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Split bond ratings and rating migration ☆

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Abstract

This paper examines the relationships between split ratings and ratings migration. We find that bonds with split ratings are more likely to have future rating changes. A one-notch (more-than-one-notch) split rating increases the probability of rating change within one year of initial issuance by about 3% (6%). Furthermore, we find that about 30% of split rated bonds have their two ratings converge after four years of initial issuance. The rating convergence tapers off after three years, and the rating agency with a higher (lower) initial rating generally maintains a higher (lower) rating in subsequent years if the two ratings do not converge. We also show that rating transition estimation can be improved by taking into consideration split ratings. We find that one-year rating transition matrices are significantly different between non-letter-split rated bonds and letter-split rated bonds, and we show that the difference has an economically significant impact on the pricing of credit spread options and VaR-based risk management models. Overall, our results suggest that split ratings contain important information about subsequent rating changes.

JEL classification: G10; G12; G14; G23

Keywords: Ratings; Rating migration; Split rating; Risk management; VaR; Information content

1. Introduction

Approximately 20% of US corporate and municipal bonds have letter split ratings, and about 50% of sub-ratings or notch-level ratings are split (see, for example, Jewell and Livingston, 1998; Livingston et al., 2007). While split rated corporate bonds are common, their influence on subsequent rating changes has received little attention. A better understanding of this relationship is important because changes in credit ratings can have a significant impact on bond yields and prices. In turn, bond yields influence a firm's investment policy, as well as the decisions and behavior of other financial market participants. In this paper, we examine the link between split ratings and rating migration.

Earlier studies investigate the causes of split ratings and impact of split ratings on bond yields. For example, Ederington (1986), Morgan (2002) and Livingston et al. (2007) investigate the causes of split ratings, while Billingsley et al. (1985), Hsueh and Kidwell (1988), Cantor et al. (1997), Jewell and Livingston (1998) and Santos (2006) examine the impact of split ratings on bond yields and/or underwriter spreads. Additional research also shows that split ratings convey valuable information and are priced by the bond market (e.g., Livingston et al., 2008; Jewell and Livingston, 1998). To the extent that split ratings contain additional information, they may also have an impact on future rating changes.

We find that bonds with split ratings are more likely to have a rating change after the initial bond issuance.

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A one-notch split rating increases the probability of a Moody's (S&P) rating change within one year of initial issuance by 2.94% (2.72%), and a more-than-one-notch split rating increases the probability of a Moody's (S&P) rating change by 5.47% (5.56%). Furthermore, the rating agencies that assign a higher (lower) initial rating on a split rated bond are more likely to downgrade (upgrade) their ratings. A higher initial rating by Moody's (S&P) increases the probability of a downgrade by Moody's (S&P) by 3.56% (4.55%), and a lower initial rating by Moody's (S&P) increases the probability of an upgrade by Moody's (S&P) by 4.34% (5.64%) within one year of initial issuance. These rating change probabilities are highly significant, taking into account that only about 16% of all bonds have a rating change within one year of initial issuance.

Furthermore, we find that about 30% of split rated bonds have their two ratings converge after four years of initial issuance. However, rating convergence tapers off after three years, and the majority of split rated bonds remain split rated. In addition, the two rating agencies mostly maintain their relative ratings for those non-converged split rated bonds; that is, the rating agency with a higher (lower) initial rating generally maintains a higher (lower) rating in subsequent years if the two ratings do not converge.

The convergence results also shed some light on the cause of split ratings. While Ederington (1986) argues that there is no systematic difference between the two rating agencies and split ratings are caused by random errors, Morgan (2002) and Livingston et al. (2007) show that issuers of split rated bonds have more opaque assets. Ederington's random error hypothesis implies that the split rated bonds will have their two ratings converge over time. On the other hand, the asset opaqueness hypothesis implies that the split rated bonds tend to remain split rated if the firm's assets remain opaque. We find that the majority of split rated bonds remain split rated, and they generally maintain their initial relative ratings. This finding lends more support to the asset opaqueness hypothesis and suggests that split ratings are not, in general, caused by random errors as argued by Ederington (1986).

Other interesting findings emerge in this study. For example, we find that split rated utility and financial issues are also more likely to be upgraded than industrial issues, and financial issues are less likely to be downgraded, consistent with the findings reported by Nickell et al. (2000). Highly rated bonds (AA and A) are less likely to be upgraded and more likely to be downgraded than BBB bonds. There is no clear pattern for below-investment grade bonds, except that BB bonds are more likely to be upgraded than BBB bonds. This result is consistent with Kisgen's (2006, 2007) findings that firms at the borderline of an investment grade rating take greater efforts (issuing less debt and reducing leverage ratio) to achieve (or maintain) investment grade rating.

This study also contributes to the research on rating transition matrices. There are numerous studies that relate initial bond ratings with future rating changes using transition matrices (see Duffie and Singleton, 2003, for a summary of rating transition studies). In these studies, probabilities of future upgrades and downgrades by Moody's (S&P) are estimated conditional on the existing Moody's (S&P) ratings. Our study shows that the rating transition estimation can be improved by taking into consideration split ratings. We find that one-year rating transition matrices are different between non-letter-split rated bonds and letter-split rated bonds.

The results of this study also have a practical implication for the pricing of credit derivatives as well as credit risk management. We use the two rating transition matrices from the split and non-split rated bonds to value a set of credit spread put options. The option premiums are significantly higher when the underlying obligators are split rated. More volatile future bond ratings increase the volatility of the credit spread, leading to a higher option premium. In addition, we show that the value-at-risk (VaR) for a split rated bond portfolio is much higher than an otherwise similar non-split rated bond portfolio. These results suggest that improved estimation of rating transition probabilities for split and non-split rated bonds has significant practical implications.

The rest of the paper is organized as follows. Section 2 describes the data and variable definitions. Section 3 provides a univariate and rating convergence analysis of split ratings and rating migration, while Section 4 provides a multivariate analysis and ratings transition matrices. Section 4 also provides evidence on the economic significance of the results by examining associated pricing effects on credit spread derivatives and VaR risk management effects. Section 5 discusses the findings and concludes the paper.

