# Asset Opaqueness and Split Bond Ratings

**Miles Livingston, Andy Naranjo, and Lei Zhou***

*We examine the relation between asset opaqueness and split ratings. We find that firms with asset opaqueness problems are more likely to receive split bond ratings from Moody's and S&P rating agencies. Our results suggest that there is a causal link between asset opaqueness and split ratings.*

Most publicly issued corporate and municipal bonds are rated by two rating agencies: Moody's and S&P. However, the two rating agencies do not always agree on the ratings for a particular issue, resulting in a split rating. Since 1982, Moody's and S&P have provided sub-ratings or notch ratings, which subdivide the letter ratings (e.g., A+, A, A-). About 20% of U.S. corporate and municipal bonds have letter split ratings, and approximately 50% of sub-ratings or notch-level ratings are split.[1] In this paper, we focus on notch-level split ratings. We examine the link between asset opaqueness and split ratings since credit ratings can have a significant impact on bond yields and prices, which influence both a firm's investment policy and the decisions and behavior of other financial market participants.

Two earlier papers motivate our research. Ederington (1986) argues that split ratings are caused by random errors by the two rating agencies, implying that split-rated bonds are likely to have credit risks bordering the rating cutoff points.[2] We call Ederington's (1986) split rating hypothesis "the random error hypothesis of split ratings." Morgan (2002) finds that banks are more likely to receive split ratings than firms from other industries due to asset opaqueness problems of banking firms. We call Morgan's (2002) split rating hypothesis "the asset opaqueness hypothesis of split ratings."

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**Miles Livingston is a Professor of Finance at the University of Florida in Gainesville, FL and at Erasmus University in Rotterdam, the Netherlands. Andy Naranjo is the Emerson-Merrill Lynch Associate Professor of Finance at the University of Florida in Gainesville, FL. Lei Zhou is an Assistant Professor of Finance at Northern Illinois University in DeKalb, IL.*

[1]Jewell and Livingston (1998) report that about 17% of U.S. industrial bond issues from 1983 to 1993 receive different letter ratings from Moody's and S&P. Moon and Stotsky (1993) find 21% of municipal bonds in 1981 have letter rating split. We find a similar percentage of letter rating split among industrial bonds in our sample.

[2]Ederington (1986) also finds that there is no systematic difference in the rating scales used by the two major rating agencies and that the two rating agencies assign similar weights to the commonly used factors, such as firm size and leverage ratio, in estimating the credit risks. Two other studies investigate whether there are systematic differences in rating methodologies and rating scales between rating agencies. Cantor and Packer (1997a) find that there are systematic differences between the two major rating agencies (S&P and Moody's) and the two smaller rating agencies (Fitch and DCR), but do not compare the S&P and Moody's ratings. Moon and Stotsky (1993) find that there are systematic differences between the S&P and Moody's ratings on municipal bond issues. However, Moon and Stotsky use outstanding municipal debts, while Ederington and our study use newly issued bonds. Observed split ratings for outstanding debt issues might be caused by asynchronous changes in ratings over time.

Our paper provides evidence that asset opaqueness problems explain, at least in part, the split ratings of non-banking firms. This evidence supports and complements Morgan's (2002) findings for banking firms. First, we find that firms with more opaque assets are more likely to receive split bond ratings. Six out of our seven proxies for asset opaqueness have a significant impact on the probability of split ratings. Second, the split ratings are not symmetric between the two rating agencies. Instead, split ratings are more lopsided, with Moody's consistently on the downside. This pattern suggests that split ratings are not completely caused by random errors. Third, we find that split ratings are persistent. Two thirds of the bonds that were initially split-rated remain split-rated after four years of initial issuance, while most initially non-split-rated remain non-split-rated. This evidence indicates that firms with split-rated bonds are inherently different from firms with non-split-rated bonds.

Our results have important implications. If split ratings are purely due to random errors, then split-rated bonds should be priced at the average of the two ratings, because the underlying credit risk lies between the two ratings. On the other hand, if the split ratings reflect issuing firms' asset opaqueness problems, then split-rated bonds should be priced below the simple average of the two ratings to account for the underlying asset opaqueness problem.

The rest of the paper is organized as follows. Section I describes our data and variable definitions. In Section II, we examine the relation between asset opaqueness and split bond ratings. In Section III, we discuss the findings and conclude the paper.

## I. Data and Variables

We use two data sources to collect information on bond issues and ratings history. First, we use the Warga tape, which contains bond issues in the Lehman Brothers Index from 1970 to March 1996. The Warga tape has monthly updates on bond ratings. For the period after 1995, we use the Fixed Income Security Database (FISD), which contains bonds that mature after 1996. FISD also provides us with ratings upgrade and downgrade information.

Our sample period is from 1983 to 2000. We start in 1983 because the market microstructure data that we use begins in 1983, and Moody's started to have notch ratings only after April 1982. We exclude financial issues because Morgan (2002) has shown banking firms are much more likely to have split ratings given the nature of their assets. We also exclude utility issues because utilities are regulated industries and have more information disclosure than other industries. This makes utility firms more transparent and less like to have split ratings as shown by Morgan (2002). All the issues included in the study have both S&P and Moody's ratings.

We start with 3,213 domestic bond issues. Some firms have multiple issues over a short period of time. The ratings on these multiple issues are mostly the same and are unlikely to convey additional information. Thus, we exclude additional bond issues of the same issuing firm within the same month, eliminating 61 issues. COMPUSTAT has complete accounting information for 2,194 issues. We note that the accounting ratios we use in the study are the five-year averages before the bond issue. We cannot find accounting information for 136 issues, while we do not have complete information over the five-year period for 822 issues, largely due to lack of data on intangible assets.

