast, the results of the McNemar test suggest that the proportion of correct bond ratings are not data source dependent, that is, the results suggest that Compustat data may produce correct bond rating predictions similar to those produced by Mergent data.

CHAPTER 5

CONCLUSIONS

The structure of this chapter is as follows. Section 5.1 provides a summary of the study. Section 5.2 provides an overview of the results and implications of the study. Finally, a summary of the contributions, limitations and possible extensions of the study is found in Section 5.3.

Summary of the Study

I use the bond ratings classification model developed by Kamstra et al. (2001) in exploring the relationship between two sources of financial statement information (Compustat, Mergent) for independent variables, and two sources of bond ratings (Moody's, Standard and Poor's) as dependent variables (that is, four data source combinations). Ordered logit regression is the primary data analysis technique. There are five independent variables in the various bond rating classification models developed for this study: interest coverage ratio; debt ratio; return on assets ratio; assets; and subordination status. The analysis was initially performed using dependent variables comprised of fifteen bond rating categories. Thereafter, a supplemental analysis using six bond rating categories was performed in order gain additional insights as well as to better compare the results of this study to Kamstra et al. (2001).

As stated in Chapter 1, data intermediaries provide financial statement data to financial professionals and academic researchers. Prior research provides evidence that data provided by one data intermediary differs from the data provided by another data intermediary. However, no research that I am aware of has analyzed Mergent data. The divergent results in classification rates produced by Ederington (1985) and Kamstra et al. (2001), in spite of the fact that both use fairly similar models but different financial statement data, mandates evidence to address this research gap. Given the mixed results of the research to date, the following research question is addressed: Do different data sources yield models that differ considerably with respect to overall performance of bond rating classification?

The primary objective of this study is to analyze the relationship between data sources and the correct classification rates of bond rating models. I explore differences in the bond rating model predictions associated with the various data source combinations, that is, the various combinations of different bond rating data sources and different financial statement data sources. Additionally, I determine whether certain industries are associated with a specific pattern of differences in bond rating predictions. 333 bond issues are included in the analyses after all incomplete observations have been excluded as described in Chapter 3. These bonds are rated by both Moody's and Standard and Poor's.

Results and Implications

The results of the Wilk's Lambda test show that the bond ratings models using Compustat data do not produce the predicted probabilities for each bond ratings similar to those produced by the bond rating models using Mergent data. In contrast, the results of the McNemar test show that bond rating models using Compustat data may produce correct bond rating predictions similar to those produced by the bond rating models using Mergent data. As stated in Chapter 4, the difference in the test results between the Wilk's Lambda and McNemar tests may relate to the level of precision of the tests. There is a loss of information when the probabilities are converted into predicted bond ratings. Wilk's Lambda test focuses on the predicted probabilities of the bond rating while the McNemar test focuses on the bond ratings.

There are two major implications of the overall results of the study. First, the results support the concern that "analysts and researchers need to exercise great care when selecting databases and variables from those databases (Kern and Morris, 1994)." Stated otherwise, the results suggest that an association exists between data intermediaries and bond rating classification model prediction accuracy. Second, Compustat users should consider the implications of using Compustat's proprietary standardized data. Similarly, Mergent users (as well as EDGAR and Value Line users) should consider the implications of using "as reported" data. Basically, both user groups need to evaluate the merits of the alternative data provider. Stated otherwise, inconsistent predictions of bond ratings do not imply one data source is better than another, it merely implies that results are data source dependent.

Generally speaking, if a model is developed using Moody's bond ratings, then the Mergent database should be used for independent variables. Similarly, if a model is developed using S&P bond ratings, then the Compustat database should be used for independent variables. Intuitively, when using a model for decision making purposes, if the model is grounded in Mergent data, then the decision inputs should also come from the Mergent database. Similarly, when using a model for decision making purposes, if the model is grounded in Compustat data, then the decision inputs should also come from the Compustat database.

As an aside, the results of this study may also have implications for the XBRL community. XBRL (eXtensible Business Reporting Language) is a worldwide standard for the publishing, exchange, and analysis of financial reports and data. XBRL makes it easier to prepare and publish financial documents. It is an implementation of Extensible Markup Language (XML). XBRL represents a possible competitor to Compustat (as well as other data intermediaries). Given that the results of this study suggest that decision outcomes vary with the data intermediary, then the XBRL community may be able to effectively compete for consumers as a data intermediary providing "as reported" data versus a data intermediary providing "standardized data." Tie (2005) reports that Charles Hoffman, CPA (a.k.a., "The father of XBRL") states that "XBRL will significantly improve the ability of CPA financial managers to distribute information to stakeholders precisely as reported, rather than as condensed or otherwise modified by third-party data aggregators to facilitate distribution." Please see www.xbrl.org for additional information regarding XBRL capabilities.

Contributions to Literature

My study differs from previous research in several ways. First, an analysis of annual financial statement data provided by Compustat versus annual financial statement data provided by Mergent has not appeared in the literature. Previous research, such as Yang et al. (2003) and Kern and Morris (1994), address differences in annual financial statement data provided by Compustat and annual financial statement data provided by Value Line. Second, the use of a multivariate model when comparing annual financial statement data sources has not appeared in the literature. Prior research, such as Yang et al. (2003) and Kern and Morris (1994), use individual measures of financial statement data. Third, a direct comparison of the overall performance of bond rating classification models using the four data source combinations (employed in this study) has not appeared in the literature. Fourth, an analysis of comparison of the predicted probabilities generated by different models using Wilk's Lambda has not appeared in the literature. Perry (1985) uses a sign test to test whether Moody's bond ratings were more conservative (lower) that the S&P bond ratings. I lose less information by using the predicted probabilities of bond ratings rather than just the bond ratings themselves and the Wilk's Lambda test allows me to consider the vector of predicted probabilities as well as test at the individual (bond rating) level. Since the predicted probabilities of the bond ratings (where the sum of each set of probabilities is one) represent compositional data, I transformed the data in order to avoid spurious interpretations. The need to transform compositional data was not an issue in the previous literature since that research focused on bond ratings and not the predicted probabilities of the bond ratings. Finally, in addition to testing for differences in the predicted probabilities of bond ratings, I also test for differences in the correctly predicted bond ratings. While previous research has identified the extent of correct predictions, no studies of which I am aware test for significant differences in correct predictions among different models or the use of the McNemar test to consider such differences.

Limitations

I focus on bond ratings related to new bond issues in order to minimize potential influence of bond rating lag. Baker and Mansi (2002) suggest that investors would like to see ratings updated immediately to reflect all relevant information, even if a change is likely to be reversed in the near future. In addition, Howe (2001) suggests that agencies are traditionally slow to respond to changes in credit conditions. One of the possible differences in the Moody's and S&P bond ratings may be the response time each agency would take to change the ratings to reflect current credit risk.

Error persistence is also a possible limitation of this study. Unexplained differences represent "noise" (i.e., random errors). In contrast, explained differences may stem from several sources. First, annual financial statements data and Compustat data will, to varying degrees, be different due to Compustat's proprietary data standardization process. Given that Compustat fully discloses how it adjusts the various annual financial statements data, I do not consider such "explained" differences as errors. Second, annual financial statements data and Compustat data could be different due to timing differences associated with data updates. However, by selecting new bond issues for the most recent calendar years available at the time of this study, I believe that I was able to minimize the chance that data was updated by one data intermediary but not the other. Third, annual financial statements data and Compustat data could be different due to data transmission or transcription errors as well as reporting errors.

Extensions

Three possible extensions of this study are provided in this section. First, classification rates could be analyzed using recursive partitioning techniques such as

Classification and Regression Trees (CART). CART is particularly powerful because it can deal with missing data efficiently, that is, CART does not require "the elimination of whole observation vectors when even one of their elements is missing" (Feldman and Gross, 2005). Results from such techniques could triangulate (confirm) the results of this study and/or provide additional insights if differences exist. Unfortunately, there was not enough variability in the common classification rates, that is, there were not enough observations within each subgroup of the sample in this study to justify the use of the CART procedure. Second, integer programming could be used to test the equality of bond rating intervals (i.e., classes). For example, the interval associated with the Aaa bond rating may not be equal to the interval associated with the Aa bond rating. Finally, data could be analyzed from additional sources and additional years.

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APPENDIX A

COMPUSTAT DATA DESCRIPTIONS

Compustat Data Descriptions

Compustat provides "standardized" financial statement data. They standardize the data by using specific data item definitions. The proprietary data item definitions for the variables used in this study are as follows.

—

PANEL 1: Assets – Total

Mnemonic AT
Data Item Number A6
Units Millions of dollars

This item represents current assets plus net property, plant, and equipment plus other noncurrent assets (including intangible assets, deferred items and investments and advances).
Total liabilities and stockholders' equity represents current liabilities plus long-term debt plus other long-term liabilities plus stockholders' equity.

PANEL 2: Net Income

Mnemonic NI
Annual Data Item Number A172
Units Millions of dollars

This item represents the income or loss reported by a company after expenses and losses have been subtracted from all revenues and gains for the fiscal period including extraordinary items and discontinued operations.

This item, for banks, includes securities gains and losses.

PANEL 3: Interest Expense

Mnemonic XINT
Annual Data Item Number A15
Units Millions of dollars

This item represents the periodic expense to the company of securing short- and long-term debt. Where possible, this item is collected as a gross figure (for example, if interest expense is reported net by the company, interest income and/or interest capitalized will be added back to arrive at a gross figure).

This item includes

1. Amortization of debt discount or premium
2. Amortization of deferred financing costs
3. Discount on the sale of receivables of a finance subsidiary
4. Dividends/interest expense on securities of Subsidiary Trusts
5. Expenses related to the issuance of debt (such as, underwriting fees, brokerage costs, advertising costs, etc.)
6. Factoring charges (unless included in Cost of Goods Sold or Selling, General, and Administrative Expenses)
7. Financing charges
8. Interest expense net of income of unconsolidated finance subsidiaries for Retail companies
9. Interest expense on both short- and long-term debt
10. Interest expense on deferred compensation
11. Interest on tax settlements, when included with other interest expense
12. Non-debt interest expense, when it is not a Special Item
13. Underwriting fees

This item excludes

1. Interest expense on deposits for Savings and Loan companies (include in Cost of Goods Sold)
2. Interest income
3. Interest on tax settlements, when reported as a separate line item (include in Special Items)

This item may be estimated if not reported.

PANEL 4: Total Debt

Mnemonic DT
Concept Calculation DLTT+DLC
Units Millions of dollars

This concept is the sum of Total Long-Term Debt, which is defined as debt obligations due more than one year from the company's balance sheet date, plus Debt in Current Liabilities, which is defined as the total amount of short-term notes and the current portion of long-term debt (debt due in one year).

PANEL 5: Debt in Current Liabilities

Mnemonic DLC
Annual Data Item Number A34
Units Millions of dollars

This item represents the total amount of short-term notes and the current portion of long-term debt, which is also stated as Notes Payable (NP) + Debt Due in 1st Year (DD1).

This item includes

1. Bank acceptances and overdrafts
2. Loans payable to the officers of the company
3. Loans payable to stockholders
4. Loans payable to parents, and consolidated and unconsolidated subsidiaries
5. Notes payable to banks and others
6. Installments on a loan
7. Sinking fund payments
8. Brokerage companies' drafts payable

This item may include mortgage indebtedness for banks (included in Current Liabilities - Other if identifiable).

This item excludes notes payable to subsidiaries (included in Current Liabilities - Other).

PANEL 6: Long Term Debt

Mnemonic DLTT
Annual Data Item Number A9
Units Millions of dollars

The item represents debt obligations due more than one year from the company's balance sheet date.