2. Data and descriptive statistics

2.1. Data

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. 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.[3]

Our sample period is from 1983 to 2000. We start in 1983 because Moody's started to have notch ratings only after April 1982. We stop in 2000 because we track the

[3] We note that Moody's does not have a default rating category and may assign a non-D rating to bonds in default. In that case, the Moody's rating measures the severity of the default (Christensen et al., 2004). Thus, Moody's rating for a bond in default can still change from, say, CC to C. This type of change may over-estimate the frequency of Moody's rating changes, especially for very low rated bonds. We thank the referee for this point.

rating changes up to four years after the initial issuance. All the issues included in the study have both S&P and Moody's ratings. We exclude issues that mature or are retired in four years or less. As a data quality filter, we also exclude 13 bond issues that are rated D by at least one rating agency because it is highly unlike that firms with D ratings have access to the public debt market. For firms that have multiple bond issues within the same month, we use the bond issue with the longest maturity because ratings on these multiple issues are mostly the same and unlikely to convey additional information. Our results do not change when we choose the bonds with the shortest maturity. The final sample has 9431 bond issues from 1983 to 2000. Slightly more than half of the bond issues are industrial issues. Financial and utility issues account for about 30% and 18% of the sample, respectively.

As shown in Table 1, 4559 bond issues have the same ratings from Moody's and S&P, while 4872 bond issues have split ratings at the notch-level. Among issues with a split rating at the notch-level, 3747 issues have the two ratings differ by one-notch (for example, A+ and A, or BBB− and BB+), and 1125 issues have the two ratings differ by more-than-one-notch. Furthermore, about 20% of the sample has a split-rating at the letter level. Previous studies report similar findings (e.g., Morgan, 2002).

Table 1
Descriptive statistics

	A	B	C	D
	Whole sample	Non-split	Split-with-one-notch	Split-with-more-than-one-notch
Maturity	14.77	14.43	14.77	16.17***
(years)	(10.00)	(10.00)	(10.00)	(10.08)***
Issue size (million)	206.60	203.40	208.86	212.05
	(140.00)	(135.00)	(140.00)	(150.00)***
	8.80	8.75	8.71	9.28***
Moody's rating	(8.00)	(8.00)	(8.00)	(9.00)***
	8.67	8.75	8.58	8.66
S&P rating	(8.00)	(8.00)	(8.00)	(8.00)
Percentage of industrial issues	51.60%	52.18%	52.04%	47.73%***
Percentage of utility issues	18.09%	19.2 6%	18.47%	12.09%***
Percentage of financial issues	30.31%	28.56%	29.49%	40.18%***
Percentage of split at notch-level	51.66%	0.00%	100.00%	100.00%
Percentage of split at letter level	20.03%	0.00%	27.73%	75.56%
Number of observations	9431	4559	3747	1125

This table reports the descriptive statistics for the sample. Maturity is the number of years to final maturity. Issue Size is the gross proceeds of the bond issue in millions of dollars. Moody's (S&P) rating is an ordinal number ranging from 1 for AAA rated bonds by Moody's (S&P) to 19 for C rated bonds by Moody's (S&P). Column A gives the means and median (in parenthesis) for the whole sample. Columns B to D give the means and medians (in parenthesis) for the non-split, split-with-one-notch, and split-with-more-than-one-notch sub-samples, respectively. *t*-Tests (Wilcoxon Mann-Whitney tests) are performed to test the differences in the variable means (medians) between the non-split and split sub-samples.

***, ** indicate significantly different from non-split sample at the 1% and 5% levels, respectively.

2.2. Descriptive statistics

Table 1 reports descriptive statistics for the whole sample, the non-split sub-sample, split-with-one-notch sub-sample, and the split-with-more-than-one-notch sub-sample. The average issue size is about $206 million for the whole sample. Bonds with split ratings have a slightly larger issue size. The average maturity for the whole sample is 14.77 years. Issues with more-than-one-notch split ratings have an average maturity of 16.17 years, significantly longer than the non-split issues.

In terms of credit rating, we create two ordinal variables, Moody's rating and S&P rating, which range from 1 (if rated AAA by Moody's or S&P), 2 (if rated AA+ by Moody's or S&P) to 19 (if rated C by Moody's or S&P). The average Moody's and S&P ratings for the whole sample are 8.80 and 8.67, respectively, or between BBB+ and BBB. Average ratings for split rated bonds are similar to the non-split rated sample, except for Moody's ratings of issues with more-than-one-notch split (which are significantly different from the non-split sample at the 1% level).

With regard to industry category, there are significant differences between the non-split sample and split rated samples. While less than 29% of the non-split rated sample are financial issues, over 40% of the split-with-more-than-one-notch sample are financial issues. This is consistent with Morgan's (2002) finding that banking firms are more likely to have split ratings due to asset opaqueness problems.

Finally, Table 1 shows that about 28% of bonds with one-notch split ratings are also split at the letter level, while 76% of bonds with more-than-one-notch split rating are split at the letter level.

3. Split ratings and rating migration: Univariate and rating convergence analysis

3.1. Rating changes: Univariate analysis

To better understand the link between bond split ratings and rating changes, we trace the rating history of the bonds in our sample one, two, three, and four years after their initial issuance. Table 2 reports the percentage of the bonds in our sample that have experienced at least one rating change within one, two, three, and four years of their initial issuance. Panel A reports the Moody's rating changes, and panel B reports the S&P rating changes.

The first column in Table 2 reports the percentage of bonds with at least one rating change for the whole sample. About 15.94% (16.55%) of bonds experienced a change in Moody's (S&P) rating within one year of initial issuance. The percentage increases to about 53.98% (54.68%) for Moody's (S&P) ratings within four years of initial issuance.