Matching with Institutional Brokers Estimates System (IBES) data reduces the sample to 2,072 issues. Furthermore, we eliminate issuing firms with less than three stock analysts, reducing the sample to 1,877. We also exclude 98 issues that do not have enough trading data to allow us to calculate the market microstructure variables that we use. Our final sample has 1,779 bond issues from 1983 to 2000.

## A. Variable Definitions

The variables we use as proxies for asset opaqueness include accounting-based proxies, opinion-based proxies, a market microstructure-based proxy, and other proxies.

### 1. Accounting-based Proxies

Our accounting-based proxies include the market-to-book ratio and percentage of intangible assets. We define the market-to-book value as follows: market to book equals market value of equity minus book value of equity plus total assets divided by total assets. The market-to-book ratio has been widely used in the corporate finance literature to measure a firm's growth opportunities. Firms with larger growth opportunities tend to be younger firms in newer industries, making them more opaque and harder to value (see, for example, McLaughlin, Safieddine, and Vasudevan, 1998).

As an additional accounting proxy for asset opaqueness, we also use the amount of intangible assets as a percentage of a firm's total assets. We define intangible assets as intangible assets divided by total assets. Intangible assets, by nature, are harder to value. In the finance literature, R&D expenditures are often used to proxy for information asymmetry (e.g., Aboody and Lev, 2000). We do not use R&D expenditure in this study because a large number of issuing firms do not report this item in their financial statements.

To calculate the market-to-book ratio and percentage of intangible assets, we collect the underlying annual accounting variables for the last five years before the bond issue from Compustat and use the five-year averages to smooth yearly fluctuations.

We expect firms with large market-to-book ratios and firms with large intangible assets to have assets that are more opaque.

### 2. Opinion-based Proxies

The basic idea for our opinion-based proxies is that asset opaqueness problems make it harder for investors and stock analysts to evaluate the value of the firm, and as a result, different opinions about the firm's future earnings and stock price are more likely. To capture the difference in opinions, we use the standard deviation in analysts' earnings forecasts. Analysts have more difficulty agreeing with each other if a firm has asset opaqueness problems. We define the standard deviation of analysts' earnings forecasts (stdev of forecasts) as the standard deviation of forecasted EPS divided by the stock price.

Some small firms are followed by only one stock analyst, resulting in zero standard deviation in the analyst forecast. To eliminate the bias of a small number of stock analysts, we exclude firms that have fewer than three stock analysts. We note that stock analysts' earnings forecast errors are also often used to proxy for asset opaqueness. We do not use this measure because it only captures a one-time earnings surprise. Furthermore, it is likely to be correlated with the standard deviation in analysts' forecasts.

We also use the number of stock analysts to proxy for asset opaqueness. More stock analysts could result in more information flows to investors, thus reducing asset opaqueness (Brennan and Subrahmanyam, 1995). We expect firms with higher standard deviations in earnings forecasts and less relative stock analyst coverage to have assets that are more opaque, and thus be more likely to have split ratings.

### 3. Market Microstructure Proxy

Market microstructure studies often measure asset opaqueness by the adverse selection component of the bid-ask spread of a firm's stock. The bid-ask spread can generally be decomposed into three components: order processing, inventory costs, and adverse selection. Holding the other two components fixed, a wider bid-ask spread means a larger adverse selection component for firms with more asset opaqueness.

Many studies in financial research use the adverse selection component of the bid-ask spread as a measure of asset opaqueness. For example, Flannery, Kwan, and Nimalendran (2004) use the adverse selection component of banks' bid-ask spread to measure the relative opaqueness of the bank's assets. In this study, we use the methods proposed by George, Kaul, and Nimalendran (1991) to estimate the adverse selection component of the bid-ask spread. We expect that firms with a larger adverse selection component in their stock bid-ask spread are more likely to receive split ratings.

#### 4. Other Proxies

Firm size is another proxy for asset opaqueness. Large firms are often under more scrutiny by the financial media. Also, large firms generally access capital markets more frequently and reveal more information to investors to lower their cost of capital. We define firm size as the natural log of (number of shares times the stock price) and denote it by the log of firm size. The stock price that we use is the average of the highest and lowest daily closing prices for the year of bond issue. The number of shares is the number of shares outstanding at the end of bond issue year.

Firms with asset opaqueness problems are more likely to experience mis-pricing of their securities as investors have a harder time understanding and analyzing the firm's value and future prospects. Long term debt and equity are more likely to be mispriced due to the long investment horizon. Flannery (1986) argues that firms with large information asymmetries (such as high-growth firms) are more likely to issue short-term debt, while firms with smaller information asymmetries are more likely to issue long-term debt. In this study, we use the natural log of bond maturity, which we measure in months to maturity, as another proxy for asset opaqueness problems. We use the log of maturity because the relation between asset opaqueness and debt maturity is likely to be nonlinear. The difference in asset opaqueness between firms issuing one-year bonds and firms issuing ten-year bonds is likely much bigger than between firms issuing twenty-year bonds and firms issuing thirty-year bonds.