This item includes

1. Purchase obligations and payments to officers (when listed as long-term liabilities)
2. Notes payable, due within one year and to be refunded by long-term debt when carried as a non-current liability
3. Long-term lease obligations (capitalized lease obligations)
4. Industrial revenue bonds
5. Advances to finance construction
6. Loans on insurance policies
7. Indebtedness to affiliates
8. Bonds, mortgages, and similar debt
9. All obligations that require interest payments
10. Publishing companies' royalty contracts payable
11. Timber contracts for forestry and paper
12. Extractive industries' advances for exploration and development
13. Production payments and advances for exploration and development

This item excludes

1. Subsidiary preferred stock (included in Minority Interest)
2. The current portion of long-term debt (included in Current Liabilities)
3. Accounts payable due after one year (included in Liabilities - Other)
4. Accrued interest on long-term debt (included in Liabilities - Other)
5. Customers' deposits on bottles, kegs, and cases (included in Liabilities - Other)
6. Deferred compensation

Long-term debt should be reported net of premium or discount. Standard and Poor's Compustat will collect the net figure.

APPENDIX B

SAMPLE DISTRIBUTION BY YEAR

(333 Issues; 275 Companies)

Sample Distribution By Year (333 Issues; 275 Companies)

NOTE: The 275 companies included in this study are listed in this appendix. For each company, the related new bond issues included in this study are specified by year. There are 333 new bond issues included in this study—133 in 2004, 105 in 2005, and 95 in 2006.

Name of the Company	Year	Year	Year
ABBOTT LABORATORIES	2004		2006
ACCURIDE CORP		2005	
ADESA INC	2004		
ADVANCED MICRO DEVICES	2004		
AEP INDS INC		2005	
AFFILIATED COMPUTER SVCS INC		2005	
AGCO CORP	2004		
AGRIUM INC			2006
AIR PRODS & CHEMS INC		2005	
AIRGAS INC	2004		
ALBEMARLE CORP		2005	
ALDERWOODS GROUP INC		2005	
ALERIS INTL INC		2005	
ALLERGAN INC			2006
ALLIANCE IMAGING INC		2005	
ALLIANT TECHSYSTEMS INC			2006
ALLIED WASTE NORTH AMER INC			2006
ALLIS CHALMERS CORP			2006
ALTRIA GROUP INC	2004		
AMERICAN GREETINGS CORP			2006
AMERICAN INTERNATIONAL GROUP	2004		
AMERICAN STD COS INC		2005	
AMERISOURCEBERGEN CORP		2005	
AMGEN INC	2004		
AMKOR TECHNOLOGY INC	2004		2006
ANHEUSER BUSCH COS INC	2004	2005	2006
ANIXTER INC		2005	
ARAMARK SVCS INC		2005	
ARCHER DANIELS MIDLAND CO		2005	
ARMOR HOLDINGS INC	2004		
ASBURY AUTOMOTIVE GROUP INC	2004		
ATLAS PIPELINE PARTNERS L P			
ATLAS PIPELINE FIN CORP		2005	
AUTONATION INC			2006
AUTOZONE INC			2006
AVERY DENNISON CORP	2004		

AVNET INC		2005	
AVON PRODS INC			2006
AZTAR CORP	2004		
BALL CORP			2006
BASIC ENERGY SVCS INC NEW			2006
BAXTER FINCO B V		2005	2006
BEMIS CO INC		2005	
BIO-RAD LABORATORIES INC	2004		
BLACK & DECKER CORP	2004		
BLOCKBUSTER INC			2006
BLOUNT INTL INC	2004		
BOSTON SCIENTIFIC CORP	2004	2005	2006
BOWATER INC	2004		
BOYD GAMING CORP	2004		2006
BRINKER INTL INC	2004		
BRISTOL-MYERS SQUIBB CO	2004		
BROWN SHOE INC NEW		2005	
BRUNSWICK CORP	2004		
BUILDING MATLS CORP AMER		2005	
BUNGE LTD FIN CORP		2005	
BURLINGTON NORTHERN SANTA FE	2004		
CADMUS COMMUNICATIONS CORP	2004		
CAMERON INTERNATIONAL CORP	2004		
CANADIAN NATIONAL RAILWAY CO	2004		2006
CARRIAGE SVCS INC		2005	
CASE NEW HOLLAND INC			2006
CELESTICA INC	2004		
CENTEX CORP	2004	2005	2006
CENTURY ALUM CO		2005	
CHARTERED SEMICONDUCTOR MFG LTD		2005	
CHATTEM INC	2004		
CHC HELICOPTER CORP -CL A	2004		
CHEMTURA CORPORATION			2006
CHIQUITA BRANDS INTL INC	2004	2005	
CHURCH & DWIGHT INC		2005	
CLEAR CHANNEL COMMUNICATIONS	2004		2006
CLOROX CO	2004	2005	
COCA COLA BOTTLING CO CONS		2005	
COLGATE PALMOLIVE CO		2005	
COMMERCIAL METALS	2004		
COMMERCIAL VEH GROUP INC			2006
CONSTAR INTL INC		2005	

CONVERGYS CORP	2004		
COOPER U S INC		2005	
CORNELL COMPANIES INC	2004		
CORNING INC	2004	2005	
CORRECTIONS CORP AMER		2005	2006
CROWN AMERS LLC /			
CROWN AMERS CAP CORP		2005	
CVS CORP	2004		
D R HORTON INC	2004	2005	2006
DEAN FOODS CO			2006
DELUXE CORP	2004		
DENNYS HLDGS INC		2005	
DRS TECHNOLOGIES INC			2006
EATON CORP	2004	2005	
ELI LILLY SVCS INC		2005	
ELIZABETH ARDEN INC	2004		
EMERSON ELEC CO		2005	
ESCHELON OPER CO		2005	
ETHAN ALLEN GLOBAL INC			2006
FINLAY ENTERPRISES INC	2004		
FISHER SCIENTIFIC INTL INC		2005	2006
FOREST CITY ENTERPRISES INC		2005	
FORTUNE BRANDS INC			2006
FREEPORT-MCMORAN COP&GOLD	2004		
FREESCALE SEMICONDUCTOR INC	2004		
FTI CONSULTING INC		2005	
GARDNER DENVER INC		2005	
GAYLORD ENTERTAINMENT CO	2004	2005	
GENENTECH INC		2005	
GENERAL CABLE CORP/DE	2004		
GENERAL MOTORS CORP	2004		
GENESIS HEALTHCARE CORP	2004		
GIBRALTAR INDS INC		2005	
GLATFELTER P H CO			2006
GOODYEAR TIRE & RUBR CO		2005	2006
GRANT PRIDECO INC			2006
GSC HLDGS CORP / GAMESTOP INC			2006
GTECH HOLDINGS CORP	2004		
GULFMARK OFFSHORE INC		2005	
HANGER ORTHOPEDIC GROUP INC			2006
HANOVER COMPRESSOR CO	2004		2006
HARRAHS OPER CO INC			2006
HAWK CORP		2005	
HCA INC	2004		2006

HEALTHSOUTH CORP			2006
HERCULES INC	2004		
HEWLETT PACKARD CO			2006
HEXCEL CORP		2005	
HILLENBRAND INDUSTRIES	2004		
HOME DEPOT INC	2004	2005	2006
HONEYWELL INTL INC			2006
HORNBECK OFFSHORE SVCS INC	2004		
HOVNANIAN ENTERPRISES INC		2005	
IKON OFFICE SOLUTIONS INC			2006
IMAX CORP	2004		
INTEGRATED ALARM SVCS GROUP	2004		
INTERFACE INC -CL A	2004		
INTERLINE BRANDS INC			2006
INTERNATIONAL BUSINESS MACHS CORP	2004	2005	
INTERNATIONAL LEASE FIN CORP			2006
INTERPOOL INC			2006
INTERPUBLIC GROUP OF COS	2004		
INTL PAPER CO	2004		
INTL SPEEDWAY CORP -CL A	2004		
INTRAWEST CORP	2004		
ISLE OF CAPRI CASINOS INC	2004		
JACUZZI BRANDS INC	2004		
JO-ANN STORES INC	2004		
JOHNSON CTLS INC			2006
JONES APPAREL GROUP INC		2005	
K2 INC		2005	
KB HOME	2004	2005	2006
KROGER CO	2004		
LAMAR MEDIA CORP		2005	
LAS VEGAS SANDS CORP		2005	
LEAR CORP		2005	
LEGGETT & PLATT INC		2005	
LENNAR CORP			2006
LIBBEY GLASS INC			2006
LIMITED BRANDS INC	2004		
LOWES COS INC		2005	
LUBRIZOL CORP	2004		
M / I HOMES INC		2005	
MAC GRAY CORP		2005	
MAGELLAN MIDSTREAM PRTNRS LP	2004		
MARRIOTT INTL INC		2005	2006

MASSEY ENERGY CO			2006
MATTEL INC			2006
MCCORMICK & CO INC		2005	
MCDONALD'S CORP	2004		
MEDIANEWS GROUP INC	2004		
MERCER INTL INC		2005	
MERCK & CO	2004	2005	
MGM MIRAGE	2004	2005	2006
MOHAWK INDS INC			2006
MONSANTO CO NEW		2005	
MOOG INC		2005	
MOTOROLA INC	2004		
MTR GAMING GROUP INC			2006
NAVISTAR INTERNATIONAL CORP	2004		
NBTY INC			2006
NEWMONT MNG CORP		2005	
NOBLE CORPORATION			2006
NORFOLK SOUTHERN CORP	2004	2005	
NORTHROP GRUMMAN CORP	2004		
NORTHWEST AIRLINES CORP	2004		
NOVA CHEMICALS CORP	2004		
O'CHARLEY'S INC	2004		
OMNICARE INC		2005	
OMNICOM GROUP INC			2006
OVERSEAS SHIPHOLDING GROUP	2004		
OWENS & MINOR INC			2006
OXFORD INDUSTRIES INC	2004		
PANTRY INC	2004		
PARK OHIO HOLDINGS CORP	2004	2005	
PEABODY ENERGY CORP	2004		
PENN NATIONAL GAMING INC	2004	2005	
PEP BOYS-MANNY MOE & JACK	2004		
PEPSIAMERICAS INC		2005	2006
PEPSICO INC	2004		
PFIZER INC	2004		2006
PHELPS DODGE CORP	2004		
PHI INCORPORATED			2006
PHILLIPS-VAN HEUSEN CORP	2004		
PINNACLE ENTERTAINMENT INC	2004		
PLAYTEX PRODUCTS INC	2004		
PORTOLA PACKAGING INC	2004		
PROCTER & GAMBLE CO	2004	2005	2006
PSYCHIATRIC SOLUTIONS INC		2005	
PULTE HOMES INC			2006

QUEST DIAGNOSTICS INC		2005	
R H DONNELLEY CORP		2005	2006
REPUBLIC SVCS INC		2005	
RES CARE INC		2005	
REVLON CONSUMER PRODS CORP		2005	
REYNOLDS AMERN INC			2006
RITE AID CORP		2005	
RPM INTERNATIONAL INC	2004		
RUSSEL METALS INC	2004		
RYLAND GROUP INC		2005	2006
SABRE HLDGS CORP			2006
SAFEWAY INC	2004		2006
SAMSONITE CORP	2004		
SANMINA – SCI CORP		2005	2006
SCIENTIFIC GAMES CORP		2005	
SERVICE CORP INTERNATIONAL	2004	2005	
SLM CORP	2004	2005	
SMITH INTL INC			2006
SMITHFIELD FOODS INC	2004		
SOLECTRON CORP	2004		
SONOCO PRODUCTS CO	2004		
SOUTHERN COPPER CORP		2005	2006
SOUTHWEST AIRLINES	2004	2005	
STANDARD PACIFIC CP	2004		
STATER BROS HOLDINGS INC	2004		
STATION CASINOS INC	2004		2006
STATS CHIPPAC LTD -ADR	2004		
STEEL DYNAMICS INC	2004		
STEINWAY MUSICAL INSTR INC			2006
STEWART ENTERPRISES INC		2005	2006
SYSCO CORP	2004	2005	
TECHNICAL OLYMPIC USA INC			2006
TENET HEALTHCARE CORP	2004	2005	
TENNECO AUTOMOTIVE INC		2005	
TEREX CORP	2004		
TEVA PHARMACEUTICAL FIN LLC			2006
TEXTRON INC	2004	2005	2006
THERMADYNE HOLDINGS CORP	2004		
THERMO ELECTRON CORP		2005	
THOMSON CORP	2004		
TRAILER BRDG INC		2005	
TRANSCANADA PIPELINES LTD			2006
TRANSDIGM INC			2006
TRINITY INDUSTRIES	2004		

