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Credit Spreads, Rating Downgrades, and Downside Performance: A Market-Informed Approach to Monitoring Credit Risk[†]

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Abstract

This paper studies the differential credit risks embedded in the cross-section of credit spreads. Using corporate bond data from 1999 to 2018, we find that credit spreads relative to those of peers—defined as bonds with the same stated credit rating—contain reliable information about future bond performance and credit migration. Bonds with substantially higher credit spreads relative to those of their peers have higher rates of future downgrades. Using the midpoint between the peer spread curve and the next-lower-rated spread curve as a threshold, we observe that the downgrade frequency in the next three to 12 months is three to four times higher, on average, for bonds above the midpoint compared to those below. We also find that bonds with considerably wider credit spreads behave more in line with bonds with lower credit ratings in terms of average return, volatility, and downside performance. Our results suggest that complementing stated credit ratings with real-time market price data can improve credit risk monitoring.

1. Introduction

Assessing credit risk is a key aspect of understanding fixed income markets and evaluating fixed income securities. Nationally recognized statistical rating organizations (NRSROs), such as Standard & Poor's and Moody's, rate the creditworthiness of a wide range of issuers. They are the prominent sources of information that investors use to make credit risk assessment.[1] Meanwhile, numerous market participants assess the credit quality of fixed income securities using information that includes but is not limited to stated credit ratings. As a result, market prices of bonds or, equivalently, bond yields should reflect the aggregate expectations and market assessment of credit risk in real time. For a fixed maturity, bonds with larger coupons generally have shorter duration; thus, their yields might also reflect information about term (duration) risk, compared to bonds with smaller coupons. To take coupons into account, we calculate the credit spread of each bond relative to a cash flow-matched synthetic Treasury. Throughout the paper, we use these spreads to study credit risk in the cross-section of corporate bonds.

Using a comprehensive set of corporate bond panel data from 1999 to 2018, we test whether cross-sectional variation in credit spreads within a credit rating contains reliable information about subsequent downgrades and downside performance.

There is a large dispersion in corporate bonds' credit spreads conditional on the same credit rating. A sizable portion of bonds exhibit much higher credit spreads than same-rated peers. If we use the midpoint between the peer and the next-lower spread curve as a threshold, on average the credit spread of 14% of the bonds by count and 15.6% by market value exceeds the midpoint threshold in our sample–effectively, these bonds have yields closer to those of lower-rated bonds. This group

[1] While NRSROs may vary their credit rating methodology by the issuer's industry, they generally use a common framework to analyze an issuer's business risk and financial risk profiles. Within their framework, NRSROs typically consider information taken from historical financial statements, cash flow forecasts, and meetings with an issuer's management to arrive at a stated credit rating.

also has a total market value outstanding of $144 billion as of December 2018, which represents an economically meaningful portion of the corporate bond market.

We find that bonds with substantially higher credit spreads relative to those of their rating peers are more likely to be downgraded in the future. Our analysis focuses on rating downgrades as one manifestation of increased credit risk, which provides a rich dynamic to study the differential credit risks embedded in the cross-section of credit spreads. Compared to bond defaults, rating changes happen much more frequently and can vary in magnitude, ranging from one notch to multiple notches. If we classify bonds based on whether their credit spreads are above or below the midpoint between the spread curve for their stated credit rating and the spread curve for the next-lower credit rating, the subsequent downgrade frequency is on average three to four times higher for bonds above the midpoint compared to those below. The above-midpoint group has an average downgrade frequency of 12.1%, 20.1%, and 32.4% in the next three, six, and 12 months, respectively, compared to 2.7%, 5.6%, and 11.4% for the below-midpoint group. Results from logistic and linear regressions also confirm that a greater distance between a bond's credit spread and the midpoint reliably indicates a greater probability and a larger magnitude of a future downgrade in the next three to 12 months.