#### 5. Other Variables

The other variables we use in this study are bond ratings and bond split dummy variables. We use two methods to measure bond ratings. The first one, which we call the S&P rating, is an ordinal variable ranging from one (if rated AAA by S&P), two (if rated AA+ by S&P) to 19 (if rated CCC- by S&P). Our second method uses a series of zero/one dummy variables to capture the categorical nature of bond rating. For example, AAA equals one if a bond is rated AAA by S&P, and zero otherwise. To minimize the number of dummy variables in this measure of bond ratings, we consider only letter ratings. Throughout the paper, we use the S&P rating to measure the level of credit risk. Using Moody's rating provides very similar results.

To measure the split in ratings between S&P and Moody's, we use two variables. The first one, SPLIT, is a zero/one dummy variable that equals one if the S&P rating differs from the Moody's rating at the notch level, and zero if S&P rating is the same as the Moody's rating.

The second variable, SPLIT LEVEL, captures the degree of rating split between the S&P and the Moody's. We define the variable as follows: SPLIT LEVEL equals zero if the S&P and Moody's ratings are the same, SPLIT LEVEL equals one if S&P and Moody's ratings differ by only one notch, and SPLIT LEVEL equals two if S&P and Moody's ratings differ by more than one notch.

### B. Descriptive Statistics

Table I provides descriptive statistics for the sample. Column A reports the variable means for the whole sample. Columns B, C, and D provide the variable means for the non-split subsample, split with one notch subsample, and split-with-more-than-one notch subsample, respectively. Column E shows the differences in variable means between the non-split subsample and the split-with-one-notch subsample. Column F shows the differences in variable means between the non-split subsample and the split-with-more-than-one notch subsample.

Table I shows that 908 bond issues have the same ratings from Moody's and S&P, and 871 bonds issues have split ratings. Thus, about 49% of industrial bonds in our sample have split ratings at the notch level. This pattern is similar to Morgan's (2002) finding that about 50% of bond issues by non-banking firms from 1983 to 1993 have split ratings at the notch level. Cantor and Packer (1995) also find that about 47% of sovereign debt has split ratings at the notch level.

The results in Table I indicate that issuing firms with non-split ratings are larger, have a lower market-to-book ratio, fewer intangible assets, lower standard deviation in analyst earnings forecasts, more stock analysts, a smaller adverse selection component in their stock bid-ask spread, and issue longer-term debt. Split ratings are also more common for bonds with lower ratings. This result supports our hypothesis that issuing firms with more asset opaqueness problems are more likely to have split bond ratings.

We note that we find a small number of bond issues (45) that have ratings split between investment grade and below investment grade. We compare the means of the proxies for asset opaqueness between this group of split rated bonds and other split rated bonds and do not detect significant differences between them.

Although we define split ratings at the notch level, we also examine split ratings at the letter level. In unreported results, we find that out of the 1,779 observations in our sample, 318 bond issues have different letter ratings from Moody's and S&P. Of those split at the letter level, 205 are split with one notch (for example, BBB+/A-), and 113 are split with more than one notch (for example, BBB+/A). A small number of bond issues (35) have the same letter ratings, but the ratings differ by more than one notch (for example, A+/A-). For bond issues with one notch splits, there are no significant differences in the proxies for asset opaqueness between bond issues with and without letter splits. But for bond issues with letter split ratings, those with more than one notch split have significantly higher asset opaqueness problems than do those with one notch split, as indicated by the proxies for asset opaqueness. These results suggest that splits at the letter level do not indicate more asset opaqueness problems beyond the split at the notch level.

Although not tabulated, we also examine the correlations among the variables. First, we find that the variable SPLIT LEVEL is negatively correlated with firm size, number of analysts, and debt maturity, and positively correlated with market-to-book ratio, intangible assets, and standard deviation of analyst forecasts. These correlations are significant at the 1% or 5% level. This result supports our hypothesis that firms with opaque assets are more likely to receive split ratings. Second, most of the proxies for asset opaqueness we use in this study are also correlated. The high correlations are not surprising since all of the variables are proxies for asset opaqueness.

## II. Split Bond Ratings and Asset Opaqueness

In this section, we relate our proxies for asset opaqueness to split ratings in a multivariate model. To do so, we estimate several probit models to examine the influence that our proxies for asset opaqueness have on split ratings. Since the number of analysts and firm size are highly correlated, we scale the independent variable, No. of Analysts, by the market value of the firm's

## Table I. Descriptive Statistics

This table reports the descriptive statistics for our asset opaqueness proxies and other variables. The upper number in each cell reports the average value of the variable. The lower number in parenthesis reports the standard deviation of each variable. Log of Firm Size is the natural log of the market value of the firm's equity in millions of dollars. We use the five-year average annual Compustat data to calculate the market-to-book ratios and intangible assets before the bond issues. The IBES dataset is used to obtain the opinion-based proxies for asset opaqueness, standard deviation of forecasts and number of analysts. We define the standard deviation of analysts' earnings forecasts as the standard deviation of forecast EPS/stock price. To calculate these opinion-based proxies, we use the analysts forecast data nine months before the end of prior fiscal year of the bond issues. For the adverse selection component of bid-ask spread, we use the method proposed by George, Kaul, and Nimalendran (1991) to find the adverse selection component of the bid-ask spread as a percentage of issuing firm's stock price. Log of maturity is the natural log of the months to final maturity. S&P rating is an ordinal number ranging from one (for AAA rated bonds by S&P) to nineteen (for CCC- rated bonds by S&P). Column A gives the means for the whole sample. Columns B, C and D give the means for the non-split, split-with-one-notch, and split-with-more-than-one-notch subsamples, respectively. Column E gives the differences in the means for the non-split and split-with-one-notch subsamples, and Column F gives the differences for the non-split and split-with-more-than-one-notch subsamples.