Table 2
Percentage of bonds with rating change

	Whole sample	Non-split	Split-with-one-notch	Split-with-more-than-one-notch
Panel A: Moody's rating changes				
Percentage of bonds with rating change in one year	15.94%	13.73%	17.24%***	20.53%***
Percentage of bonds with rating change in two years	33.55%	29.83%	35.71%***	41.42%***
Percentage of bonds with rating change in three years	46.08%	42.03%	48.52%***	54.40%***
Percentage of bonds with rating change in four years	53.98%	49.77%	56.20%***	63.64%***
Panel B: S&P rating changes				
Percentage of bonds with rating change in one year	16.55%	14.59%	17.69%***	20.71%***
Percentage of bonds with rating change in two years	35.38%	32.86%	36.64%***	41.42%***
Percentage of bonds with rating change in three years	47.65%	44.99%	49.21%***	53.24%***
Percentage of bonds with rating change in four years	54.68%	52.18%	55.91%***	60.71%***
Number of observations	9431	4559	3747	1125

This table reports the percentage of bonds that have at least one rating change within one, two, three, and four years of the initial bond issuance. Panel A reports the Moody's rating changes, and panel B reports the S&P rating changes. t-Tests are performed to test the differences in the variable means between the non-split and split samples.
***, ** indicate significantly different from non-split sample at the 1% and 5% levels, respectively.

Next, we separate our sample into three sub-samples: non-split, split-with-one-notch, and split-with-more-than-one-notch. In every case, the sample of bonds with more-than-one-notch split has the highest percentage of rating changes, while the non-split sample has the lowest percentage of rating changes. The t-statistics for the differences between the non-split sub-sample and the split rated sub-samples are all significant at the 1% level. This shows that bonds with split ratings are much more likely to experience a rating change than the bonds with no split ratings at the initial issuance. We also find that, conditional on a rating change, the magnitude of rating changes are significantly larger for bonds with more-than-one-notch split than non-split rated bonds.

Bond issues from different industries could also have different rating change probabilities. Nickell et al. (2000), for example, find that Moody's bond ratings of banking issues are less stable than ratings on industrial issues. In Table 3 we report the rating changes by three industry categories: financial, industrial, and utility issues. Panel A provides the rating changes for the whole sample, while Panel B reports the rating change for non-split rated and split rated samples.

For the whole sample, we observe interesting differences between Moody's and S&P rating changes. Industrial issues seem to have fewer rating changes by Moody's than financial issues within one year of initial issuance, consistent with Nickell et al.'s (2000) results. However, the difference between the industrial issues and financial issues disappears three and four years after the initial issuance. Utility issues seem to have the most stable Moody's ratings in two, three, and four years of initial issuance. On the other hand, there is not much difference in the S&P rating changes among different industry categories within one year of initial issuance. For longer periods, financial issues seem to have the most stable S&P ratings.

We observe similar patterns for the split rated and non-split rated sub-samples. In addition, the split rated subsample always has a higher percentage of rating changes in all industry categories than non-split rated bonds. t-Tests show that the differences are significant at 1% or 5% levels, except for S&P ratings on utility issues.

Table 4 examines whether split rated bonds are more likely to be upgraded or downgraded within one year of initial issuance. For the non-split sub-sample, 5.75% (5.64%) of bond issues are upgraded by Moody's (S&P), while 7.83% (8.66%) are downgraded by Moody's (S&P) within one year of the initial issuance. This pattern of non-symmetric upgrades and downgrades has also been documented by other studies (e.g., Covitz and Harrison, 2000). For split rated issues, we separate them into two sub-samples: bonds with higher Moody's (lower S&P) ratings and bonds with lower Moody's (higher S&P) ratings. 11.74% (13.71%) of bonds with lower initial Moody's (S&P) rating are upgraded by Moody's (S&P), which is significantly higher than the non-split sample. Furthermore, 11.55% (13.82%) of bonds with higher initial Moody's (S&P) rating are downgraded by Moody's (S&P), which is again significantly higher than the non-split sample. These patterns are also observed for rating changes within two, three, and four years of initial issuance. These findings suggest that split rated bonds are more likely to receive an upgrade (downgrade) from the rating agency that assigns a lower (higher) initial rating.

3.2. Split ratings and rating convergence

In the previous section, we find that split rated bonds are more likely to receive an upgrade (downgrade) from the rating agencies that assigns a lower (higher) initial rating. This pattern suggests that the two rating agency may change their rating toward the other's rating, which may result in a convergence of the two ratings. In this section, we examine the possible rating convergence of split rated bonds.

Table 5 reports the rating convergence one, two, three, and four years after the initial issuance. First, for the initially non-split issues, 85.13% remain non-split after one

Table 3
Rating changes by industry categories

	Moody's rating changes			S&P rating changes		
	Financial	Industrial	Utility	Financial	Industrial	Utility
Panel A: Whole sample						
Percentage of bonds with rating change in one year	18.68%	14.61%	15.12%	16.68%	16.17%	17.41%
Percentage of bonds with rating change in two years	35.05%	33.52%	31.12%	32.84%	36.91%	35.29%
Percentage of bonds with rating change in three years	46.66%	47.27%	41.74%	42.22%	50.92%	47.421%
Percentage of bonds with rating change in four years	54.39%	55.24%	49.71%	49.18%	57.56%	55.69%
Number of observations	2859	4866	1706	2859	4866	1706
Panel B: Non-split rated sample (split rated sample)						
Percentage of bonds with	16.13%***	12.53%***	13.44%**	14.75%***	13.79%***	16.52%
Rating change in one year	(20.81%)	(16.61%)	(16.91%)	(18.30%)	(18.46%)	(18.36%)
Percentage of bonds with	31.49%***	29.97%***	26.99%***	29.65%***	33.96%***	34.62%
Rating change in two years	(38.02%)	(36.91%)	(35.51%)	(35.52%)	(39.73%)	(35.99%)
Percentage of bonds with	42.63%***	43.55%***	37.01%***	39.25%***	47.79%***	45.90%
Rating change in three years	(50.03%)	(50.82%)	(46.74%)	(44.70%)	(53.92%)	(49.03%)
Percentage of bonds with	49.08%***	51.45%***	46.24%***	46.08%***	54.73%***	54.33%
Rating change in four years	(58.83%)	(58.87%)	(53.38%)	(51.77%)	(60.27%)	(57.13%)
Number of observations	1302	2379	878	1302	2339	878
	(1557)	(2487)	(828)	(1557)	(2487)	(828)

This table reports the percentage of bonds that have at least one rating change within one, two, three, and four years of the initial bond issuance in different industry categories. Panel A reports the rating changes for the whole sample, and panel B reports the rating changes for the non-split and split rated samples. *t*-Tests are performed to test the differences in the variable means between the non-split and split samples.
***, ** indicate significantly different from non-split sample at the 1% and 5% levels, respectively.