TYSON FOODS INC			2006
U S CONCRETE INC	2004		2006
UNIFI INC			2006
UNION PACIFIC CORP	2004		
UNISYS CORP		2005	
UNITED PARCEL SERVICE INC	2004		
UNITED RENTALS INC	2004		
UNITED TECHNOLOGIES CORP			2006
UNITEDHEALTH GROUP INC	2004		
UNIVERSAL CORP/VA	2004		
UNIVERSAL HEALTH SVCS INC			2006
VAIL RESORTS INC	2004		
VALEANT PHARMACEUTICALS INTL	2004		
VALMONT INDUSTRIES	2004		
VALSPAR CORP		2005	2006
VISTEON CORP	2004		
WAL MART STORES INC	2004	2005	2006
WASTE MANAGEMENT INC	2004		
WCA WASTE CORP			2006
WESTLAKE CHEM CORP			2006
WHIRLPOOL CORP			2006
WILLIAMS PARTNERS L P / WILLIAMS PARTNERS FIN CORP			2006
WYETH		2005	
XEROX CORP			2006
YUM BRANDS INC			2006
Total Issues by Year (Overall Total = 333)	133	105	95

APPENDIX C

INDIVIDUAL NEW BOND ISSUE MISCLASSIFICATIONS

(MOODY'S RATINGS WITH 15 CATEGORIES)

Individual New Bond Issue Misclassifications (Moody's Ratings with15 Categories)

NOTE: Number in each cell under the various data source combination models represents "Actual Ratings, Predicted Ratings." Ratings of Caa1 and below or CCC+ and below were assigned a value of 0; B3 or B- a value of 1; B2 or B a value of 2; B1 or B+ a value of 3; Ba3 or BB- a value of 4; Ba2 or BB a value of 5; Ba1 or BB+ a value of 6; Baa3 or BBB- a value of 7; Baa2 or BBB a value of 8; Baa1 or BBB+ a value of 9; A3 or A- a value of 10; A2 or Aa value of 11; A1 or A+ a value of 12; Aa3 or AA- a value of 13; Aa2 and above or AA and above a value of 14.

Name of the New Bond Issue	Year	MC	MM	SQMM	SQMC
ABBOTT LABORATORIES	2004	12,11	12,11		12,11
ABBOTT LABS	2006	12,11	12,11		
ADESA INC	2004	3,4	3,4	3,4	3,4
ADVANCED MICRO DEVICES	2004			3,4	3,4
AEP INDS INC	2005	2,1	2,3	2,1	2,1
AFFILIATED COMPUTER SVCS INC	2005	7,11	7,11	7,8	7,11
AIR PRODS & CHEMS INC	2005	11,8	11,8	11,8	11,8
AIRGAS INC	2004	5,1	5,1	5,3	5,1
ALBEMARLE CORP	2005	7,4	7,3	7,4	7,4
ALDERWOODS GROUP INC	2005	2,5	2,4	2,4	2,4
ALERIS INTL INC	2005	1,3	1,3	1,3	1,3
ALLERGAN INC	2006	10,11	10,11	10,8	10,8
ALLIANCE IMAGING INC	2005	1,0	1,0	1,0	1,0
ALLIANT TECHSYSTEMS INC	2006	2,1	2,3	2,3	2,3
ALLIED WASTE NORTH AMER INC	2006	2,3	2,3	2,5	2,5
ALLIS CHALMERS CORP	2006	1,4	1,4	1,3	1,3
ALTRIA GROUP INC	2004	10,13	10,13	10,13	10,13
AMERICAN GREETINGS CORP	2006	5,8			
AMERICAN INTERNATIONAL GROUP	2004	12,13	12,5	12,8	12,13
AMERICAN STD COS INC	2005	7,8	7,8	7,8	7,8
AMERISOURCEBERGEN CORP	2005	6,8	6,8	6,8	6,8
AMGEN INC	2004	11,13			11,12
AMKOR TECHNOLOGY INC	2006	0,1	0,1	0,1	0,1
ANHEUSER BUSCH COS INC	2005	12,8	12,8	12,8	12,8
ANHEUSER BUSCH COS INC	2006	12,8	12,8	12,8	12,8
ANHEUSER-BUSCH COS INC	2004	12,8	12,8	12,8	12,8
ANIXTER INC	2005	6,8	6,5	6,4	6,5

ARAMARK SVCS INC	2005	7,5	7,5	7,5	7,5
ARCHER DANIELS MIDLAND CO	2005	11,8	11,8	11,8	11,8
ARMOR HOLDINGS INC	2004	3,1	3,1	3,1	3,1
ATLAS PIPELINE PARTNERS L P ATLAS PIPELINE FIN CORP	2005	3,8	3,8	3,5	3,5
AUTONATION INC	2006	5,8	5,8	5,8	5,8
AVERY DENNISON CORP	2004	10,8	10,8	10,8	10,8
AVON PRODS INC	2006				11,8
AZTAR CORP	2004	4,1	4,1	4,1	4,1
BASIC ENERGY SVCS INC NEW	2006	3,8	3,8	3,5	3,5
BAXTER FINCO B V	2006	9,8	9,8	9,8	9,8
BAXTER INTL INC	2005	9,8	9,8	9,8	9,8
BEMIS CO INC	2005	9,8	9,8	9,7	9,8
BIO-RAD LABORATORIES INC	2004	4,3	4,3	4,3	4,3
BLOUNT INTL INC	2004	1,0	1,0	1,0	1,0
BOSTON SCIENTIFIC CORP	2004	10,8	10,8	10,8	10,8
BOSTON SCIENTIFIC CORP	2005	9,11	9,11	9,11	9,11
BOSTON SCIENTIFIC CORP	2006	7,8	7,8	7,8	7,8
BOWATER INC	2004	4,3	4,3	4,3	4,3
BOYD GAMING CORP	2004	3,1	3,1	3,1	3,1
BOYD GAMING CORP	2006	3,1	3,1	3,1	3,1
BRISTOL-MYERS SQUIBB CO	2004	12,8	12,11	12,11	12,11
BROWN SHOE INC NEW	2005	3,8	3,8	3,5	3,5
BRUNSWICK CORP	2004	9,8	9,8	9,5	9,7
BUILDING MATLS CORP AMER	2005	2,8	2,8	2,5	2,5
CADMUS COMMUNICATIONS CORP	2004	2,0	2,0	2,0	2,0
CAMERON INTERNATIONAL CORP	2004	9,8	9,8	9,5	9,8
CANADIAN NATIONAL RAILWAY CO	2004	10,8	10,8	10,8	10,8
CANADIAN NATL RY CO	2006	10,8	10,8	10.11	10,8
CARRIAGE SVCS INC	2005	2,3	2,3	2,3	2,3
CASE NEW HOLLAND INC	2006	4,8	4,8	4,8	4,8
CELESTICA INC	2004	2,1	2,1	2,3	2,1
CENTEX CORP	2004		8,4	8,5	
CENTEX CORP	2005		8,5		
CENTEX CORP	2006		8,4		
CENTURY ALUM CO	2005	3,5	3,4	3,4	3,4
CHARTERED SEMICONDUCTOR MFG LTD	2005	7,4	7,3	7,4	7,4
CHATTEM INC	2004	2,1	2,1	2,1	2,1
CHC HELICOPTER CORP -CL A	2004	2,1	2,3	2,1	2,1

CHEMTURA CORPORATION	2006	6,3	6,3	6,3	6,4
CHIQUITA BRANDS INTL INC	2004	1,8	1,8	1,5	1,5
CHIQUITA BRANDS INTL INC	2005	1,8	1,5	1,4	1,5
CHURCH & DWIGHT INC	2005	4,1	4,1	4,1	4,1
CLEAR CHANNEL COMMUNICATIONS	2004	7,8	7,8	7,11	7,8
CLEAR CHANNEL COMMUNICATIONS INC	2006	7,8	7,8	7,8	7,8
CLOROX CO	2005	10,11	10,11	10,8	10,8
CLOROX CO/DE	2004	10,11	10,8	10,8	10,8
COCA COLA BOTTLING CO CONS	2005	8,3	8,3	8,1	8,1
COLGATE PALMOLIVE CO	2005	13,8	13,8	13,8	13,8
COMMERCIAL METALS	2004			8,5	8,5
COMMERCIAL VEH GROUP INC	2006	4,8	4,8	4,5	
CONVERGYS CORP	2004	8,11			
COOPER U S INC	2005	11,8	11,8	11,8	11,8
CORNELL COMPANIES INC	2004	1,3	1,3		
CORNING INC	2004	7,4	7,4	7,5	7,5
CORNING INC	2005	7,1	7,1	7,1	7,1
CORRECTIONS CORP AMER	2005	4,3	4,3	4,3	4,3
CORRECTIONS CORP AMER	2006	4,3	4,3	4,3	4,3
CROWN AMERS LLC / CROWN AMERS CAP CORP	2005			3,4	3,4
D R HORTON INC	2004	6,8	6,8	6,8	6,8
D R HORTON INC	2005	7,8	7,8	7,8	7,8
D R HORTON INC	2006	7,8	7,8	7,8	7,8
DEAN FOODS CO	2006	5,3	5,4		
DELUXE CORP	2004	7,8	7,13	7,11	7,8
EATON CORP	2004	11,8	11,8	11,8	11,8
EATON CORP	2005	11,8	11,8	11,8	11,8
ELI LILLY SVCS INC	2005	13,8	13,8	13,11	13,11
ELIZABETH ARDEN INC	2004	2,1	2,1	2,1	2,1
EMERSON ELEC CO	2005	11,8	11,8	11,8	11,8
ETHAN ALLEN GLOBAL INC	2006	8,13	8,11		8,12
FINLAY ENTERPRISES INC	2004	1,4	1,3	1,3	1,3
FISHER SCIENTIFIC INTL INC	2005	5,3	5,3	5,4	5,4
FISHER SCIENTIFIC INTL INC	2006	5,3	5,3	5,4	5,4
FOREST CITY ENTERPRISES INC	2005	4,1	4,1	4,3	4,3
FORTUNE BRANDS INC	2006	8,5			
FREEPORT-MCMORAN COP&GOLD	2004	2,3	2,4	2,4	2,4
FREESCALE SEMICONDUCTOR INC	2004	6,5	6,3	6,3	6,4

FTI CONSULTING INC	2005	5,8	5,8		
GARDNER DENVER INC	2005	2,3	2,3	2,1	2,1
GAYLORD ENTERTAINMENT CO	2004	1,5	1,4	1,4	1,4
GAYLORD ENTMT CO	2005	1,4	1,3	1,3	1,4
GENENTECH INC	2005	12,13	12,8	12,8	12,13
GENERAL CABLE CORP/DE	2004	2,3	2,3	2,3	2,3
GENERAL MOTORS CORP	2004	0,13	0,13	0,14	0,13
GENESIS HEALTHCARE CORP	2004	2,1	2,1	2,1	2,1
GIBRALTAR INDS INC	2005	4,3	4,3	4,3	4,3
GLATFELTER P H CO	2006	6,8	6,5	6,4	6,5
GOODYEAR TIRE & RUBR CO	2005	1,5	1,5	1,8	1,8
GOODYEAR TIRE & RUBR CO	2006	1,5	1,5	1,8	1,8
GRANT PRIDECO INC	2006	6,8	6,8	6,8	6,8
GSC HLDGS CORP / GAMESTOP INC	2006	4,5	4,8	4,8	
GTECH HOLDINGS CORP	2004	7,8	7,8	7,8	7,5
GULFMARK OFFSHORE INC	2005	2,3	2,3	2,1	2,1
HANGER ORTHOPEDIC GROUP INC	2006	1,3	1,3		
HANOVER COMPRESSOR CO	2006	1,3			1,3
HARRAHS OPER CO INC	2006	7,3	7,4	7,8	7,5
HAWK CORP	2005	2,3	2,3	2,1	2,1
HCA INC	2004	5,8	5,8	5,8	5,8
HCA INC	2006		5,8	5,8	5,8
HEALTHSOUTH CORP	2006	1,0	1,0	1,0	1,0
HERCULES INC	2004	4,1	4,1	4,1	4,1
HEWLETT PACKARD CO	2006	10,13	10,13	10,13	10,13
HILLENBRAND INDUSTRIES	2004	10,8	10,8	10,8	10,8
HONEYWELL INTL INC	2006	11,8			
HORNBECK OFFSHORE SVCS INC	2004	4,3	4,3	4,1	4,1
HOVNANIAN ENTERPRISES INC	2005	4,8	4,8	4,8	4,5
INTEGRATED ALARM SVCS GROUP	2004	1,3			
INTERFACE INC -CL A	2004	0,1	0,1	0,1	0,1
INTERNATIONAL BUSINESS MACHS CORP	2005	12,13	12,13	12,14	12,13
INTERNATIONAL LEASE FIN CORP	2006	12,4	12,5	12,8	12,8
INTERPOOL INC	2006	2,1	2,3	2,3	2,1
INTERPUBLIC GROUP OF COS	2004	6,5	6,4	6,5	6,5
INTL BUSINESS MACHINES CORP	2004	12,13	12,13	12,13	12,13
INTL PAPER CO	2004	7,5	7,8	7,8	7,8
INTRAWEST CORP	2004			3,4	3,4
ISLE OF CAPRI CASINOS INC	2004	2,1	2,1	2,1	2,1
JACUZZI BRANDS INC	2004	2,3	2,3	2,1	2,3