| | A | B | C | D | E | F |
|---|---|---|---|---|---|---|
| | **Whole Sample** | **Non-Split** | **Split with one notch** | **Split with more than one notch** | **B-C** | **B-D** |
| Log of Firm Size | 8.102 | 8.193 | 8.080 | 7.652 | 0.113 | 0.541*** |
| (in millions) | (1.50) | (1.56) | (1.46) | (1.26) | | |
| Market to Book | 2.446 | 2.244 | 2.558 | 3.132 | -0.314** | -0.888** |
| | (4.44) | (2.91) | (3.71) | (10.88) | | |
| Intangible Assets | 0.095 | 0.087 | 0.092 | 0.156 | -0.005 | -0.069*** |
| | (0.13) | (0.12) | (0.13) | (0.19) | | |
| Stdev of Forecasts | 0.006 | 0.005 | 0.006 | 0.014 | -0.001 | -0.009*** |
| | (0.02) | (0.01) | (0.01) | (0.06) | | |
| No. of Analysts | 16.873 | 17.587 | 16.697 | 13.338 | 0.890** | 4.249*** |
| | (9.17) | (9.53) | (8.86) | (7.32) | | |
| Adverse Selection | 0.141 | 0.137 | 0.144 | 0.140 | -0.007 | -0.001 |
| | (0.14) | (0.13) | (0.13) | (0.15) | | |
| Log of Maturity | 4.837 | 4.886 | 4.795 | 4.740 | 0.091*** | 0.146*** |
| | (0.70) | (0.71) | (0.69) | (0.68) | | |
| S&P Rating | 8.232 | 7.813 | 8.542 | 9.284 | -0.639*** | -1.471*** |
| | (3.98) | (3.99) | (3.79) | (4.52) | | |
| No. of Obs. | 1,779 | 908 | 723 | 148 | | |

*** Significant at the 0.01 level.
** Significant at the 0.05 level.

equity in the probit regression analyses. This allows us to separate the effect of firm size from the number of analysts.

First, we construct a model in which we regress the variable SPLIT LEVEL on log of firm size, market-to-book ratio, intangible assets, standard deviation of analyst forecasts, number of analysts, the adverse selection component of issuing firms' stock bid-ask spread, and log of bond maturity.[3]

[3]We note that we also use the variable, SPLIT, as the dependent variable, and the results are essentially the same as those reported.

Based on our previous discussion about the proxy variables for asset opaqueness and our hypothesis that split ratings are a result of a firm's asset opaqueness problem, we expect the coefficients for firm size, number of analysts, and bond maturity to be negative, and the coefficients for market-to-book ratio, intangible assets, standard deviation of forecast, and adverse selection component to be positive.

Table II, Model 1, reports the results for this model. All the coefficients have the expected signs, except the coefficient on adverse selection which is not significant. Six out of the seven coefficients are significant at the 1% level. In Model 1 and the other two probit regression models that follow, we also include a series of zero/one year dummy variables to control for possible differences in split ratings over time. None of the year dummy variables are significant. For the sake of brevity, we do not report the coefficients on the year dummies.

Next, we add the ordinal rating variable, S&P Rating, to the model to see if firms with higher credit risk are more likely to receive a split rating. Model 2, in Table II, reports the results for this model specification. The coefficient for S&P Rating is not statistically significant.

In Model 3, we use the cardinal rating dummies in the probit model instead of the ordinal rating variable. The base case is BBB-rated bonds. We use the BBB-rated bonds as the base case for three reasons. First, we have a large number of observations in the BBB category, while the number of AAA- or CCC-rated bonds is small. Second, BBB-rated bonds can be split with either a higher or a lower rating, while AAA-rated bonds can only split with a lower rating. Finally, BBB is the lowest rating for investment grade bonds. Comparing other ratings with BBB-rated bonds can show us if there is a systematic difference between investment grade and junk bonds.

The results in Model 3 provide several additional insights. First, the coefficient on AAA is negative and significant. This negative effect is not surprising since AAA can only split with a lower rating, but BBB bonds can split with either a higher or a lower rating. Thus, AAA-rated bonds are less likely to have a split rating than BBB-rated bonds. The coefficients for AA and A are either negative or not significant, indicating that AA and A are not more or less likely than BBB bonds to have a split rating. The coefficients for BB and CCC are positive and significant, suggesting they are more likely to have split ratings than BBB bonds.

Overall, the results from Model 3 indicate that there is not a monotonic relation between credit risk and split ratings. Thus, the coefficient for the S&P Rating in Model 2 cannot detect any trend. On the other hand, it also seems that junk bonds are more likely to have split ratings than are investment grade bonds. This pattern is consistent with the Livingston, Naranjo, Nimalendren, and Zhou (2005) findings that firms with more opaque assets tend to receive lower bond ratings. Furthermore, the significance level for some coefficients in Model 3, where we control for the categorical rating variables, is lower. For example, the coefficient for Log of Firm Size becomes marginally significant in Model 3 and the coefficient on Standard Deviation of Earnings Forecast is significant in Models 1 and 2 at the 1% level, but only significant at the 5% level in Model 3. These results further suggest that when assigning ratings, the rating agencies take into consideration asset opaqueness problems.