We document that the above-midpoint bonds display return behavior more in line with that of lower-quality bonds than their same-rated peers. In particular, we study their downside performance by examining returns conditional on months when the credit spread widens. For example, we find that the above-midpoint BBB rated bonds underperform the below-midpoint BBB rated bonds by 46 basis points (bps) per month on average in months when the credit spread between investment grade and high yield bonds (i.e., between BBB and BB) widens. The average underperformance increases further as we condition on months when the BB-minus-BBB credit spread widens by a larger amount. These performance differences further confirm that there is information about credit risk reflected in the cross-section of credit spreads after controlling for stated ratings.

Our empirical results are not indicative of mispricing. Instead, they highlight the important role markets play in aggregating and disseminating information in real time. The findings also do not indicate that credit rating agencies misrate bonds systematically or intentionally. In fact, our methodology and analyses are built on the understanding that stated credit ratings contain valuable information about credit risk and can serve as a useful input along with other market data.

Our results have several key implications. First, a credit monitoring process that includes information from stated credit ratings and information from current market prices may provide a more complete representation of an issuer's credit quality. This implication is particularly relevant for practitioners investing in fixed income securities, and it is increasingly practical as the fixed income markets become more transparent with the expansion of TRACE[2] and other similar

[2] TRACE stands for the Trade Reporting and Compliance Engine. Introduced in July 2002, the system captures and disseminates consolidated information on secondary market transactions in publicly traded, TRACE-eligible corporate bonds, closing the information gap between customers and dealers.

systems.[3] Second, investors evaluating fixed income portfolios should look beyond the stated credit rating of portfolio holdings. If a portfolio holds bonds with substantially higher credit spreads than those of peers (as a result of "reaching for yield," for example), the effective credit risk exposure may be greater than what might be inferred from stated ratings. Finally, given regulators and policy makers have long been trying to improve the risk monitoring of banks and asset managers, our findings suggest that a greater use of market data may be an effective risk-monitoring tool.

Our paper extends the growing literature on the informational content in bond yields and credit spreads. In theory, several factors should determine credit spreads: the probability of default, the expected loss in the event of a default, the expected premium as compensation for the potential loss from defaults, and possibly liquidity and taxes. Adding to previous studies that attempt to disentangle the effects of different components (Covitz and Downing, 2007; Elton et al., 2001; Fama, 1986; Giesecke et al., 2011; Longstaff, Mithal, and Neis, 2005; Nozawa, 2017), our analysis highlights the credit risk aspect. Our results extend existing studies that find bonds tend to have higher yields and exhibit greater risks when the issuer-paid ratings are more positive than benchmark investor-paid ratings (Badoer, Demiroglu and James, 2019). Our findings are also consistent with previous evidence that prices in stock and credit default swap (CDS) markets contain firm credit risk information and anticipate upcoming rating changes (Hull, Predescu, and White, 2004; Lee, Naranjo, and Velioglu, 2018).

More broadly, our paper contributes to the literature on modeling and measuring credit risk. A variety of credit risk models have been proposed following such seminal papers as Black and Scholes (1973) and Merton (1974) on the structural approach and Duffie and Singleton (1999) on reduced-form models (see, for example, Duffie and Singleton, 2012, for an overview). Our approach is different in that we use real-time market data and present a parameter-free way to measure instantaneous credit risk. To a lesser extent, this paper is related to studies that examine the behavior and implications of credit rating agencies (Altman and Rijken, 2004; Becker and Milbourn, 2011; Cornaggia and Cornaggia, 2013; Jiang, Stanford, and Xie, 2012; Jorion, Liu, and Shi, 2005; White, 2010). While our primary focus is not on credit rating agencies, our results suggest that market data can be used to complement the information and methodology employed by rating agencies.

The remainder of this paper proceeds as follows. Section 2 describes the corporate bond data. In Section 3, we outline the methodology for constructing credit spreads for individual bonds and spread curves for each credit rating, which we use to document the cross-sectional dispersion in bonds' credit spreads relative to those of their peer curves. Sections 4 and 5 discuss our empirical results on the relation between credit spreads and subsequent rating downgrades and return performance. Robustness checks are presented in Section 6. The final section features our conclusions.