JO-ANN STORES INC	2004	1,3	1,3	1,3	1,3
JOHNSON CTLS INC	2006	9,8	9,8	9,8	9,8
K2 INC	2005	3,5	3,5	3,4	3,4
KB HOME	2004	6,8	6,8	6,8	6,8
KB HOME	2005	6,8	6,8	6,8	6,8
KB HOME	2006	6,8	6,8	6,8	6,8
KROGER CO	2004	8,5			
LAMAR MEDIA CORP	2005	4,1	4,1	4,1	4,1
LAS VEGAS SANDS CORP	2005	3,8	3,8	3,8	3,8
LEAR CORP	2005	2,8	2,8	2,8	2,8
LEGGETT & PLATT INC	2005	11,8	11,8	11,8	11,8
LIBBEY GLASS INC	2006	2,3	2,1	2,1	2,1
LOWES COS INC	2005	11,8			
LUBRIZOL CORP	2004	7,8	7,8	7,5	7,5
M / I HOMES INC	2005	5,8	5,8		
MAC GRAY CORP	2005	3,4	3,4		
MAGELLAN MIDSTREAM PRTNRS LP	2004	7,4	7,5	7,4	7,4
MCCORMICK & CO INC	2005	11,8	11,8	11,8	11,8
MCDONALD'S CORP	2004	11,8	11,8	11,8	11,8
MEDIANEWS GROUP INC	2004	2,1	2,1	2,1	2,1
MERCER INTL INC	2005	0,1	0,1	0,1	0,1
MGM MIRAGE	2004	5,3	5,3	5,8	5,4
MGM MIRAGE INC	2005	5,3	5,4		
MGM MIRAGE INC	2006	5,3	5,4		
MOHAWK INDS INC	2006	7,5	7,5	7,5	7,5
MONSANTO CO NEW	2005	9,8	9,8	9,8	9,8
MOOG INC	2005	4,3	4,3	4,3	4,3
NAVISTAR INTERNATIONAL CORP	2004			3,4	3,4
NEWMONT MNG CORP	2005	9,8	9,8	9,8	9,8
NOBLE CORPORATION	2006	9,8	9,8	9,8	9,8
NORFOLK SOUTHERN CORP	2004	9,5	9,8	9,8	9,8
NORFOLK SOUTHN CORP	2005	9,8	9,8	9,8	9,8
NORTHROP GRUMMAN CORP	2004			8,11	8,11
NORTHWEST AIRLINES CORP	2004	0,3	0,3	0,5	0,5
NOVA CHEMICALS CORP	2004		5,4	5,4	5,4
O'CHARLEY'S INC	2004	4,1	4,1	4,1	4,1
OMNICARE INC	2005	4,3	4,3		4,3
OMNICOM GROUP INC	2006	9,8	9,8	9,8	9,8
OVERSEAS SHIPHOLDING GROUP	2004	6,5	6,5	6,4	6,4
OWENS & MINOR INC	2006	5,8	5,8		

OXFORD INDUSTRIES INC	2004	3,5	3,5	3,4	3,4
PARK OHIO HOLDINGS CORP	2004	0,1	0,1	0,1	0,1
PARK OHIO INDS INC OHIO	2005	0,1	0,1	0,1	0,1
PEABODY ENERGY CORP	2004	4,5	4,5	4,5	4,5
PENN NATIONAL GAMING INC	2004	4,1	4,1	4,1	4,1
PENN NATL GAMING INC	2005	3,1	3,1	3,1	3,1
PEPSIAMERICAS INC	2005	9,8	9,5	9,5	9,5
PEPSIAMERICAS INC	2006	9,5	9,5	9,5	9,5
PEPSICO INC	2004			13,12	13,12
PHELPS DODGE CORP	2004	8,5	8,5	8,5	8,5
PHILLIPS-VAN HEUSEN CORP	2004	3,5	3,4		3,4
PINNACLE ENTERTAINMENT INC	2004	0,1	0,1		0,1
PLAYTEX PRODUCTS INC	2004	2,1	2,1	2,1	2,1
PORTOLA PACKAGING INC	2004	0,1	0,1	0,1	0,1
PROCTER & GAMBLE CO	2004	13,11			
PROCTER & GAMBLE CO	2005	13,11			
PULTE HOMES INC	2006	7,8	7,8	7,11	7,8
R H DONNELLEY CORP	2005	0,1	0,1	0,1	0,1
R H DONNELLEY CORP	2006	0,1	0,1	0,1	0,1
REPUBLIC SVCS INC	2005		8,5	8,5	8,5
RES CARE INC	2005	3,4	3,5		
REYNOLDS AMERN INC	2006	5,8	5,8	5,8	5,8
RITE AID CORP	2005	2,3	2,4	2,5	2,4
RPM INTERNATIONAL INC	2004	7,5	7,5	7,5	7,4
RUSSEL METALS INC	2004			5,3	5,4
RYLAND GROUP INC	2005	7,8	7,8	7,8	7,8
RYLAND GROUP INC	2006	7,8	7,8	7,8	7,8
SABRE HLDGS CORP	2006	7,8	7,8	7,8	7,8
SAFEWAY INC	2004	8,3	8,3	8,5	8,5
SAFEWAY INC	2006	8,5	8,5		
SANMINA - SCI CORP	2006	3,1	3,0	3,1	3,1
SANMINA CORP	2005				3,4
SCIENTIFIC GAMES CORP	2005	3,1	3,1	3,1	3,1
SERVICE CORP INTERNATIONAL	2004	4,8	4,8	4,8	4,8
SERVICE CORP INTERNATIONAL	2005	4,8	4,8	4,8	4,8
SLM CORP	2004	11,5	11,8		11,8
SLM CORP	2005	11,3			11,8
SMITH INTL INC	2006	9,8	9,8	9,8	9,8
SOLECTRON CORP	2004	2,1	2,1	2,3	2,3
SONOCO PRODUCTS CO	2004	10,8	10,8	10,5	10,5
SOUTHERN COPPER CORP	2005	6,13	6,13	6,11	6,11

SOUTHERN COPPER CORP	2006	6,13	6,13	6,12	6,11
SOUTHWEST AIRLINES	2004	9,8	9,8	9,8	9,8
SOUTHWEST AIRLINES	2005	9,8	9,8	9,8	9,8
STATER BROS HOLDINGS INC	2004	3,1	3,1	3,1	3,1
STATION CASINOS INC	2004	4,1	4,1	4,1	4,1
STATION CASINOS INC	2006	3,1	3,1	3,1	3,1
STATS CHIPPAC LTD -ADR	2004	5,3	5,3	5,3	5,3
STEEL DYNAMICS INC	2004	5,3	5,3	5,3	5,3
STEINWAY MUSICAL INSTR INC	2006	4,3	4,3	4,3	4,3
STEWART ENTERPRISES INC	2005	3,8	3,5	3,4	3,5
SYSCO CORP	2004	12,8	12,8	12,8	12,8
SYSCO CORP	2005	12,8	12,8	12,11	12,8
TECHNICAL OLYMPIC USA INC	2006	4,8	4,8	4,5	4,5
TENET HEALTHCARE CORP	2004			1,3	1,3
TEREX CORP	2004	0,1	0,1	0,1	0,1
TEVA PHARMACEUTICAL FIN LLC	2006	8,11		8,11	8,11
TEXTRON FINL CORP	2005	10,8	10,5	10,8	10,8
TEXTRON FINL CORP	2006	10,5	10,3	10,4	10,8
TEXTRON INC	2004	10,5	10,3	10,3	10,8
THERMADYNE HOLDINGS CORP	2004	0,13	0,1	0,1	0,13
THERMO ELECTRON CORP	2005	9,11	9,8	9,8	9,8
THOMSON CORP	2004	10,8	10,8	10,8	10,8
TRANSCANADA PIPELINES LTD	2006	11,5	11,8	11,8	11,8
TRINITY INDUSTRIES	2004	4,5			
TYSON FOODS INC	2006	6,8	6,5	6,8	6,8
UNIFI INC	2006	0,3	0,1	0,1	0,1
UNION PACIFIC CORP	2004			8,11	8,11
UNISYS CORP	2005	4,8	4,5	4,5	4,5
UNITED PARCEL SERVICE INC	2004	13,11	13,11	13,12	13,12
UNITED RENTALS INC	2004	3,1	3,1	3,1	3,1
UNITED TECHNOLOGIES CORP	2006			11,12	11,12
UNIVERSAL CORP/VA	2004	7,5	7,5	7,4	7,4
UNIVERSAL HEALTH SVCS INC	2006	7,8	7,8	7,8	7,8
VAIL RESORTS INC	2004	2,1	2,1	2,1	2,1
VALEANT PHARMACEUTICALS INTL	2004	3,1	3,1	3,1	3,1
VALMONT INDUSTRIES	2004	4,3	4,3	4,3	4,3
VALSPAR CORP	2005			8,5	8,5
VALSPAR CORP	2006			8,5	8,5
VISTEON CORP	2004	5,3	5,3	5,3	5,4
WASTE MANAGEMENT INC	2004	7,5	7,8	7,8	7,8

WCA WASTE CORP	2006	2,1	2,1	2,1	2,1
WESTLAKE CHEM CORP	2006	5,8	5,8	5,8	5,8
WILLIAMS PARTNERS L P / WILLIAMS PARTNERS FIN CORP	2006	4,8	4,8	4,8	4,8
WYETH	2005	9,8	9,8	9,11	9,11
XEROX CORP	2006	5,8	5,8	5,8	5,8
YUM BRANDS INC	2006	7,8	7,8	7,8	7,8

APPENDIX D

NEW BOND ISSUE MISCLASSIFICATIONS

(S&P RATINGS FOR 15 CATEGORIES)

New Bond Issue Misclassifications
(S&P Ratings—15 Categories)

NOTE: Number in each cell under the various data source combination models represents "Actual Ratings, Predicted Ratings." Ratings of Caa1 and below or CCC+ and below were assigned a value of 0; B3 or B- a value of 1; B2 or B a value of 2; B1 or B+ a value of 3; Ba3 or BB- a value of 4; Ba2 or BB a value of 5; Ba1 or BB+ a value of 6; Baa3 or BBB- a value of 7; Baa2 or BBB a value of 8; Baa1 or BBB+ a value of 9; A3 or A- a value of 10; A2 or Aa value of 11; A1 or A+ a value of 12; Aa3 or AA- a value of 13; Aa2 and above or AA and above a value of 14.