The last two columns in Table II report the estimated magnitude of the impact of each explanatory variable on the probabilities of one notch and more-than-one-notch split ratings. To estimate the magnitude of impact, we use the results in Model 3. For each explanatory variable, we calculate the predicted probabilities of one notch and more-than-one-notch split rating at two values: half a standard deviation above and half a standard deviation below its sample value, while holding other variables at their observation values. The difference between the predicted probabilities at the two values reflects the changes in the probability of split rating when the explanatory variable changes by one standard deviation. We repeat this calculation for all observations in the sample and average the differences in probabilities. Thus, the numbers

## Table II. Asset Opaqueness and Split Ratings: Probit Regressions of Split Rating

This table reports the results of probit regressions of the level of splits on proxies for asset opaqueness and bond ratings. The dependent variable is Split Level, set equal to zero if non-split, one if split with one notch, and two if split with more than one notch. Because the number of analysts is highly correlated with firm size, we scale the independent variable, No. of Analysts, by the market value of firm's equity. Doing so avoids multicollinearity problems. Log of Firm Size is the natural log of the market value of the firm's equity in millions of dollars. The standard deviation of analysts' earnings forecasts is the standard deviation of forecast EPS/stock price. We use the method proposed by George, Kaul, and Nimalendran (1991) to find the adverse selection component of the bid-ask spread as a percentage of issuing firm's stock price. Log of maturity is the natural log of the months to final maturity. S&P rating is an ordinal number ranging from one (for AAA rated bonds by S&P) to nineteen (for CCC- rated bonds by S&P). In Model 1, we use only the proxies for asset opaqueness. In Model 2, we add the ordinal rating variable, S&P Rating, to the regression. In Model 3, we add the cardinal rating variables to the regression. In this model, the base case is BBB-rated bonds by S&P. In all the three models, we use a series of zero/one year dummy variables to control for possible differences in split ratings over time. None of the year dummy variables are significant. For the sake of brevity, we do not report the coefficients on the year dummies. Columns 6 and 7 report the estimated magnitude of the impact of each explanatory variable on the probabilities of one notch and more-than-one-notch split ratings. To estimate the magnitude of the impact, we use the results in Model 3. For each explanatory variable, we calculate the predicted probabilities of one notch and more-than-one-notch split ratings at two values: half a standard deviation above and half a standard deviation below its sample value, while holding other variables at their observation values. The difference between the predicted probabilities at the two values reflects the changes in the probability of split rating when the explanatory variable changes by one standard deviation. We repeat this calculation for all observations in the sample and average the differences in probabilities. Thus, the numbers reported in Columns 6 and 7 are the changes of probabilities of a bond issue being a one notch or more-than-one-notch split rated if the explanatory variable varies by one standard deviation. Since the six rating variables are categorical variables, the estimated impact reflects the changes in the probabilities of split rating if the bond rating changes from BBB (the base case) to any specific rating. The numbers in the parentheses are p-values. We adjust the p-values for potential clustering problems that might arise, for instance from multiple bond issues by issuing firms.

| | Predicted Signs | Model 1 | Model 2 | Model 3 | Changes in Prob. of One Notch Split | Changes in Prob. of More-Than-One-Notch Split |
|---|---|---|---|---|---|---|
| Log Firm Size | − | -0.105*** | -0.070* | -0.075* | -2.66% | -1.61% |
| | | (0.00) | (0.10) | (0.08) | | |
| Market to Book | + | 0.020*** | 0.017*** | 0.021*** | 2.22% | 1.34% |
| | | (0.01) | (0.01) | (0.01) | | |
| Intangible Assets | + | 0.851*** | 0.794*** | 0.765*** | 2.37% | 1.43% |
| | | (0.01) | (0.01) | (0.01) | | |
| Stdev of Forecasts | + | 5.656*** | 4.947*** | 3.611** | 1.77% | 1.07% |
| | | (0.00) | (0.00) | (0.04) | | |
| No. of Analysts | − | -0.010*** | -0.010*** | -0.008** | -2.03% | -1.24% |
| | | (0.01) | (0.01) | (0.05) | | |
| Adverse Selection | + | -0.166 | -0.168 | -0.169 | -0.57% | -0.34% |
| | | (0.53) | (0.52) | (0.53) | | |
| Log of Maturity | − | -0.117*** | -0.110*** | -0.110*** | -1.83% | -1.10% |
| | | (0.01) | (0.01) | (0.01) | | |
| S&P Rating | | | 0.020 | | | |
| | | | (0.17) | | | |

**Table II. Asset Opaqueness and Split Ratings: Probit Regressions of Split Rating (*Continued*)**

| | Predicted Signs | Model 1 | Model 2 | Model 3 | Changes in Prob. of One Notch Split | Changes in Prob. of More-Than-One-Notch Split |
|---|---|---|---|---|---|---|
| AAA | | | | -0.819*** | -22.96% | -6.37% |
| | | | | (0.01) | | |
| AA | | | | 0.004 | 0.10% | 0.05% |
| | | | | (0.98) | | |
| A | | | | -0.158* | -4.18% | -2.12% |
| | | | | (0.09) | | |
| BB | | | | 0.302*** | 6.90% | 5.02% |
| | | | | (0.01) | | |
| B | | | | -0.163 | -4.39% | -2.08% |
| | | | | (0.17) | | |
| CCC | | | | 0.743** | 11.00% | 16.42% |
| | | | | (0.05) | | |
| No. of Obs. | | 1,779 | 1,779 | 1,779 | | |

*** Significant at the 0.01 level.
** Significant at the 0.05 level.
* Significant at the 0.10 level.

reported in the last two columns of Table II are the changes in the probabilities of a bond issue being one notch or more-than-one-notch split rated if the explanatory variable varies by one standard deviation. Since the six rating variables are categorical variables, the estimated impact reflects the changes in the probabilities of split rating if the bond rating changes from BBB (the base case) to any specific rating.