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[3] For example, the Electronic Municipal Market Access (EMMA) system serves as the official source for municipal securities disclosures and related market data in the US. For financial markets in the EU, the Markets in Financial Instruments Directive (MiFID II) imposes reporting requirements and tests across different asset classes, including fixed income, to improve the transparency and record-keeping of transactions.

2. Corporate Bond Data

We use a comprehensive panel of US corporate bonds, which includes all corporate bond constituents of the Bloomberg/Barclays US Aggregate Bond Index and the Bloomberg/Barclays US High Yield Bond Index from January 1999 to December 2018. The data contain maturity, coupon, yield, return, market value, country of issuance, credit ratings from major credit rating agencies, and optionality on a monthly frequency.

We apply several filters to the data. Country of issuance is limited to the US. Bonds with option features (except for make-whole bonds) are excluded because their yields reflect information about optionality (see, for example, Duffee, 1998) that may confound the results.[4] For coupon type, we only allow fixed coupons and exclude bonds with floating coupons, step-ups, etc. from the analysis. We filter out bonds with maturities greater than 35 years due to the limited number of issues and liquidity concerns that can affect their pricing. For similar reasons, we also restrict credit ratings to AAA, AA, A, BBB, BB, and B based on S&P's ratings.[5] To make proper cash flow assumptions for calculating yields and credit spreads, we exclude bonds with data points that are likely erroneous, including negative yields, bond issue dates later than reporting dates, and reported time to maturity differing from that implied by the maturity date by more than half a year.

After applying these filters, the resulting sample contains 1,270 unique issuers and 11,298 unique issues from January 1999 to December 2018 and an average of 546 issuers and 2,665 issues per month. This sample represents a sizable portion of the US corporate bond market. The market value of these bonds totals \$1.74 trillion on average and \$1.63 trillion as of the end of 2018. As shown in **Table 1**, the credit rating distribution peaks at A and BBB, while becoming less populated as we move towards the higher or lower ends of the credit quality spectrum. The maturity distribution, on the other hand, tends to be denser in the ranges lower than 10 years and between 20 and 30 years.

3. Constructing Credit Spreads and Spread Curves

In this section, we describe our methodology for calculating the credit spread of a corporate bond with respect to its cash flow-matched synthetic Treasury and constructing spread curves for each credit rating.

First, we use US Treasury data[6] contained in the Bloomberg Barclays US Aggregate universe to construct zero-coupon (or spot) Treasury curves for each month using a bootstrap method. Because the Bloomberg Barclays data exclude bonds with maturities of less than one year, we supplement with one-month, three-month, and six-month Treasury bill data from Morningstar and the Federal Reserve Board. Beginning with the shortest-maturity Treasury, we iteratively calculate spot rates

[4] Make-whole calls allow issuers to pay off debt early, typically by way of a lump sum payment based on the net present value of future coupon payments that will not be paid because of the call. Because the cost is often high, these call options are rarely exercised and therefore have a limited impact on yields. Bonds with meaningful options features, such as callable, putable, and sinkable bonds, are excluded.

[5] While S&P's credit ratings are used for filtering the data and conducting the analyses, results are robust if we use Moody's ratings or index ratings provided by Bloomberg.

[6] If there is more than one Treasury with the same maturity date, we include the one issued more recently ("on-the-run") and exclude the others ("off-the-run").

from Treasuries' prices. The spot rates are then grouped into different maturity buckets. We take the simple average of the spot rates and associated maturities within each maturity bucket and use linear interpolation to construct the Treasury spot curve.

Second, we derive the credit spread of each corporate bond with respect to a synthetic Treasury security that matches the bond's promised cash flows. That is, a corporate bond's credit spread is defined as the parallel shift in the Treasury spot curve that sets the synthetic Treasury's price equal to the corporate bond's price. For each corporate bond, we solve numerically the credit spread s that satisfies

$$P_{Corporate} = \sum_{i=1}^{N} \frac{CF_{t_i}}{\left[1 + \frac{Z_{t_i} + s}{f}\right]^{t_i f}}, \tag{1}$$

where $CF_{t_i}'s$ are the cash flows of the corporate bond at time $t_1 < \cdots < t_N$, Z_{t_i}'s are the Treasury spot rates derived in the first step, and f is the coupon frequency of the bond. Following Gilchrist and Zakrajsek (2012) and Nozawa (2017), we choose cash flow-matching over maturity- or duration-matching Treasuries, as credit spreads are calculated more accurately for different shapes and changes of the Treasury yield curves using this approach.