Name of the New Bond Issue	Year	SM	SC	LOGSC	LOGSM
AMERICAN GREETINGS CORP	2006	6,7	6,8	6,4	6,4
AMERICAN INTERNATIONAL GROUP	2004	13,3		13,14	13,8
AMERICAN STD COS INC	2005	7,8	7,8	7,8	7,8
AMERISOURCEBERGEN CORP	2005	7,8	7,8	7,8	7,8
AMGEN INC	2004	12,11	12,13	12,11	
AMKOR TECHNOLOGY INC	2004	0,2	0,2	0,2	0,2
AMKOR TECHNOLOGY INC	2006	0,2	0,2	0,2	0,2
ANHEUSER BUSCH COS INC	2005	12,8	12,8	12,11	12,11
ANHEUSER BUSCH COS INC	2006	12,8	12,8	12,8	12,11
ANHEUSER-BUSCH COS INC	2004	12,8	12,8	12,11	12,11
ANIXTER INC	2005	6,7	6,7	6,4	6,4
ARAMARK SVCS INC	2005		7,3		
ARCHER DANIELS MIDLAND CO	2005	11,8	11,8	11,8	
ARMOR HOLDINGS INC	2004	3,2	3,2	3,2	3,2
ATLAS PIPELINE PARTNERS L P ATLAS PIPELINE FIN CORP	2005	3,8	3,8	3,2	3,2
AUTONATION INC	2006	6,8	6,8	6,8	6,8
AUTOZONE INC	2006	9,8	9,8	9,8	9,8
AVERY DENNISON CORP	2004	10,8	10,8	10,8	10,8
AZTAR CORP	2004	3,2	3,2	3,2	3,2
BALL CORP	2006	5,7	5,7	5,7	5,7
BASIC ENERGY SVCS INC NEW	2006	2,8	2,8	2,3	2,3
BAXTER FINCO B V	2006	10,8	10,8	10,11	10,11
BAXTER INTL INC	2005	10,7	10,8	10,8	10,8
BEMIS CO INC	2005	11,8	11,8	11,8	11,7
BIO-RAD LABORATORIES INC	2004	4,3	4,3	4,2	4,3
BLOUNT INTL INC	2004	2,0	2,0	2,0	2,0
BOSTON SCIENTIFIC CORP	2004	11,8	11,8	11,8	11,8
BOSTON SCIENTIFIC CORP	2005	9,11	9,11	9,11	9,11

BOSTON SCIENTIFIC CORP	2006	9,8	9,8	9,8	9,8
BOWATER INC	2004	3,2			
BOYD GAMING CORP	2004	3,2	3,2	3,2	3,2
BOYD GAMING CORP	2006	3,2	3,2	3,2	3,2
BRINKER INTL INC	2004			8,7	8,7
BRISTOL-MYERS SQUIBB CO	2004	12,11	12,11	12,11	12,11
BROWN SHOE INC NEW	2005	4,8	4,8	4,3	
BRUNSWICK CORP	2004	9,7	9,8	9,7	9,7
BUILDING MATLS CORP AMER	2005	3,7	3,7		
BURLINGTON NORTHERN SANTA FE	2004	9,8	9,8	9,11	9,11
CADMUS COMMUNICATIONS CORP	2004	2,0	2,0	2,0	2,0
CAMERON INTERNATIONAL CORP	2004	9,8	9,8	9,7	9,4
CANADIAN NATIONAL RAILWAY	2004	10,8	10,8	10,8	10,8
CANADIAN NATL RY CO	2006	10,8	10,8	10,11	10,11
CARRIAGE SVCS INC	2005	1,3	1,3	1,2	1,2
CASE NEW HOLLAND INC	2006	4,7	4,8	4,8	4,8
CELESTICA INC	2004				2,3
CENTEX CORP	2004	8,3			
CENTEX CORP	2005	8,3			
CENTEX CORP	2006	8,3		8,11	
CENTURY ALUM CO	2005	4,3	4,3	4,3	4,3
CHARTERED SEMICONDUCTOR MFG LTD	2005	7,3	7,3	7,4	7,3
CHATTEM INC	2004			2,1	2,1
CHEMTURA CORPORATION	2006	6,3	6,3	6,3	6,3
CHIQUITA BRANDS INTL INC	2004	1,8	1,7	1,4	1,4
CHIQUITA BRANDS INTL INC	2005	1,7	1,7	1,4	1,4
CHURCH & DWIGHT INC	2005	3,2	3,2	3,2	3,2
CLEAR CHANNEL COMMUNICATIONS	2004	7,8	7,8	7,11	7,11
CLEAR CHANNEL COMMUNICATIONS INC	2006	7,8	7,8	7,8	7,8
CLOROX CO	2005	10,11	10,11	10,11	10,11
CLOROX CO/DE	2004	10,11	10,11	10,11	10,11
COCA COLA BOTTLING CO CONS	2005	8,2	8,2	8,2	8,2
COLGATE PALMOLIVE CO	2005	13,11	13,8	13,11	13,11
COMMERCIAL METALS	2004			8,7	8,7
COMMERCIAL VEH GROUP INC	2006	3,8	3,7		

CONSTAR INTL INC	2005	0,2	0,2	0,2	0,2
CONVERGYS CORP	2004	8,11	8,11		
COOPER U S INC	2005	10,8	10,8	10,8	10,8
CORNELL COMPANIES INC	2004	0,2	0,2	0,2	0,2
CORNING INC	2004	8,3	8,3	8,7	8,7
CORNING INC	2005	7,0	7,2	7,2	7,2
CORRECTIONS CORP AMER	2005	4,3	4,3	4,3	4,3
CORRECTIONS CORP AMER	2006	4,3	4,3	4,3	4,3
CROWN AMERS LLC / CROWN AMERS CAP CORP	2005	2,3	2,3	2,7	2,4
CVS CORP	2004	9,11	9,11	9,11	9,11
D R HORTON INC	2004	6,8	6,7	6,8	6,8
D R HORTON INC	2005	7,8	7,8	7,8	7,11
D R HORTON INC	2006	7,11	7,8	7,11	7,11
DEAN FOODS CO	2006	4,3	4,3	4,7	4,7
DELUXE CORP	2004	7,13	7,8		7,11
EATON CORP	2004	11,8	11,8	11,8	11,8
EATON CORP	2005	11,8	11,8	11,8	11,8
ELI LILLY SVCS INC	2005	13,11	13,11	14,11	14,11
ELIZABETH ARDEN INC	2004	1,2	1,2		1,2
EMERSON ELEC CO	2005	11,8	11,8		
ESCHELON OPER CO	2005	0,2	0,2		0,1
ETHAN ALLEN GLOBAL INC	2006	10,11	10,13	10,11	10,7
FINLAY ENTERPRISES INC	2004	1,3	1,3	1,2	1,2
FISHER SCIENTIFIC INTL INC	2005	6,2	6,2	6,4	6,4
FISHER SCIENTIFIC INTL INC	2006	6,3	6,3	6,4	6,4
FOREST CITY ENTERPRISES INC	2005	4,2	4,2	4,3	4,3
FORTUNE BRANDS INC	2006	8,7	8,7		
FREEPORT-MCMORAN COP&GOLD	2004	2,3	2,3	2,4	2,4
FREESCALE SEMICONDUCTOR INC	2004	7,3	7,3	7,4	7,3
FTI CONSULTING INC	2005	3,8	3,8		
GAYLORD ENTERTAINMENT CO	2004	1,3	1,3	1,3	1,3
GAYLORD ENTERTAINMENT CO	2005	1,3	1,3	1,3	1,3
GENENTECH INC	2005	12,11	12,13	12,14	12,11
GENERAL CABLE CORP/DE	2004	2,3	2,3		
GENERAL MOTORS CORP	2004	1,13	1,13	1,12	1,11
GIBRALTAR INDS INC	2005	3,2	3,2	3,2	3,2
GLATFELTER P H CO	2006	6,7	6,7	6,3	6,3
GOODYEAR TIRE & RUBR CO	2005	1,7	1,7	1,8	1,8

GOODYEAR TIRE & RUBR CO	2006	1,7	1,7	1,8	1,8
GRANT PRIDECO INC	2006	5,11	5,8	5,8	5,8
GSC HLDGS CORP / GAMESTOP INC	2006	3,8		3,4	3,4
GTECH HOLDINGS CORP	2004		8,7	8,7	8,7
GULFMARK OFFSHORE INC	2005			3,2	3,2
HANGER ORTHOPEDIC GROUP INC	2006	0,3	0,2	0,2	0,2
HANOVER COMPRESSOR CO	2006			2,3	
HARRAHS OPER CO INC	2006	7,3	7,3	7,8	7,8
HAWK CORP	2005			2,1	2,1
HCA INC	2004	6,8	6,8	6,8	6,11
HCA INC	2006	6,8	6,8	6,8	6,8
HEALTHSOUTH CORP	2006			0,1	
HERCULES INC	2004	3,2	3,2	3,2	3,2
HEWLETT PACKARD CO	2006	10,11	10,13	10,12	10,11
HEXCEL CORP	2005			2,1	
HILLENBRAND INDUSTRIES	2004	11,8	11,8	11,8	11,8
HOME DEPOT INC	2005			13,14	13,14
HORNBECK OFFSHORE SVCS INC	2004	4,2	4,2	4,2	4,2
HOVNANIAN ENTERPRISES INC	2005	2,8	2,7	2,7	2,8
IKON OFFICE SOLUTIONS INC	2006	5,3	5,3	5,4	5,4
IMAX CORP	2004	1,2	1,2	1,0	1,0
INTEGRATED ALARM SVCS GROUP	2004	1,2	1,3		1,0
INTERFACE INC -CL A	2004			0,1	
INTERNATIONAL LEASE FIN CORP	2006	13,3	13,8	13,8	13,8
INTERPOOL INC	2006	3,2	3,2		
INTERPUBLIC GROUP OF COS	2004	4,3	4,7	4,8	4,7
INTL BUSINESS MACHINES CORP	2004	12,13	12,13	12,14	12,14
INTL BUSINESS MACHINES CORP	2005	12,13	12,13	12,14	12,14
INTL SPEEDWAY CORP -CL A	2004	7,8	7,8		
ISLE OF CAPRI CASINOS INC	2004		2,0		
JACUZZI BRANDS INC	2004		2,3		
JO-ANN STORES INC	2004	2,3	2,3		
JOHNSON CTLS INC	2006	10,8	10,11	10,11	10,11
K2 INC	2005	5,3	5,7	5,3	5,3
KB HOME	2004	6,8	6,7	6,8	6,8
KB HOME	2005	6,8	6,7	6,8	6,8
KB HOME	2006	6,8	6,8	6,8	6,8
KROGER CO	2004	7,8		7,8	7,8

LAS VEGAS SANDS CORP	2005	2,8	2,8	2,8	2,8
LEAR CORP	2005	1,8	1,8	1,8	1,8
LEGGETT & PLATT INC	2005	12,8	12,8	12,8	12,8
LENNAR CORP	2006	8,11		8,11	8,11
LIMITED BRANDS INC	2004	8,11			8,11
LOWES COS INC	2005	12,11	12,11	12,11	12,11
LUBRIZOL CORP	2004			7,4	7,4
M / I HOMES INC	2005	5,8	5,7	5,3	5,4
MAC GRAY CORP	2005	4,3	4,3	4,2	4,2
MAGELLAN MIDSTREAM	2004	8,3	8,3	8,3	8,3
MARRIOTT INTL INC	2005	9,8	9,8	9,8	9,11
MARRIOTT INTL INC	2006	9,8	9,8	9,8	9,8
MASSEY ENERGY CO	2006	4,2	4,3	4,3	4,3
MATTEL INC	2006	7,8	7,8	7,8	7,8
MCCORMICK & CO INC	2005	11,8	11,8	11,7	11,8
MCDONALD'S CORP	2004	11,8	11,8		
MEDIANEWS GROUP INC	2004		2,0		
MERCK & CO	2004			13,14	13,14
MERCK & CO INC	2005			13,14	13,14
MGM MIRAGE	2004	5,3	5,3	5,7	5,7
MGM MIRAGE INC	2005	5,3	5,3	5,8	5,7
MGM MIRAGE INC	2006	5,3	5,3	5,8	5,8
MOHAWK INDS INC	2006			7,8	7,8
MONSANTO CO NEW	2005	10,8	10,8	10,8	10,8
MOOG INC	2005	3,2	3,2	3,2	3,2
MOTOROLA INC	2004	10,8	10,8	10,11	10,11
MTR GAMING GROUP INC	2006	1,2	1,2	1,0	1,0
NAVISTAR INTERNATIONAL CORP	2004	4,3	4,3	4,7	
NBTY INC	2006	3,2	3,2	3,2	3,2
NEWMONT MNG CORP	2005	9,8	9,8	9,8	9,8
NOBLE CORPORATION	2006	10,8	10,8	10,8	10,8
NORFOLK SOUTHERN CORP	2004	9,7	9,7	9,8	9,8
NORFOLK SOUTHN CORP	2005	9,8	9,8	9,11	9,11
NORTHROP GRUMMAN CORP	2004	9,11	9,11	9,11	9,11
NORTHWEST AIRLINES CORP	2004	0,3	0,3	0,7	0,7
NOVA CHEMICALS CORP	2004	4,3	4,3		
OMNICARE INC	2005	6,2	6,2	6,3	6,3
OMNICOM GROUP INC	2006	10.8	10,8	10,11	10,11
OVERSEAS SHIPHOLDING GROUP	2004	6,3	6,3	6,3	6,4