Among our proxies for asset opaqueness, the Log of Firm Size has the largest impact on the probabilities of split ratings and Adverse Selection has the smallest. The small impact of Adverse Selection is not surprising because the coefficients on Adverse Selection are not significant in the probit regression estimations. A triple-A rating significantly lowers the probability of split ratings. This result is expected because AAA-rated bonds can only split down, not up. Further, AAA-rated bonds are issued by large companies that often have more transparent assets. Also, CCC-rated bonds are 11% (16%) more likely than BBB-rated bonds to have a one-notch (more-than-one-notch) split rating.

Overall, the results in Table II indicate that firms with more asset opaqueness problems are more likely to have split ratings. This finding is consistent with Morgan's (2002) results that, due to their opaque assets, banks are more likely to receive split ratings than are non-financial firms. Our results are also robust with respect to subperiod tests. Estimates over the 1983 to 1995 and 1996-2001 subperiods yield similar results.

### A. Lopsided or Symmetric Split Ratings

Morgan (2002) also finds that the split ratings are lopsided, with Moody's consistently on the downside. He builds a model to show that lopsided split ratings are more consistent with the asset opaqueness hypothesis. On the other hand, Ederington's (1986) random error hypothesis implies that the split ratings should be symmetric, with no rating agency consistently on the up or downside.

We examine the relative ratings of the two rating agencies and report the results in Table III. We convert both kinds of ratings from an alphanumerical system to an ordinal number ranging from one (for AAA-rated bonds) to 19 (for CCC-rated bonds). For both the whole sample and the split-rated sample, we find that the Moody's ratings are consistently on the downside and that the difference is significant at the 1% level. Furthermore, only 20.57% (42.02%) of issues in the whole (split-rated) sample have better Moody's ratings, but 28.34% (57.97%) of issues in the whole (split-rated) sample have better S&P ratings. This pattern confirms Morgan's (2002) finding that split ratings are lopsided, with Moody's consistently on the downside, and is consistent with the asset opaqueness hypothesis.

Morgan's (2002) model also shows that "the splits are more lopsided in the more opaque sectors." To examine the relation between asset opaqueness and the lopsided aspect of split ratings, we first construct an asset opaqueness index (OI) and then divide our sample into two subsamples, transparent bond issues and opaque bond issues, according to the issue's opaqueness index.

The asset opaqueness index (OI) is the weighted average of the ranks of the seven proxies of asset opaqueness. That is:

$$OI_i = \frac{1}{N}\frac{1}{K}\sum_{k=1}^{7} Rank_k\left(X_{i,k}\right), \tag{1}$$

where $X_{i,k}$ is the $k^{th}$ measure of opaqueness for bond issue $i$ in the sample. The rank function ranks each observation from least opaque to most opaque. That is, the most opaque issue has a rank of $N$, and the least opaque issue has a rank of one. We then average the ranks of the seven proxies and scale this average by the number of observations. Thus, the opaqueness index, OI, ranges from zero (least opaque) to one (most opaque). The construction of the opaqueness index is similar to Butler, Grullon, and Weston's (2005) liquidity index.

By construction, the mean of the OI is 0.5. Thus, we divide our sample into two subsamples: those with OI less than or equal to 0.5 (transparent issues), and those with OI greater than 0.5 (opaque issues). The last two rows of Table III report the relative ratings of Moody's and S&P for the two subsamples. The rating difference between Moody's and S&P is 0.15 for the opaque issue sample, but only 0.08 for the transparent issue sample. These findings are consistent with Morgan's (2002) argument that split ratings are more lopsided for more opaque issues.

### B. Persistence of Split Ratings

To further examine the asset opaqueness hypothesis, we investigate the persistence of split ratings. It is highly unlikely that firms can change their asset structure in a short period of time to make them transparent. Thus, asset opacity should not change rapidly, which implies that split-rated bonds will tend to remain split-rated and non-split-rated bonds will tend to remain non-split. On the other hand, the random error hypothesis implies that ratings for split-rated and non-split bonds will tend to change over time.

To examine the persistence of split ratings, we track the Moody's and S&P ratings of each bond to see if split-rated bonds remain split-rated or if the two ratings converge after one, two, three, and four years after the initial issuance. Figure 1 reports the percentage of split-rated bonds several years after the initial issuance for three subsamples: 1) initial non-split-rated bond, 2) initial split with one notch, and 3) initial split with more than one notch. Although there is some rating convergence for the initially split-rated samples, it