Finally, using the credit spreads and duration of individual bonds as inputs, we construct spread curves for each credit letter rating (AAA, AA, A, BBB, BB and B) each month by fitting a smooth cubic spline.[7] We denote the resulting spread curve for each credit rating CR as S^{CR}. For a given duration m, the corresponding value on the spread curve is $S^{CR}(m)$.

We are interested in whether the variation of credit spreads across same-rated bonds contains additional information about differential credit quality. For the main tests, we use the midpoint between the spread curve of peer credit rating and the spread curve of next-lower credit rating (midpoint, in short) as a threshold[8] and calculate the distance of each corporate bond's credit spread to the midpoint (distance to midpoint, in short). For corporate bond i with spread s_i, duration m_i, letter rating CR_i and next-lower letter rating LCR_i, the distance to midpoint is calculated as the following:

$$d_i = s_i - \frac{1}{2}\left[S^{CR_i}(m_i) + S^{LCR_i}(m_i)\right]. \tag{2}$$

By definition, when d_i is positive, the spread s_i is closer to the spread curve of the next-lower credit rating than the peer spread curve of the same credit rating. The more positive d_i is, the more the spread of bond i exceeds the midpoint threshold. In the next sections, we will test the embedded credit risk for same-rated bonds with different distances to midpoint.

Table 2 shows that there is meaningful cross-sectional dispersion in distance to midpoint: the monthly averages of the cross-sectional 10th percentile, median, and 90th percentile across all bonds

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7 We follow the algorithm developed by Ripley and Maechler (cf. R Smooth.Spline Package, https://stat.ethz.ch/R-manual/R-devel/library/stats/html/smooth.spline.html) and apply equal weighting to credit spreads of all bonds within each credit rating group. The derived spread curves and our main results are similar if we use different setups for fitting the smooth splines, including applying market-value weighting to credit spreads of individual bonds.

8 In Section 6, we explore alternative thresholds as part of the robustness checks.

are –1.82%, –0.56%, and 0.25%, respectively. The dispersion of distance to midpoint also tends to be larger for bonds with lower credit ratings. For example, the monthly average of the cross-sectional standard deviation increases from 0.20% for AAA rated bonds to 1.89% for BB rated bonds.

4. Rating Downgrades

To study the information about credit risk embedded in credit spreads, we start with the impact of current credit spreads on the frequency of subsequent rating downgrades. Downgrades are a manifestation of increased credit risk and, compared to bond defaults, provide a richer dynamic because rating changes happen more frequently than bond defaults and can vary in magnitude (number of notches). Throughout the paper, rating changes are based on the granular S&P credit rating scale with the plus/minus modifiers; for example, a rating change from BBB to BBB- is counted as a downgrade.[9]

4.1. Downgrade Frequency

We split the sample period from January 1999 to December 2018 into non-overlapping periods of different lengths—three, six, or 12 months—and examine rating changes over these various horizons. At the beginning of each period, we divide same-rated bonds into two groups, "Below Midpoint" and "Above Midpoint," based on their credit spreads relative to the midpoint threshold between the peer curve and the curve of the next-lower credit rating (see detailed definition in Section 3). We then calculate the percentage of bonds in each group that are downgraded at the end of the period. For example, to study the three-month downgrade frequency, we group bonds at the end of each quarter and compute the percentage of bonds within each group that are downgraded at the end of the next quarter. Similarly, we use semi-annual periods ending in June and December to examine the six-month downgrade frequency and calendar years to study the 12-month downgrade frequency. We then average these frequencies across the non-overlapping periods.