OWENS & MINOR INC	2006	7,8	7,8	7,4	7,4
OXFORD INDUSTRIES INC	2004	2,7	2,3	2,3	2,3
PANTRY INC	2004	0,2	0,2	0,2	0,2
PARK OHIO INDS INC OHIO	2005	0,2	0,2	0,1	0,1
PEABODY ENERGY CORP	2004	4,3	4,7	4,7	4,7
PENN NATIONAL GAMING INC	2004	3,2	3,2	3,2	3,2
PENN NATIONAL GAMING INC	2005	3,2	3,2	3,2	3,2
PEP BOYS-MANNY MOE & JACK	2004	0,2	0,2	0,2	0,2
PEPSIAMERICAS INC	2005	11,7	11,7	11,7	11,7
PEPSIAMERICAS INC	2006	11,7	11,7	11,7	11,7
PEPSICO INC	2004	12,13	12,13	12,14	12,14
PHELPS DODGE CORP	2004	8,7	8,7	8,7	8,7
PHI INCORPORATED	2006	4,3	4,3	4,2	4,2
PHILLIPS-VAN HEUSEN CORP	2004	5,3	5,3	5,3	5,3
PINNACLE ENTERTAINMENT INC	2004	1,0	1,0	1,0	1,0
PORTOLA PACKAGING INC	2004	0,2	0,2	13,12	13,14
PROCTER & GAMBLE CO	2004			13,12	13,14
PROCTER & GAMBLE CO	2005			13,12	13,14
PSYCHIATRIC SOLUTIONS INC	2005	1,2	1,2	1,2	1,2
PULTE HOMES INC	2006	8,11		8,11	8,11
QUEST DIAGNOSTICS INC	2005	9,11	9,8	9,8	9,8
R H DONNELLEY CORP	2005			2,3	2,3
R H DONNELLEY CORP	2006				2,3
REPUBLIC SVCS INC	2005	9,7	9,7	9,7	9,7
RES CARE INC	2005	2,3	2,3		
REYNOLDS AMERN INC	2006	5,11	5,11	5,11	5,11
RITE AID CORP	2005			3,4	3,7
RPM INTERNATIONAL INC	2004	8,7	8,3	8,4	8,4
RUSSEL METALS INC	2004	5,3	5,3	5,2	5,2
RYLAND GROUP INC	2005	7,11	7,8	7,8	7,8
RYLAND GROUP INC	2006	7,8	7,8	7,8	7,8
SAFEWAY INC	2004	7,3	7,3		
SAFEWAY INC	2006			7,8	7,8
SAMSONITE CORP	2004	2,0	2,0	2,0	2,0
SANMINA - SCI CORP	2006	2,0	2,0		2,1
SANMINA CORP	2005			2,4	2,3
SCIENTIFIC GAMES CORP	2005	3,2	3,2	3,2	3,2
SERVICE CORP INTERNATIONAL	2004	5,7	5,8	5,8	5,8
SERVICE CORP INTERNATIONAL	2005	5,7	5,8	5,8	5,8
SLM CORP	2004	11,8	11,8	11,8	11,8
SLM CORP	2005		11,8	11,8	

SMITH INTL INC	2006	9,8	9,8	9,8	9,8
SMITHFIELD FOODS INC	2004	5,7	5,3	5,7	5,7
SOLECTRON CORP	2004	1,2	1,2	1,3	1,3
SONOCO PRODUCTS CO	2004	9,8	9,8	9,7	9,7
SOUTHERN COPPER CORP	2005	7,13	7,13	7,11	7,11
SOUTHERN COPPER CORP	2006	7,13	7,11	7,11	7,14
SOUTHWEST AIRLINES	2004	11,8	11,8	11,8	11,8
SOUTHWEST AIRLINES	2005	11,8	11,8	11,8	11,8
STANDARD PACIFIC CP	2004	5,7	5,3	5,4	5,7
STATER BROS HOLDINGS INC	2004	3,2	3,2	3,2	3,2
STATION CASINOS INC	2004	4,2	4,2	4,2	4,2
STATION CASINOS INC	2006	3,2	3,2	3,2	3,2
STATS CHIPPAC LTD -ADR	2004	5,3	5,3	5,2	5,2
STEEL DYNAMICS INC	2004	5,3	5,3	5,3	5,3
STEINWAY MUSICAL INSTR INC	2006	4,3	4,3	4,2	4,2
STEWART ENTERPRISES INC	2005	3,7	3,7	3,4	3,4
STEWART ENTERPRISES INC	2006				3,2
SYSCO CORP	2004	12,11	12,8	12,11	12,11
SYSCO CORP	2005	12,11	12,11	12,11	12,11
TECHNICAL OLYMPIC USA INC	2006	3,7	3,7	3,4	3,7
TENET HEALTHCARE CORP	2004			2,3	2,3
TENET HEALTHCARE CORP	2005	2,0	2,0		
TEREX CORP	2004	3,2	3,2	3,2	3,2
TEVA PHARMACEUTICAL FIN LLC	2006	8,11	8,11	8,11	8,11
TEXTRON FINL CORP	2005	10,7	10,8	10,8	10,8
TEXTRON FINL CORP	2006	10,3	10,7	10,8	10,4
TEXTRON INC	2004	10,2	10,7	10,8	10,3
THERMADYNE HOLDINGS CORP	2004	0,2	0,13	0,14	
THERMO ELECTRON CORP	2005	9,8	9,11	9,11	9,8
THOMSON CORP	2004	10,8	10,8	10,11	10,11
TRAILER BRDG INC	2005	1,2	1,2	1,0	1,0
TRANSCANADA PIPELINES LTD	2006	10,7	10,7	10,8	10,8
TRANSDIGM INC	2006	1,2	1,2	1,2	1,2
TRINITY INDUSTRIES	2004	5,3	5,3	5,3	5,3
TYSON FOODS INC	2006	8,7	8,7		
U S CONCRETE INC	2004	1,2	1,2		1,2
U S CONCRETE INC	2006	1,2	1,2		
UNIFI INC	2006	0,2	0,3	0,2	0,2
UNION PACIFIC CORP	2004	8,11	8,11	8,11	8,11
UNISYS CORP	2005	4,7	4,7	4,7	4,7

UNITED PARCEL SERVICE INC	2004	13,11	13,11	14,12	14,11
UNITED RENTALS INC	2004	3,2	3,2	3,2	3,2
UNIVERSAL CORP/VA	2004	9,3	9,3	9,4	9,4
UNIVERSAL HEALTH SVCS INC	2006	9,8	9,8	9,8	9,8
VAIL RESORTS INC	2004				
VALEANT PHARMACEUTICALS INTL	2004	4,2	4,2	4,2	4,2
VALMONT INDUSTRIES	2004	3,2	3,2	3,2	3,2
VALSPAR CORP	2005	8,7		8,7	8,7
VALSPAR CORP	2006	8,7	8,7	8,7	8,7
VISTEON CORP	2004	3,2			
WASTE MANAGEMENT INC	2004	8,7	8,7		
WCA WASTE CORP	2006	1,2	1,2		
WESTLAKE CHEM CORP	2006	6,11	6,8	6,8	6,8
WILLIAMS PARTNERS L P /	2006	4,8	4,8	4,8	4,8
XEROX CORP	2006	6,8	6,8	6,8	6,11
YUM BRANDS INC	2006	8,11			8,11

APPENDIX E

NEW BOND ISSUE MISCLASSIFICATIONS

(MOODY'S RATINGS FOR SIX CATEGORIES)

New Bond Issue Misclassifications
(Moody's Ratings for Six Categories)

NOTE: Number in each cell under the various data source combination models represents "Actual Ratings, Predicted Ratings." Ratings of Caa1 and below or CCC+ and below were assigned a value of 0; B3 or B-, B2 or B, B1 or B+ a value of 1; Ba3 or BB-, Ba2 or BB, Ba1 or BB+ a value of 2; Baa3 or BBB-, Baa2 or BBB, Baa1 or BBB+ a value of 3; A3 or A-, A2 or A, A1 or A+ a value of 4; Aa3 or AA-, Aa2 and above or AA and above a value of 5.

Name of New Bond Issue	Year	MM	MC	SQMM	SQMC
ADESA INC	2004	1,2		1,2	
ADVANCED MICRO DEVICES	2004				1,2
AFFILIATED COMPUTER SVCS INC	2005	3,4	3,4		3,4
AIR PRODS & CHEMS INC	2005	4,3	4,3	4,3	4,3
AIRGAS INC	2004	2,1	2,1	2,1	2,1
ALBEMARLE CORP	2005	3,2	3,2	3,1	3,2
ALDERWOODS GROUP INC	2005	1,2	1,2	1,2	1,2
ALLERGAN INC	2006			4,3	4,3
ALLIANCE IMAGING INC	2005	1,0	1,0	1,0	1,0
ALLIED WASTE NORTH AMER INC	2006			1,2	1,2
ALLIS CHALMERS CORP	2006	1,2	1,2		
ALTRIA GROUP INC	2004	4,5		4,5	4,5
AMERICAN GREETINGS CORP	2006	2,3	2,3		
AMERICAN INTERNATIONAL GROUP	2004	4,2	4,5	4,3	4,5
AMERISOURCEBERGEN CORP	2005	2,3	2,3	2,3	2,3
AMKOR TECHNOLOGY INC	2006	0,1	0,1	0,1	0,1
ANHEUSER BUSCH COS INC	2006	4,3	4,3	4,3	4,3
ANHEUSER BUSCH COS INC	2005	4,3	4,3		4,3
ANHEUSER-BUSCH COS INC	2004	4,3	4,3	4,3	4,3
ANIXTER INC	2005		2,3		
ARAMARK SVCS INC	2005	3,2	3,2	3,2	3,2
ARCHER DANIELS MIDLAND CO	2005	4,3	4,3	4,3	4,3
ATLAS PIPELINE PARTNERS L P					
ATLAS PIPELINE FIN CORP	2005	1,3	1,3	1,2	1,2
AUTONATION INC	2006	2,3	2,3	2,3	2,3
AVERY DENNISON CORP	2004	4,3	4,3	4,3	4,3
AVON PRODS INC	2006				4,3
AZTAR CORP	2004	2,1	2,1	2,1	2,1
BALL CORP	2006	2,3	2,3		
BASIC ENERGY SVCS INC NEW	2006	1,3	1,3	1,2	1,2
BIO-RAD LABORATORIES INC	2004	2,1	2,1	2,1	2,1