Table 4
Rating upgrade and downgrade within one year of initial issuance

	Percentage of bonds with same end-of-period ratings (%)	Percentage of bonds with upgrade (%)	Percentage of bonds with downgrade (%)	Number of observations
Panel A: Moody's rating				
Initially non-split bonds	86.42	5.75	7.83	4559
Bonds with lower Moody's rating	80.82	11.74***	7.44	2837
Bonds with higher Moody's rating	83.98	4.47**	11.55***	2035
Panel B: S&P rating				
Initially non-split bonds	85.70	5.64	8.66	4559
Bonds with lower S&P rating	80.89	13.71***	5.41***	2035
Bonds with higher S&P rating	82.58	3.60***	13.82***	2837

This table reports the percentage of bonds that have their ratings upgraded, downgraded or remained at their initial ratings within one year of initial issuance. Panel A gives the Moody's rating and panel B gives the S&P rating. *t*-Tests are performed to test the differences in the variable means between the non-split and split samples. We note that the sum of the percentages of rating upgrade and downgrade in this table is slightly less than the percentage of rating changes reported in Table 2. The small difference is due to multiple rating changes that have same initial and end-of-period ratings.
***, ** indicate significantly different from the non-split sample at the 1% and 5% levels.

Table 5
Percentage of rating convergence

	One year after initial issuance (%)	Two years after initial issuance (%)	Three years after initial issuance (%)	Four years after initial issuance (%)	Number of observations
Initially non-split sample	85.13	70.39	62.95	59.22	4559
Initially split with one-notch sample	15.96	26.55	31.52	32.88	3747
Initially split with more-than-one-notch sample	6.40	13.42	19.11	22.84	1125
Whole sample	48.26	46.18	45.23	44.42	9431

This table reports the percentage of bonds that have the same end-of-period ratings from Moody's and S&P in one, two, three, and four years after the initial issuance. Statistics are reported for four different samples: non-split initial ratings sample, initial split ratings at one-notch sample, initial split ratings with more-than-one-notch, and the whole sample.

year. The percentage of the initially non-split issues that remain non-split rated declines steadily to 59.22% in four years. However, the decline levels off after three years and the majority of the initially non-split issues remain non-split. Second, there is a steady increase in the rating convergence among bonds that are initially split rated. For example, after one year, 15.96% of bonds with one-notch initially split ratings converge. The percentage increases to 32.88% after four years. There is a similar pattern for the bonds with more-than-one-notch split ratings, though the percentage of rating convergence is lower. This indicates that there is some rating convergence among the split rated bonds. However, the increase in the rating convergence tapers off after three years. Furthermore, the majority of bonds with initially split ratings remain split rated even after four years of initial issuance. The percentage of rating convergence for the initially split rated bonds never exceeds 33%. This pattern indicates there is a qualitative difference between the split and non-split rated bond issues.

Next, we examine those bonds that remain split rated to test whether the two major rating agencies change their relative assessment of the bond's credit risk. Ederington (1986) argues that the split ratings are caused by random errors and that "the respective positions of the two agencies could easily have been reversed; i.e., on another day or with a slightly different set of analysts, either agency might assign a different rating".

Table 6 reports the relative ratings of the two major rating agencies. For the non-split rated sample, 23.12% (17.66%) of issues have higher (lower) Moody's rating four years after the initial issuance. For the split rated sample, we separate them into two sub-samples: those with higher initial Moody's rating and those with lower initial Moody's rating. 57.64% (54.81%) of issues with higher (lower) initial Moody's rating still have a higher (lower) Moody's rating in four years. Only 12.48% (14.13%) of issues with higher (lower) initial Moody's rating end up with a lower (higher) Moody's rating in four years. This finding suggests that split rating are not completely caused by random errors and, indeed, over half of time the two rating agencies maintain their relative assessment of the credit risk of the split rated bond four years after the initial issuance.

Table 6
Relative bond ratings after initial issuance

	Same initial ratings (%)	Lower initial Moody's (%)	Higher initial Moody's (%)
Panel A: One year after initial issuance			
Same end-of-period ratings	85.13	13.43	14.20
Lower end-of-period Moody's	6.95	83.64	3.44
Higher end-of-period Moody's	7.92	2.93	82.36
Panel B: Two years after initial issuance			
Same end-of-period ratings	70.39	24.00	22.85
Lower end-of-period Moody's rating	13.51	68.77	7.27
Higher end-of-period Moody's rating	16.10	7.23	69.88
Panel C: Three year after initial issuance			
Same end-of-period ratings	62.95	28.94	28.26
Lower end-of-period Moody's rating	16.23	59.68	9.93
Higher end-of-period Moody's rating	20.82	11.39	61.82
Panel D: Four years after initial issuance			
Same end-of-period ratings	59.22	31.05	29.88
Lower end-of-period Moody's rating	17.66	54.81	12.48
Higher end-of-period Moody's rating	23.12	14.13	57.64
Number of observations	4559	2837	2035

This table reports the relative Moody's and S&P ratings after the initial issuance. Panels A–D report the relative ratings one, two, three, and four years after the initial issuance.

4. Split ratings and rating migration: Multivariate analysis and rating transition matrices

4.1. Rating changes: Multivariate analysis

In this section, we analyze the impact of split ratings on rating changes in conditional, multivariate regression models. First, we estimate a logit regression model, where the dependent variable is a 0 (no rating change) and 1 (rating change) dummy variable. Our two test variables are split-with-one-notch dummy and split-with-more-than-one-notch dummy. The control variables include the following. Three industry dummy variables: financial, utility and industrial, where industrial issues are the base case. Seven bond rating dummy variables: AAA, AA, A, BBB, BB, B and CCC, where BBB issues are the base case.[4] Three economic cycle dummy variables: peak, normal and trough, where bonds issued in normal years are the base case. If a bond is issued in a year when the real economic growth is more than 4% (less than 3%), it is categorized as a Peak (Trough) issue. Otherwise, the bond issue is a Normal issue. Nickell et al. (2000) show that economic cycles have an impact on rating volatility. In addition to the economic cycle dummy variables, we also include a series of year dummies to control for potential variation in rating change patterns over the years. Excluding the year dummies does not materially change the results.