Table 4 summarizes the results. The columns labeled "All" provide the unconditional average downgrade frequencies across all bonds over various horizons. Bonds are more likely to migrate across credit ratings over longer horizons: the average three-month downgrade frequency is 4.1%, compared to 14.4% for one year. More interesting results emerge as we condition on the starting credit spreads. Over all horizons, the "Above Midpoint" group is associated with a meaningfully higher downgrade frequency relative to the "Below Midpoint" group. For example, on average, 12.1% of bonds with above-midpoint credit spreads are downgraded in the next three months, while the percentage is only 2.7% for bonds with credit spreads below midpoint. The average difference in downgrade frequency between these two groups is 9.4% with a t-statistic of 9.42. We observe similar patterns when extending the horizons. These results provide strong evidence that credit

[9] If a bond's rating is changed to NR (not rated), it is not counted as a downgrade in the calculation of downgrade frequency (Section 4.1) or the logistic regression analysis of downgrade probability (Section 4.2). Such observations are excluded from the linear regression analysis of the magnitude of rating changes (Section 4.3). We also follow the methodology in S&P (2019) and treat ratings "D" (default) and "NR" as absorbing states; that is, once a bond's rating becomes "D" or "NR" during the period, its rating will not change in the remaining months of the period.

spreads contain reliable information about the likelihood of future downgrades and capture differences in credit risk among same-rated bonds.

4.2. Logistic Regression

We further test the relation between current credit spreads and future rating changes using the following logistic regression specification over non-overlapping periods with different lengths:

$$Prob(\Delta CR_{i,t\to t+k} < 0) = logit^{-1}(\alpha + \gamma I_{i,t}^{IG} + \beta \cdot d_{i,t}), \qquad k = 3, 6, or\ 12$$

where $d_{i,t}$ is the distance-to-midpoint variable, defined previously as the distance from bond i's credit spread to the midpoint threshold between the bond's same-rated peer spread curve and the adjacent spread curve with lower credit rating, $\Delta CR_{i,t->t+k} = CR_{i,t+k} - CR_{i,t}$ denotes bond i's rating change from month t to month $t+k$ based on numerically coded credit ratings (AAA = -1, AA+ = -2, AA = -3, AA- = -4, …, C = -21 and D = -22), and $I_{i,t}^{IG}$ is the indicator variable for whether bond i is rated investment grade or high yield in month t. By definition, $\Delta CR_{i,t\to t+k} < 0$ means bond i has been downgraded from t to $t+k$. The indicator variable $I_{i,t}^{IG}$ accounts for the difference in unconditional downgrade frequency between investment grade and high yield bonds.[10] The non-overlapping three-, six-, and 12-month periods are the same as in Section 4.1.

Since rating downgrades tend to be clustered around periods of economic turmoil, we use the Fama-MacBeth approach (Fama and MacBeth, 1973) to account for this potential time-series effect. We run cross-sectional regressions for the non-overlapping periods and report the average coefficients across periods. Results in **Table 5** show that credit spreads contain reliable information about future downgrade probabilities, as evidenced by positive slope coefficients and t-statistics above 7. The greater a bond's credit spread, the more positive its distance to the midpoint, the more likely the bond is going to be downgraded in the near future.

4.3. Linear Regression

So far, we have focused on the probability of downgrade or, in other words, the sign of rating changes. In the next specification, we examine the relation between the magnitude of rating changes and credit spreads relative to the midpoint threshold.

$$\Delta CR_{i,t\to t+k} = \alpha + \gamma I_{i,t}^{IG} + \beta \cdot d_{i,t} + \epsilon_{i,t+k}, \quad k = 3, 6, or\ 12$$

The notation is the same as that in the logistic regression model of the previous section, and $\epsilon_{i,t+k}$ is the error term.

The results from Fama-MacBeth regressions over non-overlapping three-, six-, and 12-month periods are summarized in **Table 6**. Time-series average slope coefficients are reliably negative across all horizons, indicating that greater credit spreads and therefore greater distance to the midpoint are associated with more significant future downward adjustments in credit ratings. These

[10] For example, the S&P 2018 Annual Corporate Default Study and Rating Transition Study reports that, on average, the annual transition rates from current letter rating to lower letter ratings (1981-2018) are about 4%–9% for investment grade (AAA-BBB rated) bonds and about 8%–29% for high yield (BB-CCC/C rated) bonds.

results, together with the findings in previous sections, provide compelling support for the relation between the current credit spreads and future rating downgrades.