## Table III. Lopsided or Asymmetric Split Ratings

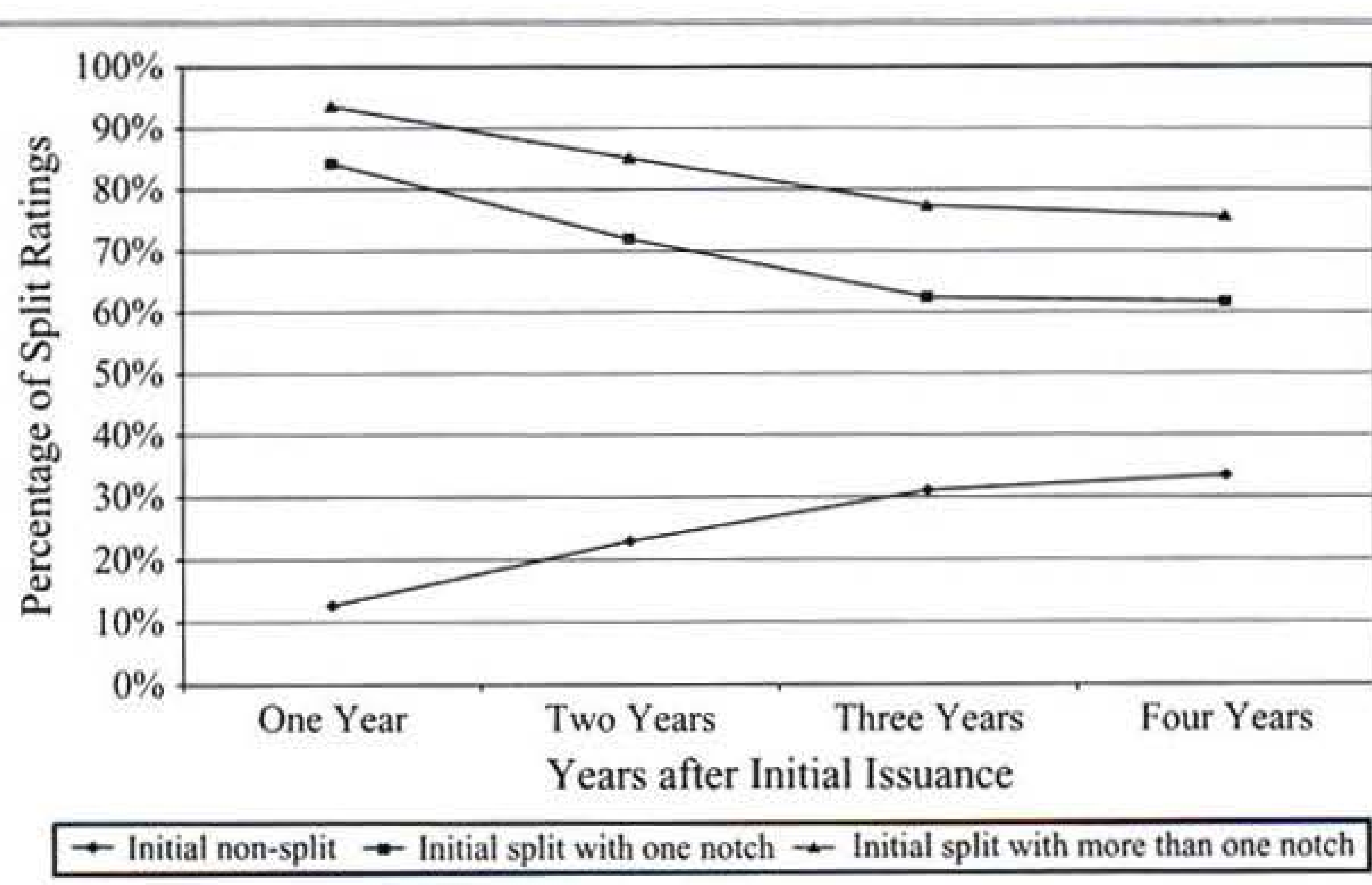
This table compares the ratings from the two major rating agencies: Moody's and S&P for the whole sample and some sub-samples. Columns 2 and 3 report the average Moody's and S&P numerical ratings. We convert both ratings from an alphanumerical system to an ordinal number ranging from one (for AAA rated bonds) to nineteen (for CCC- rated bonds). Column 4 gives the difference between the Moody's and S&P ratings. Columns 5 and 6 give the percentage of bond issues that receive better Moody ratings and S&P ratings respectively. Row 2 reports the results for the whole sample. Row 3 reports the results for the split-rated sub-sample. Rows 4 and 5 report the result for the opaque issues and transparent issues sub-samples. We classify a bond issue as an opaque (transparent) issue if the opaqueness index (OI) of the issue is greater than (less than) 0.5. We construct the opaqueness index from the seven proxies of asset opaqueness. The index ranges from zero (least opaque) to one (most opaque).

| | Average Moody's Rating | Average S&P Rating | Difference | Percentage of Issues with Better Moody's Rating | Percentage of Issues with Better S&P Rating | No. of Obs |
|---|---|---|---|---|---|---|
| Whole Sample | 8.35 | 8.23 | 0.12*** | 20.57% | 28.34% | 1,779 |
| Split Rated Sample | 8.91 | 8.67 | 0.24*** | 42.02% | 57.97% | 871 |
| Opaque Issue Sample | 10.59 | 10.44 | 0.15*** | 21.69% | 30.81% | 899 |
| Transparent Issue Sample | 6.06 | 5.98 | 0.08*** | 19.43% | 25.91% | 880 |

*** Significant at the 0.01 level.

## Figure 1. Rating Convergence

This figure reports the percentage of split ratings one, two, three, and four years after the initial issuance for three subsamples: 1) initial non-split ratings sample, 2) initial split ratings at one notch sample, and 3) initial split ratings with more-than-one-notch sample.



tapers off after three years. About two thirds of initially split-rated bonds remain split-rated four years after the initial issuance. Also, two thirds of initially non-split-rated bonds remain non-split.

In addition to the rating history of a particular bond, we also track the rating history for issuing firms that have repeated bond issues during our sample period. We find that 320 issuing firms issued multiple bonds, and that the average time lag between the first issue and the last issue is about 5 years. We also find that 148 of the issuing firms have their first bond issue split-rated, and 94 (or 64%) of them also have their last bond issue split-rated. On the other hand, for the 172 issuing firms whose first bond issues are not split-rated, only 74 (or 43%) of them have their last bond offering split-rated.