BLOCKBUSTER INC	2006				0,1
BLOUNT INTL INC	2004	1,0	1,0	1,0	1,0
BOSTON SCIENTIFIC CORP	2005	3,4	3,4	3,4	3,4
BOSTON SCIENTIFIC CORP	2004	4,3	4,3	4,3	4,3
BOWATER INC	2004	2,1	2,1	2,1	2,1
BRISTOL-MYERS SQUIBB CO	2004		4,3		
BROWN SHOE INC NEW	2005	1,3	1,3	1,2	1,2
BRUNSWICK CORP	2004			3,2	
BUILDING MATLS CORP AMER	2005	1,3	1,3	1,2	1,2
CADMUS COMMUNICATIONS CORP	2004	1,0	1,0	1,0	1,0
CAMERON INTERNATIONAL CORP	2004			3,2	
CANADIAN NATIONAL RAILWAY CO	2004	4,3	4,3	4,3	4,3
CANADIAN NATL RY CO	2006	4,3	4,3	4,3	4,3
CARRIAGE SVCS INC	2005		1,2		
CASE NEW HOLLAND INC	2006	2,3	2,3	2,3	2,3
CENTEX CORP	2004	3,2			
CENTEX CORP	2005	3,2			
CENTEX CORP	2006	3,2			
CENTURY ALUM CO	2005	1,2	1,2		1,2
CHARTERED SEMICONDUCTOR MFG LTD	2005	3,1	3,2	3,1	3,2
CHEMTURA CORPORATION	2006	2,1	2,1	2,1	2,1
CHIQUITA BRANDS INTL INC	2005	1,2	1,3	1,2	1,2
CHIQUITA BRANDS INTL INC	2004	1,3	1,3	1,2	1,2
CHURCH & DWIGHT INC	2005	2,1	2,1	2,1	2,1
CLOROX CO	2005			4,3	4,3
CLOROX CO/DE	2004			4,3	4,3
COCA COLA BOTTLING CO CONS	2005	3,1	3,1	3,1	3,1
COLGATE PALMOLIVE CO	2005	5,3	5,3	5,3	5,3
COMMERCIAL METALS	2004			3,2	3,2
COMMERCIAL VEH GROUP	2006	2,3	2,3		
CONVERGYS CORP	2004		3,4		
COOPER U S INC	2005	4,3	4,3	4,3	4,3
CORNING INC	2005	3,1	3,1	3,2	3,1
CORNING INC	2004	3,2	3,2	3,2	3,2
CORRECTIONS CORP AMER	2005	2,1	2,1	2,1	2,1
CORRECTIONS CORP AMER	2006	2,1	2,1	2,1	2,1
CROWN AMERS LLC / CROWN AMERS CAP CORP	2005			1,2	1,2
D R HORTON INC	2004	2,3	2,3	2,3	2,3
DELUXE CORP	2004	3,4		3,4	

EATON CORP	2004	4,3	4,3	4,3	4,3
EATON CORP	2005	4,3	4,3	4,3	4,3
ELI LILLY SVCS INC	2005	5,3	5,3	5,4	5,4
EMERSON ELEC CO	2005	4,3	4,3	4,3	4,3
ETHAN ALLEN GLOBAL INC	2006	3,4	3,5		3,4
FINLAY ENTERPRISES INC	2004		1,2		
FISHER SCIENTIFIC INTL INC	2005	2,1	2,1	2,1	2,1
FISHER SCIENTIFIC INTL INC	2006	2,1	2,1		
FOREST CITY ENTERPRISES INC	2005	2,1	2,1	2,1	2,1
FREEPORT-MCMORAN COP&GOLD	2004	1,2		1,2	1,2
FREESCALE SEMICONDUCTOR INC	2004	2,1		2,1	
FTI CONSULTING INC	2005	2,3	2,3		
GAYLORD ENTMT CO	2004		1,2	1,2	1,2
GAYLORD ENTMT CO	2005	1,2	1,2		
GENENTECH INC	2005	4,3	4,5	4,3	
GENERAL MOTORS CORP	2004	0,5	0,5	0,5	0,5
GIBRALTAR INDS INC	2005	2,1	2,1	2,1	2,1
GLATFELTER P H CO	2006	2,3	2,3		
GOODYEAR TIRE & RUBR CO	2005	1,2	1,3	1,3	1,3
GOODYEAR TIRE & RUBR CO	2006	1,2	2,3	1,3	1,3
GRANT PRIDECO INC	2006	2,3		2,3	2,3
GSC HLDGS CORP / GAMESTOP INC	2006	2,3		2,3	
GTECH HOLDINGS CORP	2004				3,2
HARRAHS OPER CO INC	2006	3,2	3,1		
HCA INC	2004	2,3	2,3	2,3	2,3
HCA INC	2006	2,3	2,3	2,3	2,3
HEALTHSOUTH CORP	2006	1,0		1,0	
HERCULES INC	2004	2,1	2,1	2,1	2,1
HEWLETT PACKARD CO	2006			4,5	
HILLENBRAND INDUSTRIES	2004	4,3	4,3	4,3	4,3
HOME DEPOT INC	2004	5,4	5,4	5,4	
HOME DEPOT INC	2005	5,4	5,4		5,4
HOME DEPOT INC	2006	5,4	5,4		
HONEYWELL INTL INC	2006		4,3		
HORNBECK OFFSHORE SVCS INC	2004	2,1	2,1	2,1	2,1
HOVNANIAN ENTERPRISES INC	2005	2,3	2,3	2,3	2,3
INTERFACE INC -CL A	2004	0,1	0,1	0,1	0,1
INTERNATIONAL BUSINESS MACHS CORP	2005	4,5	4,5	4,5	4,5
INTERNATIONAL LEASE FIN CORP	2006	4,2	4,2	4,3	4,3
INTL BUSINESS MACHINES	2004	4,5		4,5	4,5

INTL PAPER CO	2004		3,2		
INTRAWEST CORP	2004	1,2	1,2		
K2 INC	2005	1,2	1,3	1,2	1,2
KB HOME	2004	2,3	2,3	2,3	2,3
KB HOME	2005	2,3	2,3	2,3	2,3
KB HOME	2006	2,3	2,3	2,3	2,3
KROGER CO	2004		3,2		
LAMAR MEDIA CORP	2005	2,1	2,1	2,1	2,1
LAS VEGAS SANDS CORP	2005	1,3	1,3	1,3	1,3
LEAR CORP	2005	1,3	1,3	1,3	1,3
LEGGETT & PLATT INC	2005	4,3	4,3	4,3	4,3
LENNAR CORP	2006			3,4	
LOWES COS INC	2005		4,3		
LUBRIZOL CORP	2004			3,2	3,2
M / I HOMES INC	2005	2,3	2,3		
MAC GRAY CORP	2005	1,2	1,2		
MAGELLAN MIDSTREAM PRTNRS LP	2004	3,2	3,2	3,2	3,1
MCCORMICK & CO INC	2005	4,3	4,3	4,3	4,3
MCDONALD'S CORP	2004	4,3	4,3	4,3	4,3
MERCER INTL INC	2005	0,1	0,1	0,1	0,1
MERCK & CO	2004		5,4		
MERCK & CO INC	2005	5,4	5,4		5,4
MGM MIRAGE	2004	2,1	2,1		
MGM MIRAGE INC	2006		2,1	2,3	
MGM MIRAGE INC	2005		2,1		
MOHAWK INDS INC	2006	3,2	3,2	3,2	3,2
MOOG INC	2005	2,1	2,1	2,1	2,1
MOTOROLA INC	2004			3,4	
NAVISTAR INTERNATIONAL	2004			1,2	1,2
NORFOLK SOUTHERN CORP	2004		3,2		
NORTHROP GRUMMAN CORP	2004			3,4	3,4
NORTHWEST AIRLINES CORP	2004	0,1	0,1	0,2	0,2
O'CHARLEY'S INC	2004	2,1	2,1	2,1	2,1
OMNICARE INC	2005	2,1	2,1	2,1	2,1
OWENS & MINOR INC	2006	2,3	2,3		
OXFORD INDUSTRIES INC	2004	1,2	1,2	1,2	1,2
PARK OHIO HOLDINGS CORP	2004	0,1	0,1	0,1	0,1
PARK OHIO INDS INC OHIO	2005	0,1	0,1	0,1	0,1
PENN NATIONAL GAMING INC	2004	2,1	2,1	2,1	2,1
PEPSIAMERICAS INC	2006	3,2	3,2	3,2	3,2
PEPSIAMERICAS INC	2005			3,2	3,2

PEPSICO INC	2004	5,4	5,4		5,4
PFIZER INC	2004		5,4		
PHELPS DODGE CORP	2004	3,2	3,2	3,2	3,2
PHI INCORPORATED	2006		1,2		
PHILLIPS-VAN HEUSEN CORP	2004	1,2	1,2		1,2
PINNACLE ENTERTAINMENT INC	2004	0,4	0,1	0,1	0,1
PORTOLA PACKAGING INC	2004	0,1	0,1	0,1	0,1
PROCTER & GAMBLE CO	2004	5,4	5,4		5,4
PROCTER & GAMBLE CO	2005	5,4	5,4		5,4
PROCTER & GAMBLE CO	2006	5,4	5,4		5,4
PULTE HOMES INC	2006			3,4	
R H DONNELLEY CORP	2005	0,1	0,1	0,1	0,1
R H DONNELLEY CORP	2006	0,1	0,1	0,1	0,1
REPUBLIC SVCS INC	2005			3,2	3,2
RES CARE INC	2005	1,2	1,2		
REYNOLDS AMERN INC	2006	2,3	2,3	2,3	2,3
RITE AID CORP	2005	1,2		1,2	1,2
RPM INTERNATIONAL INC	2004		3,2	3,2	3,2
RUSSEL METALS INC	2004			2,1	2,1
SAFEWAY INC	2004	3,1	3,1	3,2	3,2
SAFEWAY INC	2006		3,2		
SANMINA - SCI CORP	2006	1,6			
SERVICE CORP INTERNATIONAL	2004	2,3	2,3	2,3	2,3
SERVICE CORP INTL	2005	2,3	2,3	2,3	2,3
SLM CORP	2004	4,3	4,2		4,3
SLM CORP	2005		4,1		4,3
SONOCO PRODUCTS CO	2004	4,3	4,3	4,2	4,2
SOUTHERN COPPER CORP	2005	2,4	2,4	2,4	2,4
SOUTHERN COPPER CORP	2006	2,4	2,4	2,4	2,4
STANDARD PACIFIC CP	2004	2,3	2,3		
STATION CASINOS INC	2004	2,1	2,1	2,1	2,1
STATS CHIPPAC LTD -ADR	2004	2,1	2,1	2,1	2,1
STEEL DYNAMICS INC	2004	2,1		2,1	2,1
STEINWAY MUSICAL INSTR INC	2006	2,1	2,1	2,1	2,1
STEWART ENTERPRISES INC	2005	1,2	1,3	1,2	1,2
SYSCO CORP	2004	4,3	4,3	4,3	4,3
SYSCO CORP	2005		4,3		4,3
TECHNICAL OLYMPIC USA INC	2006	2,3	2,3		
TEREX CORP	2004	0,1	0,1	0,1	0,1
TEVA PHARMACEUTICAL FIN LLC	2006		3,4	3,4	3,4

TEXTRON FINL CORP	2006	4,1	4,2	4,2	4,3
TEXTRON FINL CORP	2005	4,2	4,3	4,3	4,3
TEXTRON INC	2004	4,1	4,2	4,1	4,3
THERMADYNE HOLDINGS CORP	2004	0,1	0,5	0,1	0,5
THERMO ELECTRON CORP	2005		3,4		
THOMSON CORP	2004	4,3	4,3	4,3	4,3
TRANSCANADA PIPELINES	2006	4,3	4,2	4,3	4,3
TRINITY INDUSTRIES	2004			2,1	
TYSON FOODS INC	2006	2,3	2,3	2,3	2,3
UNIFI INC	2006	0,1	0,1	0,1	0,1
UNION PACIFIC CORP	2004			3,4	3,4
UNISYS CORP	2005		2,3		
UNITED PARCEL SERVICE INC	2004	5,4	5,4	5,4	5,4
UNIVERSAL CORP/VA	2004	3,2	3,2	3,2	3,2
VALMONT INDUSTRIES	2004	2,1	2,1	2,1	2,1
VALSPAR CORP	2005			3,2	3,2
VALSPAR CORP	2006			3,2	3,2
VISTEON CORP	2004	2,1	2,1	2,1	2,1
WAL MART STORES INC	2005		5,4		
WAL-MART STORES	2004		5,4		
WASTE MANAGEMENT INC	2004		3,2		
WESTLAKE CHEM CORP	2006	2,3	2,3	2,3	2,3
WILLIAMS PARTNERS L P / WILLIAMS PARTNERS FIN CORP	2006	2,3	2,3	2,3	2,3
WYETH	2005			3,4	3,4
XEROX CORP	2006	2,3	2,3	2,3	2,3

APPENDIX F

NEW BOND ISSUES MISCLASSIFICATIONS

(S&P RATING WITH SIX CATEGORIES)

New Bond Issues Misclassifications
(S&P Ratings with Six Categories)

NOTE: Number in each cell under the various data source combination models represents "Actual Ratings, Predicted Ratings." Ratings of Caa1 and below or CCC+ and below were assigned a value of 0; B3 or B-, B2 or B, B1 or B+ a value of 1; Ba3 or BB-, Ba2 or BB, Ba1 or BB+ a value of 2; Baa3 or BBB-, Baa2 or BBB, Baa1 or BBB+ a value of 3; A3 or A-, A2 or A, A1 or A+ a value of 4; Aa3 or AA-, Aa2 and above or AA and above a value of 5.