Table 7 reports the logit model estimation for one year changes of Moody's and S&P bond ratings.[5] The coefficients for the two split rating dummy variables are 0.235 (0.199) and 0.382 (0.379) in the Moody's (S&P) regression. Both of them are significant at the 1% level, suggesting that split rated bonds are more likely to have a rating change than non-split rated bonds. To estimate the economic significance, we calculate the impact of the two split rating dummies on the probability of rating changes (i.e., marginal effects). A one-notch split rating increases the proba-

[4] In the Moody's (S&P) rating change regression, we use the Moody's (S&P) letter rating to create the rating dummies. We group CC and C rated issues into the CCC category because there are few of them.

[5] We also estimate the regression model on two, three, and four years rating changes. The coefficients on our test variables (split rating dummy variables) are always positive and significant.

Table 7
Logit model of one-year rating changes

	Moody's rating change		S&P rating change	
	Change/no change	Impact on probability of rating change (%)	Change/no change	Impact on probability of rating change (%)
Intercept	−1.199 (0.00)		−1.317 (0.00)	
Split with one-notch	0.235 (0.00)	2.94	0.199 (0.00)	2.72
Split with more-than-one-notch	0.382 (0.00)	5.47	0.379 (0.00)	5.56
Utility	0.044 (0.68)	0.58	0.119 (0.22)	1.65
Financial	0.331 (0.00)	4.50	0.067 (0.45)	0.92
AAA	−1.473 (0.00)	−11.73	−1.048 (0.00)	−10.04
AA	−0.378 (0.00)	−4.43	−0.284 (0.01)	−3.57
A	−0.226 (0.01)	−2.85	0.027 (0.74)	0.36
BB	0.035 (0.78)	0.46	0.311 (0.02)	4.58
B	−0.281 (0.01)	−3.44	−0.114 (0.24)	−1.51
CCC	0.079 (0.69)	1.05	0.188 (0.39)	2.70
Peak	−0.529 (0.03)	−6.86	−0.075 (0.73)	−1.01
Trough	−0.489 (0.01)	−5.67	−0.593 (0.00)	−7.00
Year dummies	Included		Included	
Pseudo R^2	0.02		0.01	

This table reports the results of logistic regressions of rating changes. A logistic regression of rating change (1 for rating change and 0 otherwise) is estimated for both Moody's and S&P ratings. We adjust the p-values (reported in parentheses) for potential clustering problems that might arise from multiple bond issues by issuing firms. We also estimate and report the impact of each variable on the probability of a rating change (marginal effect).

bility of a Moody's (S&P) rating change within one year of initial issuance by 2.94% (2.72%) and a more-than-one-notch split rating increases the probability of a Moody's (S&P) rating change by 5.47% (5.56%). These rating change probabilities are highly significant considering that only about 16% of all bonds have a rating change within one year of initial issuance.

Examining the other regression coefficients, we find that the coefficient on the Financial dummy is positive and significant in the Moody's regression, showing that financial issues are more likely to have a rating change by Moody's than industrial issues. Further, the coefficient on AAA and AA are negative and significant, suggesting that highly rated bonds (AAA and AA) are less likely to have rating changes than BBB rated bonds. There is no clear pattern in rating changes for below-investment grade bonds. Finally, bonds issued in peak economic years seem less likely to have subsequent rating changes by Moody's, consistent with Nickell et al.'s (2000) findings.

To further examine rating changes and split ratings in a conditional framework, we also estimate a multinomial logit model for rating upgrades and downgrades. These results are reported in Table 8. We divide the dependent variable into three categories: upgrade, downgrade, and

Table 8
Multinomial logit model of one-year rating upgrade and downgrade

	Moody's rating change				S&P rating change			
	Upgrade/ no change	Downgrade/ no change	Impact on probability of upgrade (%)	Impact on probability of downgrade (%)	Upgrade/ no change	Downgrade/ no change	Impact on probability of upgrade (%)	Impact on probability of downgrade (%)
Intercept	−2.802 (0.00)	−1.492 (0.00)			−2.929 (0.00)	−1.682 (0.00)		
High Moody's	−0.245 (0.06)	0.427 (0.00)	−1.43	3.55	0.879 (0.00)	−0.406 (0.00)	5.64	−3.31
Low Moody's	0.706 (0.00)	−0.029 (0.77)	4.34	−0.16	−0.425 (0.00)	0.508 (0.00)	−2.11	4.55
Utility	0.385 (0.01)	−0.205 (0.11)	2.42	−1.57	0.300 (0.03)	−0.012 (0.94)	1.58	−0.24
Financial	0.940 (0.00)	−0.295 (0.02)	6.26	−2.48	0.415 (0.00)	−0.290 (0.01)	2.30	−2.35
AAA		−0.537 (0.07)		−3.14		−0.293 (0.27)		−2.05
AA	−1.568 (0.00)	0.345 (0.02)	−5.34	3.32	−1.843 (0.00)	0.361 (0.01)	−5.33	3.74
A	−0.319 (0.01)	0.056 (0.61)	−1.66	0.54	−0.141 (0.25)	0.308 (0.01)	−0.79	2.60
BB	0.368 (0.02)	−0.266 (0.15)	2.42	−1.90	0.625 (0.00)	0.246 (0.16)	3.67	1.69
B	−0.350 (0.04)	−0.090 (0.48)	−1.69	−0.54	−0.406 (0.01)	0.171 (0.17)	−1.83	1.57
CCC	0.097 (0.72)	0.194 (0.45)	0.44	1.46	0.395 (0.11)	−0.002 (0.99)	2.26	−0.22
Peak	−0.076 (0.83)	−0.769 (0.01)	−0.06	−5.58	0.537 (0.15)	−0.348 (0.18)	2.77	−2.96
Trough	0.391 (0.12)	−1.335 (0.00)	2.89	−6.99	0.573 (0.04)	−1.536 (0.00)	3.92	−8.40
Year dummies	Included	Included			Included	Included		
Pseudo R^2	0.05				0.06			

This table reports the results of multinomial logistic regressions of rating upgrade, downgrade and no change for both Moody's and S&P rating. We adjust the p-values (reported in parentheses) for potential clustering problems that might arise from multiple bond issues by issuing firms. We also estimate and report the impact of each variable on the probability of a rating upgrade and downgrade (marginal effect).

no change. No change is the base case. Since the pattern of split ratings (higher Moody's rating or higher S&P rating) may have different impacts for upgrades or downgrades, we use two new test variables: high Moody's (equal to 1 if a bond issue has higher initial Moody's rating, 0 otherwise), and Low Moody's (equal to 1 if a bond issue has lower initial Moody's rating, 0 otherwise). The control variables remain the same as in the rating change logit model, except we constrain the coefficient on the AAA variable to be zero in the upgrade/no change regression because AAA bonds cannot be upgraded.