5. Downside Performance

If credit spreads are informative about credit risks, high-yielding bonds should behave differently than low-yielding bonds even though both have the same stated credit rating. We test this hypothesis by examining bonds at the boundary between investment grade and high yield ratings, which is practically relevant because the eligible universe of investment mandates often relies on the classification of investment grade and high yield. **Table 7** summarizes the performance of bonds rated BBB, BB, and BB/B from February 1999 to December 2018; the BBB rated group is further split into "Below Midpoint" and "Above Midpoint" based on the bonds' distances to midpoint between the BBB and BB spread curves. To capture the manifestation of credit risk through downside performance, we report maximum drawdown, worst rolling returns, and average returns in periods of widening credit spread in addition to average yield, annualized compound return, and standard deviation over the full sample period.

Compared to BB rated and BB/B rated bonds, all BBB rated bonds as a group have lower average yields and lower average monthly returns and exhibit less credit risk, as evidenced by their lower standard deviation and better downside performance. However, a closer look at the two subgroups within the BBB rated universe reveals significantly different patterns. In particular, the high-yielding bonds in the "Above Midpoint" group behave not like same-rated bonds in the "Below Midpoint" group but more in line with lower-rated bonds. For example, the annualized standard deviation of the "Above Midpoint" BBB rated group is 10.81%, more than double the standard deviation of the "Below Midpoint" group. The worst rolling one-year return is –30.27% for the "Above Midpoint" BBB rated group vs. –11.55% for the "Below Midpoint" BBB rated group, –23.57% for the BB rated group, and –28.45% for the BB/B rated group. We also observe performance differences between the "Above Midpoint" and "Below Midpoint" groups when the BB-minus-BBB credit spread widens.[11] For example, BB rated and BB/B rated bonds underperform BBB rated bonds, as expected, in months when the BB-minus-BBB credit spread widens by at least 10 bps. Among BBB rated bonds, the "Above Midpoint" group delivers an average monthly return of –0.40%, underperforming the "Below Midpoint" group by 72 bps per month with a t-statistic of 2.23. These downside performance results provide additional evidence that bonds with wider credit spreads than those of same-rated peers exhibit greater credit risks. For investors, using current yields to monitor credit risks can complement the information from stated credit ratings and help ensure that the portfolio holdings behave in a way that is commensurate with the intended credit risk exposure.

[11] The credit spread between BB and BBB bonds is calculated as the yield spread between the Bloomberg/Barclays US Intermediate Credit Baa Index and US Intermediate High Yield Corporate Ba Index.

6. Robustness Checks

In this section, we conduct a few robustness checks. In Sections 6.1–6.5, we repeat the main analysis on future downgrade frequencies from Section 4.1 by using an alternative curve construction, an alternative threshold for identifying outlier bonds, and various subsamples of the bond universe based on TRACE trade records, credit quality, or maturity. The results confirm that our main conclusions are robust to these alternative specifications. In Section 6.6, we run monthly cross-sectional logistic and linear regressions and adjust the standard errors of the slope coefficients using Newey-West correction for overlapping periods and possible autocorrelation in slope coefficients. The regression results are similar to those in Section 4.2 based on non-overlapping periods.

Table 8 reports the summary statistics for eligible bonds for different robustness checks.

6.1. Alternative Curve Construction

Instead of constructing spread curves relative to the Treasury spot curve, we create yield curves for each credit rating and test the credit risk information embedded in bond yields relative to yield curves of the same rating and the next-lower rating.