Name of New Bond Issue	Year	SC	SM
ABBOTT LABORATORIES	2004	5,4	5,4
ABBOTT LABORATORIES	2006	5,4	5,4
AFFILIATED COMPUTER SVCS INC	2005	2,4	2,4
AGCO CORP	2004	2,1	2,1
AIR PRODS & CHEMS INC	2005	4,3	4,3
AIRGAS INC	2004	2,1	2,1
ALBEMARLE CORP	2005	3,1	3,1
ALDERWOODS GROUP INC	2005	1,3	1,2
ALLIANCE IMAGING INC	2005	1,0	1,0
ALLIED WASTE NORTH AMER INC	2006	2,1	2,1
ALLIS CHALMERS CORP	2006		1,2
ALTRIA GROUP INC	2004	3,5	3,5
AMERICAN GREETINGS CORP	2006	2,3	2,3
AMERICAN INTERNATIONAL GROUP	2004		5,2
AMKOR TECHNOLOGY INC	2004	0,1	0,1
AMKOR TECHNOLOGY INC	2006	0,1	0,1
ANHEUSER BUSCH COS INC	2005	4,3	4,3
ANHEUSER BUSCH COS INC	2006	4,3	4,3
ANHEUSER-BUSCH COS INC	2004	4,3	4,3
ANIXTER INC	2005	2,3	2,3
ARAMARK SVCS INC	2005	3,2	
ARCHER DANIELS MIDLAND CO	2005	4,3	4,3
ATLAS PIPELINE PARTNERS L P ATLAS PIPELINE FIN CORP	2005	1,3	1,3
AUTONATION INC	2006	2,3	2,3
AVERY DENNISON CORP	2004	4,3	4,3
BALL CORP	2006	2,3	2,3
BASIC ENERGY SVCS INC NEW	2006	1,3	1,3
BAXTER FINCO B V	2006	4,3	4,3
BAXTER INTL INC	2005	4,3	4,3
BEMIS CO INC	2005	4,3	4,3

BIO-RAD LABORATORIES INC	2004	2,1	2,1
BLOCKBUSTER INC	2006	0,1	
BLOUNT INTL INC	2004	1,0	1,0
BOSTON SCIENTIFIC CORP	2004	4,3	4,3
BOSTON SCIENTIFIC CORP	2005	3,4	3,4
BROWN SHOE INC NEW	2005	2,3	2,3
BUILDING MATLS CORP AMER	2005	1,3	1,3
CADMUS COMMUNICATIONS CORP	2004	1,0	1,0
CANADIAN NATIONAL RAILWAY CO	2004	4,3	4,3
CANADIAN NATL RY CO	2006	4,3	4,3
CASE NEW HOLLAND INC	2006	2,3	2,3
CENTEX CORP	2004		3,1
CENTEX CORP	2005		3,2
CENTEX CORP	2006		3,1
CHARTERED SEMICONDUCTOR	2005	3,2	3,1
CHEMTURA CORPORATION	2006	2,1	2,1
CHIQUITA BRANDS INTL INC	2004	1,3	1,3
CHIQUITA BRANDS INTL INC	2005	1,3	1,3
COCA COLA BOTTLING CO CONS	2005	3,1	3,1
COLGATE PALMOLIVE CO	2005	5,3	5,4
COMMERCIAL VEH GROUP INC	2006	1,3	1,3
CONSTAR INTL INC	2005	0,1	0,1
CONVERGYS CORP	2004	3,4	3,4
COOPER U S INC	2005	4,3	4,3
CORNELL COMPANIES INC	2004	0,1	0,1
CORNING INC	2004	3,2	3,1
CORNING INC	2005	3,1	3,1
CORRECTIONS CORP AMER	2005	2,1	2,1
CORRECTIONS CORP AMER	2006	2,1	2,1
CVS CORP	2004	3,4	3,4
D R HORTON INC	2004	2,3	2,3
DEAN FOODS CO	2006	2,1	
DELUXE CORP	2004		3,4
EATON CORP	2004	4,3	4,3
EATON CORP	2005	4,3	4,3
ELI LILLY SVCS INC	2005	5,4	5,4
EMERSON ELEC CO	2005	4,3	4,3
ESCHELON OPER CO	2005	0,1	0,1
ETHAN ALLEN GLOBAL INC	2006	4,5	
FISHER SCIENTIFIC INTL INC	2005	2,1	2,1
FISHER SCIENTIFIC INTL INC	2006	2,1	2,1

FOREST CITY ENTERPRISES INC	2005	2,1	2,1
FREESCALE SEMICONDUCTOR INC	2004		3,1
FTI CONSULTING INC	2005	1,3	1,3
GAYLORD ENTERTAINMENT CO	2004	1,2	1,2
GAYLORD ENTMT CO	2005	1,2	
GENENTECH INC	2005	4,5	
GENERAL MOTORS CORP	2004	1,5	1,5
GLATFELTER P H CO	2006	2,3	2,3
GOODYEAR TIRE & RUBR CO	2005	1,3	1,3
GOODYEAR TIRE & RUBR CO	2006	1,3	1,3
GRANT PRIDECO INC	2006	2,3	2,4
GSC HLDGS CORP / GAMESTOP INC	2006	1,2	1,3
HANGER ORTHOPEDIC GROUP INC	2006	0,1	0,1
HARRAHS OPER CO INC	2006	3,1	3,1
HCA INC	2004	2,3	2,3
HCA INC	2006	2,3	2,3
HEALTHSOUTH CORP	2006	0,1	
HEWLETT PACKARD CO	2006	4,5	4,5
HILLENBRAND INDUSTRIES	2004	4,3	4,3
HOME DEPOT INC	2004		5,4
HOME DEPOT INC	2005	5,4	5,4
HOME DEPOT INC	2006		5,4
HORNBECK OFFSHORE SVCS INC	2004	2,1	2,1
HOVNANIAN ENTERPRISES INC	2005	1,3	1,3
IKON OFFICE SOLUTIONS INC	2006	2,3	
INTERFACE INC -CL A	2004	0,1	0,1
INTERNATIONAL BUSINESS MACHS CORP	2005	4,5	4,5
INTERNATIONAL LEASE FIN CORP	2006	5,3	5,1
INTERPUBLIC GROUP OF COS	2004	2,3	
INTL BUSINESS MACHINES CORP	2004	4,5	4,5
JOHNSON CTLS INC	2006	4,3	4,3
K2 INC	2005	2,3	
KB HOME	2004	2,3	2,3
KB HOME	2005	2,3	2,3
KB HOME	2006	2,3	2,3
LAS VEGAS SANDS CORP	2005	1,3	1,3
LEAR CORP	2005	1,3	1,3
LEGGETT & PLATT INC	2005	4,3	4,3
LENNAR CORP	2006		3,4
LIMITED BRANDS INC	2004		3,4
M / I HOMES INC	2005	2,3	2,3

MAC GRAY CORP	2005	2,1	2,1
MAGELLAN MIDSTREAM PRTNRS LP	2004	3,1	3,2
MASSEY ENERGY CO	2006	2,1	2,1
MCCORMICK & CO INC	2005	4,3	4,3
MCDONALD'S CORP	2004	4,3	4,3
MERCK & CO	2004	5,4	5,4
MERCK & CO INC	2005	5,4	
MGM MIRAGE	2004	2,1	2,1
MGM MIRAGE INC	2005	2,1	2,1
MGM MIRAGE INC	2006	2,1	2,1
MOHAWK INDS INC	2006	3,2	3,2
MONSANTO CO NEW	2005	4,3	4,3
MOTOROLA INC	2004	4,3	4,3
NAVISTAR INTERNATIONAL CORP	2004	2,1	2,1
NOBLE CORPORATION	2006	4,3	4,3
NORTHROP GRUMMAN CORP	2004	3,4	
NORTHWEST AIRLINES CORP	2004	0,1	0,1
OMNICARE INC	2005	2,1	2,1
OMNICOM GROUP INC	2006	4,3	4,3
OXFORD INDUSTRIES INC	2004	1,2	1,3
PANTRY INC	2004	0,1	0,1
PARK OHIO HOLDINGS CORP	2004	0,1	0,1
PARK OHIO INDS INC OHIO	2005	0,1	0,1
PEABODY ENERGY CORP	2004	2,3	
PEP BOYS-MANNY MOE & JACK	2004	0,1	0,1
PEPSIAMERICAS INC	2005	4,3	4,3
PEPSIAMERICAS INC	2006	4,3	4,3
PHI INCORPORATED	2006	2,1	2,1
PHILLIPS-VAN HEUSEN CORP	2004		2,1
PORTOLA PACKAGING INC	2004	0,1	0,1
PROCTER & GAMBLE CO	2004	5,4	5,4
PROCTER & GAMBLE CO	2005	5,4	
PROCTER & GAMBLE CO	2006	5,4	
PULTE HOMES INC	2006		3,4
QUEST DIAGNOSTICS INC	2005		3,4
RES CARE INC	2005	1,2	1,2
REYNOLDS AMERN INC	2006	2,4	2,3
RPM INTERNATIONAL INC	2004	3,2	
RYLAND GROUP INC	2005		3,4
SAFEWAY INC	2004	3,1	3,1

SANMINA - SCI CORP	2006		1,0
SERVICE CORP INTERNATIONAL	2004	2,3	2,3
SERVICE CORP INTL	2005	2,3	2,3
SLM CORP	2004	4,3	4,3
SLM CORP	2005	4,3	
SMITHFIELD FOODS INC	2004		2,3
SOUTHERN COPPER CORP	2005	3,4	3,4
SOUTHERN COPPER CORP	2006	3,4	3,4
SOUTHWEST AIRLINES	2004	4,3	4,3
SOUTHWEST AIRLS CO	2005	4,3	4,3
STANDARD PACIFIC CP	2004		2,3
STATION CASINOS INC	2004	2,1	2,1
STATS CHIPPAC LTD -ADR	2004	2,1	2,1
STEEL DYNAMICS INC	2004	2,1	2,1
STEINWAY MUSICAL INSTR INC	2006	2,1	2,1
STEWART ENTERPRISES INC	2005	1,3	1,3
SYSCO CORP	2004	4,3	4,3
TECHNICAL OLYMPIC USA INC	2006	1,3	1,3
TEVA PHARMACEUTICAL FIN LLC	2006	3,4	3,4
TEXTRON FINL CORP	2005	4,3	4,2
TEXTRON FINL CORP	2006	4,3	4,1
TEXTRON INC	2004	4,3	4,1
THERMADYNE HOLDINGS CORP	2004	0,5	0,1
THERMO ELECTRON CORP	2005	3,4	
THOMSON CORP	2004	4,3	4,3
TRANSCANADA PIPELINES LTD	2006	4,3	4,3
UNIFI INC	2006	0,1	0,1
UNION PACIFIC CORP	2004	3,4	
UNISYS CORP	2005	2,3	2,3
UNITED PARCEL SERVICE INC	2004	5,4	5,4
UNIVERSAL CORP/VA	2004	3,2	3,2
VALEANT PHARMACEUTICALS INTL	2004	2,1	2,1
WESTLAKE CHEM CORP	2006	2,3	2,4
WILLIAMS PARTNERS L P / WILLIAMS PARTNERS FIN CORP	2006	2,3	2,3
WYETH	2005		4,3
XEROX CORP	2006	2,3	2,3