Since no change is the base case in the multinomial logit model, a negative sign indicates a higher probability of no rating change. A positive sign suggests a higher probability of either upgrade or downgrade.

In the upgrade/no change equation, the coefficient on the Low Moody's dummy variable is positive (negative) and significant for the Moody's rating change (S&P rating change), implying that split rated bonds with lower Moody's rating are more likely (less likely) to be upgraded by Moody's (S&P) than non-split rated bonds. The coefficient for the High Moody's dummy is positive and significant for S&P rating change, indicating that split rated bonds with higher Moody's ratings are more likely to be upgraded by S&P than non-split rated bonds. The coefficient for High Moody's dummy is negative and marginally significant for Moody's rating change, which suggests that split rated bonds with higher Moody's ratings are slightly less likely to be upgraded by Moody's.

In the downgrade/no change equation, the coefficient for the High Moody's dummy variable is positive (negative) and significant for Moody's rating changes (S&P rating changes), suggesting that split rated bonds with higher Moody's rating are more likely (less likely) to be downgraded by Moody's (S&P). The coefficient for the Low Moody's dummy is positive and significant for S&P rating changes, indicating that split rated bonds with lower Moody's ratings are more likely to be downgraded by S&P than non-split rated bonds. The coefficient for the Low Moody's dummy is not significant for Moody's rating changes, which suggests that bonds with lower Moody's ratings do not have a lower probability of downgrade by Moody's than non-split rated bonds.

In summary, the multinomial logit model suggests that split rated bonds are more likely to be upgraded by the rating agency that initially assigns a lower rating and more likely to be downgraded by the rating agency that initially assigns a higher rating. Marginal effect analysis shows that a lower initial rating by Moody's (S&P) increases the probability of an upgrade by Moody's (S&P) by 4.34% (5.64%) and a higher initial rating by Moody's (S&P) increases the probability of a downgrade by Moody's (S&P) by 3.55% (4.55%). Furthermore, the likelihood of an upgrade (downgrade) from S&P is lower for bonds with a higher (lower) initial S&P rating. These conditional results are consistent with the unconditional findings reported in Table 4.

Other interesting results also emerge from the multinomial logit model analysis. First, utility and financial issues are more likely to be upgraded than industrial issues, and financial issues are also less likely to be downgraded. Second, highly rated bonds (AA and A) are less likely to be upgraded and more likely to be downgraded than BBB bonds. There is no clear pattern for below-investment grade bonds, except that BB bonds seem to be more likely to be upgraded than BBB bonds. This result is consistent with Kisgen's (2006, 2007) findings that firms at the borderline of an investment grade rating take greater efforts (issuing less debt and reducing leverage ratio) to achieve (or maintain) an investment grade rating. Finally, bonds issued in Trough years are less likely to be downgraded in the subsequent year. This pattern may suggest that financially weaker firms are less likely to issue debts in downturns.

4.2. Letter split ratings and rating transition matrices

In the previous sections, we examine split ratings at the notch-level. We also find a significant number of bond issues (1889) in our sample that have the two ratings split at the letter level; that is, the two ratings are in different letter categories. In this section, we examine the impact of letter split ratings on probabilities of rating changes in the framework of a rating transition matrix.

Numerous studies have shown that bond ratings and changes in bond ratings have significant impacts on bond prices and yields (see, for example, Kliger and Sarig, 2000; Hand et al., 1992). Thus, bond investors are concerned about the rating changes as well as the possibility of defaults. Many financial practitioners and researchers estimate the probability of future rating migration using a rating transition matrix (see Hanson and Schuermann, 2006, for a review and comparison of different estimation techniques). In these studies, probabilities of future upgrades and downgrades by Moody's (or S&P) are estimated conditional on the existing Moody's (or S&P) ratings.

Two estimation techniques have been used in the literature: multinomial/cohort based and continuous-time/duration based methods. The latter method is developed by Lando and Skødeberg (2002) and refined by Christensen et al. (2004). Hanson and Schuermann (2006) compare the two estimation techniques and conclude that continuous-time/duration based estimations are more efficient than the multinomial/cohort based estimations.

Based on the monthly rating updates, we use the continuous-time/duration based technique to estimate two Moody's one-year rating transition matrices: one for the non-letter-split sample and another for the letter-split sample.[6] Table 9 presents the two rating transition matrices. The diagonal elements of the matrices denote the probability that a bond remains at its original letter rating after one

[6] We obtain similar results for S&P rating transition matrices.

Table 9
One-year Moody's rating transition matrices

	AAA (%)	AA (%)	A (%)	BBB (%)	BB (%)	B (%)	CCC (%)	D (%)	Upgrade (%)	Downgrade (%)	Number of observations
Non-letter-split sample											
AAA	95.84	3.59	0.56	0.01	0.00[a]	0.00[a]	0.00[a]	0.00[a]	n.a	*4.16*	238
AA	0.11	91.66	7.95	0.16	0.01	0.11	0.00[a]	0.00[a]	0.11	8.23	846
A	0.04	*2.05*	*94.01*	3.65	0.20	0.05	0.00[a]	0.00[a]	*2.09*	*3.90*	2451
BBB	0.00[a]	0.24	*3.01*	*93.84*	*2.51*	0.23	0.16	0.01	*3.25*	*2.91*	1784
BB	0.00[a]	0.01	0.09	5.51	89.16	4.89	0.32	0.02	5.61	5.23	426
B	0.00[a]	0.00[a]	0.06	0.20	*0.97*	*93.87*	4.41	*0.49*	*1.23*	4.90	1712
CCC	0.00[a]	0.00[a]	0.00[a]	0.01	0.05	9.26	84.57	6.11	*9.32*	6.11	85
Letter-split sample											
AAA	83.53	9.54	6.72	0.19	0.01	0.00[a]	0.00[a]	0.00[a]	n.a.	*16.47*	30
AA	0.35	90.32	8.72	0.58	0.03	0.00[a]	0.00[a]	0.00[a]	0.35	9.33	244
A	0.01[a]	*4.34*	*90.55*	4.65	0.43	0.02	0.00[a]	0.00[a]	*4.35*	*5.10*	599
BBB	0.00[a]	0.23	*9.51*	*84.58*	*5.12*	0.54	0.02	0.00[a]	*9.74*	*5.68*	388
BB	0.00[a]	0.01	0.80	9.00	86.38	3.42	0.38	0.01	9.81	3.81	306
B	0.00[a]	0.01	0.54	1.32	*8.08*	*85.36*	4.58	*0.11*	*9.95*	4.69	196
CCC	0.00[a]	0.00[a]	0.02	0.04	0.26	5.54	89.65	4.50	*5.86*	4.50	126