These findings suggest that both split ratings and non-split ratings are persistent over time. Such persistence is consistent with the asset opaqueness hypothesis.

### C. New Split Ratings and Asset Opaqueness

Although firms with non-split-rated bonds are less likely to have asset opaqueness problems, not all such firms are necessarily transparent. Some opaque firms may have a wide range of credit risk estimates at initial issuance, but the range of credit risk estimates happens to fall within rating boundaries. Although such firms may have a non-split rating at initial issuance, small changes in the credit risk after the initial issuance may move the ranges of credit risk estimates up or down to cross a rating boundary, resulting in new split ratings.

We expect that initially non-split-rated bonds that later become split-rated tend to have assets that are more opaque than do bonds that remain non-split-rated. To test this hypothesis, we check the ratings of all the initially non-split-rated bonds two years after the initial issuance. Out of the 744 bond issues that are non-split-rated at the time of issuance and do not mature within two years, 573 remain non-split-rated and 171 become split-rated.

In Table IV, we compare the means of the seven proxies for asset opaqueness for the two subsamples. Six out of the seven proxies indicate that bonds that become split-rated two years after initial issuance have greater asset opaqueness problems at initial issuance than those that remain non-split-rated. This finding further supports the hypothesis that asset opaqueness is a determinant of the split bond ratings.

There is another reason that bonds might change from non-split to split ratings, which is asynchronous changes in ratings by the two rating agencies. This hypothesis implies that there are no differences between bonds that remain non-split and bonds that become split. Our findings do not support this explanation.

## III. Conclusions

In this paper, we relate firm asset opaqueness problems to split ratings. We find that firms with asset opaqueness problems are more likely to have split bond ratings. Further, we find that split ratings are lopsided rather than symmetric. These findings are consistent with Morgan's (2002) findings that bond issues by banks, due to their greater asset opaqueness, are more likely to have split ratings. In addition, we find that split ratings are persistent. Two thirds of split-rated bonds remain split-rated four years after the initial issuance.

Our findings have several implications. First, the findings suggest that split-rated bonds should be priced to offer additional risk premiums to compensate investors for the uncertainty about the issuing firm's fundamentals. We do not investigate the pricing of split-rated bonds, but note that

### Table IV. Bonds Remaining Non-Split Compared to Bonds that Become Split

This table reports descriptive statistics for the asset opaqueness proxies and other variables for a sample of bonds that were initially not split rated. The bonds had a maturity of at least two years and initial issuance before 1999. The upper number in each cell reports the average value of the variable, and the lower number in parenthesis reports the standard deviation of each variable. Column A gives the variable means for the whole sample. Column B gives the variable means for the subsample that remain non-split after two years of initial issuance. Column C gives the variable means for the subsample that become split after two years of initial issuance. Column D gives the difference in the means of the variable for the two subsamples, those that remain non-split and those that become split.

| | A | B | C | D |
|---|---|---|---|---|
| | **All Initially Non-Split** | **Initially Non-Split, Remain Non-Split** | **Initially Non-Split, Become Split** | **B-C** |
| Log of Firm Size | 8.155 | 8.263 | 7.79 | 0.470*** |
| (in millions) | (1.53) | (1.52) | (1.53) | |
| Market to Book | 2.035 | 2.078 | 1.892 | -0.186* |
| | (1.31) | (1.33) | (1.22) | |
| Intangible Assets | 0.079 | 0.075 | 0.091 | -0.016* |
| | (0.11) | (0.11) | (0.13) | |
| Stdev of Forecasts | 0.005 | 0.005 | 0.007 | -0.002*** |
| | (0.01) | (0.01) | (0.01) | |
| No. of Analysts | 8.174 | 18.885 | 16.579 | 2.306*** |
| | (11.75) | (9.82) | (9.22) | |
| Adverse Selection | 0.143 | 0.134 | 0.171 | -0.037*** |
| | (0.15) | (0.14) | (0.18) | |
| Log of Maturity | 4.955 | 4.990 | 4.836 | 0.154*** |
| | (0.67) | (0.68) | (0.63) | |
| No. of Obs. | 744 | 573 | 171 | |

*** Significant at the 0.01 level.
* Significant at the 0.10 level.

studies on the pricing of split-rated bonds show mixed results. Billingsley, Lamy, Marr, and Thompson (1985) and Liu and Moore (1987) find that investors pay more attention to the lower of the two ratings, but Hsueh and Kidwell (1988) and Reiter and Ziebart (1991) find that the higher of the two ratings sets market prices. Jewell and Livingston (1998) find that both higher and lower bond ratings affect bond prices and underwriter's fees. Cantor and Packer (1997b) find that the split-rated bonds are priced at the average of the two ratings. Further research on the effects of split ratings on bond pricing is warranted.

Second, we find that of our seven proxies for asset opaqueness, only the adverse selection component is consistently unrelated to the probability of split ratings. This result raises some cautions and concerns on the use of this variable to robustly measure asset opaqueness or information asymmetry in the literature. Van Ness, Van Ness, and Warr (2001) find that there is no relation between the adverse selection component and other commonly used proxies for asset opaqueness, such as the market-to-book ratio, analysts forecast errors, etc. Thus, we note that studies that use this measure as a proxy for asset opaqueness or information asymmetry are effectively joint tests of whether the adverse selection component of the spread truly measures asset opaqueness problems, and that the firms under scrutiny do have asset opaqueness problems.■

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