This table reports the one-year Moody's rating transition matrices estimated by the continuous-time/duration based method from monthly rating updates. Panel A reports the transition matrix for bond issues that have the same letter ratings from Moody's and S&P at initial issuance. Panel B reports the transition matrix for bond issues that have different letter ratings from S&P and Moody's. The diagonal elements of the matrix denote the probability that a bond remains at its original letter rating after one year. The off-diagonal elements denote the probability of a bond issue moving from a particular letter rating to another letter rating in one year. The differences between the non-letter-split and letter-split samples are significant at 1% or 5% level in the italicized cells.

[a] The element contains non-zero probability that is smaller than 0.01%.

year. For example, for the non-letter-split sample, AA-rated bonds have a 91.66% probability of remaining AA-rated by Moody's. The off-diagonal elements denote the probability of a bond issue migrating from its original letter rating to another letter rating in one year. For example, for the letter-split sample, BBB-rated bonds have a 5.12% probability of being downgraded to BB, a 9.51% probability of being upgraded to A, etc.

The diagonal elements of the non-letter-split matrix are larger than those of the letter-split matrix, except for CCC rating, suggesting that letter split rated bonds are less likely to remain at their initial Moody's letter rating. To test the statistical significance of the difference between the non-letter-split and letter-split rating transition matrices, we follow Hanson and Schuermann's (2006) bootstrap method to estimate the standard error of each rating transition probability. Specifically, for each subsample, we create B bootstrap samples by randomly sampling with replacement from the original sample. Following Hanson and Schuermann, we set $B = 10{,}000$. Each bootstrap sample has the same number of observations as the original sample. For each bootstrap sample, we estimate the continuous-time/duration based rating transition matrix. Thus, we have 10,000 bootstrap transition matrices for each subsample.

t-Tests of the differences in the diagonal elements reject the null hypotheses at the 1% level for A, BBB, and B ratings, the three rating categories with the largest number of observations. Table 9 further indicates that letter-split bond issues are more likely to be upgraded and downgraded. The differences in the probabilities of downgrades are significant for AAA, A, BBB rated issues and the differences in the probabilities of upgrade are significant for A, BBB, B and CCC rated issues.

The *t*-test only compares the individual elements of the two transition matrices. To have a more comprehensive comparison of the two transition matrices, we utilize a single value metric, called singular value decomposition (M_{SVD}), introduced by Jafry and Schuermann (2004) to compare two transition matrices. M_{SVD} is approximately the average probability of rating changes based on the rating transition matrix. The larger the value of M_{SVD}, the higher the average probability of rating change. The M_{SVD} for the non-letter-split sample is 0.078, while the M_{SVD} for the letter-split sample is 0.120. The *t*-statistics for the difference of the two M_{SVD} is 3.02.[7] In addition to statistical significance, the difference between the M_{SVD} of the two matrices, 0.042, is also economically significant. Jafry and Schuermann (2004) estimate two rating transition matrices, one during economic expansion and another during recession. The difference between the M_{SVD} of their two transition matrices is 0.043, which is close to our difference of 0.042.

Overall, these results indicate that bonds with split rating at the letter level have a higher probability of rating change than non-split rated bonds. This finding suggests that it is important to take into consideration split ratings in addition to the level of initial ratings when estimating future ratings migrations.

[7] To estimate the standard error of the M_{SVD} for each subsample, we calculate the M_{SVD} metrics for the 10,000 bootstrap transition matrices. Based on the standard errors from the bootstrapping process, we calculate the *t*-statistics.

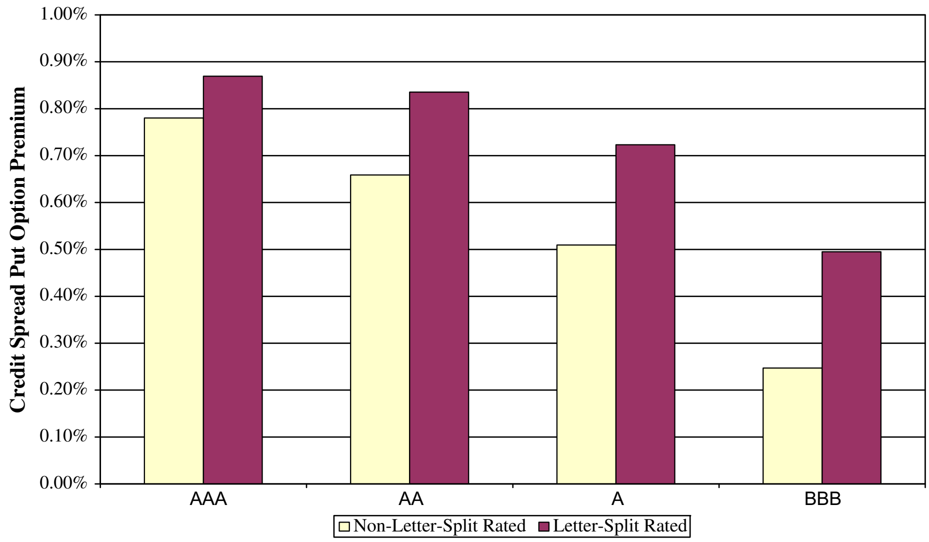

Fig. 1. Credit spread put option premium for investment grade bonds based on the non-letter-split and letter-split rating transition matrices. The credit spread put options have a strike credit spread of 150 basis points and mature in two years. The underlying obligators have a maturity of four years. We assume a 50% recovery rate at default.

4.3. Split ratings, rating transition matrices, and the value of credit spread put options

To further illustrate the economic importance of accurately estimating rating transition matrices, we use the non-letter-split and letter-split rating transition matrices to value credit spread put options. Credit spread options enable investors to bet on the changes of the credit spread of a particular bond. The premiums on credit spread options are partly dependent on the probabilities of future rating transitions because bond ratings are an important determinant of the credit spread. Thus, the rating transition matrix is a cardinal input to credit spread option models proposed by Jarrow and Turnbull (1995) and Jarrow et al. (1997). We follow a refined model by Kijima and Komoribayashi (1998) to value four hypothetical credit spread put options.

All four spread put options have two-year maturities, and the underlying obligors have four-year maturities. The options have a strike credit spread of 150 basis points, and the underlying obligors are bonds rated AAA, AA, A, and BBB, respectively. Further, we assume a recovery rate of 50% in the event of default. Other inputs to the pricing model include the risk free yield curve and term structure of credit spreads. We use the actual term structure on May 16, 1997, reported in Kijima and Komoribayashi (1998), and the Treasury yields on the same date as the risk free yield curve.

Fig. 1 compares the premiums on credit spread put options with different obligors estimated from the non-letter-split and letter-split rating transition matrices. First note that the option premiums, given a fixed strike spread, decrease with the bond ratings of the underlying bonds. The reason is that lower rated bonds have higher credit spreads and, given a fixed strike spread, the options on lower rated bonds are less likely to have a positive payoff at maturity and, hence, have lower option premiums. Second, the premiums estimated from the letter-split transition matrix are consistently higher than the premiums estimated from the non-letter-split transition matrix. For example, the option premium on a non-split A-rated bond is about 0.5%, but the option premium on a split A-rated bond is more than 0.7%, higher than the premium on a non-split AA-rated bond. This result is intuitive: bonds with split ratings have more volatile future ratings, which lead to higher volatility of the credit spread, and hence, higher premiums on credit spread options.[8] This example illustrates the importance of an improved estimation of rating transition matrix in pricing credit derivatives. Ignoring the higher rating volatility of split rated bonds results in undervalued credit spread put options. Though beyond the scope of this paper, it would be interesting to further empirically examine the potential mispricing and investment opportunities of credit spread options for split rated bonds using market credit derivative data.

4.4. Split ratings, rating transition matrices, and value-at-risk (VaR)

As an additional practical application, this study also has important implications for VaR-based risk management models. A rating transition matrix is a major input into some credit risk models, including CreditMetrics™. To estimate the impact of different transition matrices for split and non-split rated bonds, we follow Löffler (2003) to calculate the 1% and 5% VaR for a hypothetical portfo-

[8] We also observe similar patterns when we value three credit spread put options on bonds rated BB, B and CCC.

lio of BBB-rated bonds. The portfolio contains an infinite number of BBB-rated bonds of equal size. Conditional on the rating one-year from now, the value of each bond is assumed to be as follows (see CreditMetrics™ Technical Document, 1997, Table 1.2, page 10):

AAA	AA	A	BBB	BB	B	CCC
109.37	109.19	108.66	107.55	102.02	98.1	83.64

Further, as in Löffler (2003), we assume that the recovery rate in the event of default is 49.60%, and the asset value correlation between issuing firms is 0.2.

If we use the transition probabilities of non-split rated BBB bonds, the 1% (5%) VaR of the portfolio is 1.25% (0.66%). On the other hand, the 1% (5%) VaR of the portfolio increases to 1.61% (0.97%) if we use the transition probabilities of split rated BBB bonds. This higher VaR for split rated portfolio is driven by the higher probability of downgrades of these bonds. While split rated bonds are also more likely to be upgraded, gains from upgrades are much smaller. A three letter-grade upgrade from BBB to AAA increases the value of the bond by $1.82, while a three letter-grade downgrade from BBB to CCC reduces the value of the bond by $23.91.

5. Conclusions

Moody's and S&P are the two predominant Nationally Recognized Statistical Rating Organizations (NRSROs). Their credit ratings are widely regarded as an important informational tool used by firms, investors, regulators, and other financial market participants. However, these two rating agencies do not always agree on the credit risk of a particular bond issue, resulting in split ratings.

This paper relates split ratings with future rating changes. We find that split rated bonds are more likely to have future rating changes. A split rating increases the probability of a rating change within one year of initial issuance by 3–6%. Furthermore, split rated bonds are more likely to receive an upgrade (downgrade) from the rating agency that assigns a lower (higher) initial rating. These results are consistent with both the Ederington's (1986) random error hypothesis and Morgan's (2002) asset opaqueness hypothesis of split rating. Ederington argues that the creditworthiness of split rated bonds is close to the borderline between ratings, resulting a split rating. Thus, a smaller change in the issuer's credit risk can trigger a rating change by one rating agency. Morgan finds that banking firms, due to their asset opaqueness problems, are more likely to receive split ratings. If firms with asset opaqueness problems are more likely to have surprising news and information disclosure after initial issuance, then Morgan's asset opaqueness hypothesis also implies that split rated bonds will have more rating changes after the initial issuance.

In addition to the rating changes, we also examine rating convergence of split rated bonds. We find that about 30% of split rated bonds have the two ratings converge four years after the initial issuance, while about 60% of non-split rated bonds remain non-split. This pattern suggests that there is a qualitative difference between the split and non-split rated bonds. Furthermore, for split rated bonds that do not converge, the two rating agencies generally maintain their relative rating; that is, the rating agency that assigns a higher (lower) initial rating maintains a higher (lower) rating. This finding suggests that the split ratings are not caused in general by random errors as argued by Ederington (1986).

Our findings can also be used to improve the estimation of the probability of future rating changes. The current literature on rating transition mostly uses one rating, either Moody's or S&P, to estimate the probability of future rating changes. Our findings show that such estimates can be improved by taking into consideration the influence of split ratings. Our results further show that improved estimation of rating transition probabilities for split and non-split rated bonds has significant practical implications for the pricing of credit spread options and VaR-based risk management models.

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