To construct yield curves for each credit rating, we group bonds with the same rating by option-adjusted duration (OAD) buckets, (0, 1], (1, 2], (2, 3], (3,5], (5, 7], (10, 15], (15, 20], (20, 25], (25, 30], (30, 35), and calculate the market-value weighted average yield to worst and duration for each bucket. The weighted average duration-yield pairs are then linearly interpolated to form yield curves. We classify bonds into "Below Midpoint" and "Above Midpoint" groups based on a bond's (yield) distance to the midpoint—that is, the difference between the bond yield and the midpoint between the peer yield curve and the next-lower-rated yield curve at the same duration of the bond. Consistent with the main results in **Table 4**, **Table 9** shows that the downgrade frequencies in the next three, six, and 12 months are reliably higher for the "Above Midpoint" group consisting of high-yielding outliers than the "Below Midpoint" group consisting of bonds trading in line with their peers.

6.2. Alternative Threshold

Here we classify bonds based on an alternative threshold: whether a bond's credit spread is above or below the spread curve of the next-lower credit rating. **Table 10** reports the time-series average of the future downgrade frequencies, confirming that bonds with wider credit spreads are more likely to be downgraded in the future and thus exhibit greater credit risk.

6.3. Investment Grade Bonds vs. High Yield Bonds

Since the unconditional downgrade frequencies may be different between investment grade and high yield bonds (see footnote 10), it is worth checking if the main results are robust after restricting our universe to investment grade (rated AAA to BBB) or high yield (rated BB) bonds. Panels A and B of **Table 11** report the results for the investment grade bonds and BB rated bonds, respectively. While the average downgrade frequencies in Panel B are higher than those in Panel A across the board, the same pattern emerges when we compare the "Above Midpoint" and "Below Midpoint" groups within each universe, indicating a reliable relation between current credit spreads and the likelihood of future downgrades.

6.4. TRACE Filter

In this section, we split the corporate bond sample based on trades recorded in the TRACE system near month-end and examine the robustness of our results across subsamples.[12] Each month, we identify bonds as "more liquid" near month-end if the average trade quantity recorded in TRACE is at least $10,000 (in par value) in the last five business days in the month and "less liquid" otherwise. Our sample period for this analysis starts in March 2005.[13]

Table 12 shows that the results for both subsamples are consistent with those for the full sample, i.e., high-yielding bonds in the "Above Midpoint" group are more likely to be downgraded than their same-rated peers in the "Below Midpoint" group for both more liquid bonds and less liquid bonds. These results suggest that our conclusions are not sensitive to bonds' trading activity or potential lack of real-time bond pricing at month end.

6.5. Intermediate-Term Bonds vs. Long-Term Bonds

In this section, we examine the downgrade frequencies for corporate bonds in two maturity groups: intermediate term (maturity < 10 years) and long term (maturity ≥ 10 years). As shown in **Table 13**, within each maturity group, the average downgrade frequencies are reliably higher for bonds above the midpoint than those below the midpoint, suggesting that there is meaningful credit risk information embedded in current credit spreads across the maturity spectrum.

6.6. Monthly Fama-MacBeth Regressions with Newey-West Correction

In this section, we run monthly Fama-MacBeth logistic and linear regressions with Newey-West correction to account for overlapping periods and possible autocorrelation in slope coefficients. The t-statistics of the slopes are calculated by adjusting the standard errors using Newey-West correction with k-1 lags for k-month horizons, i.e., two, five, and 11 lags for three-, six-, and 12-month downgrade probability/rating change, respectively.

Results in **Table 14** and **Table 15** are consistent with those in **Table 5** and **Table 6**, respectively. The greater the distance to midpoint, the more likely the bonds are to be downgraded in the near future and the bigger the magnitude the future rating downgrade could be.

Conclusion

Real-time market prices continuously reflect new information and provide an instantaneous snapshot of forward-looking market expectations. On the fixed income side, an important piece of information embedded in bond prices is credit risk, our main focus in this paper. Controlling for

[12] We group bonds based on trading activity near month-end because the end-of-month pricing of corporate bonds from Bloomberg/Barclays could be directly quoted from a trading desk or exchange, derived from a pricing matrix, or supplied by third-party pricing vendor. See Barclays (2014).

[13] According to a FINRA news release, February 07, 2005, in Phase 3B of TRACE regulatory changes there was "real-time dissemination of transaction and price data for 99 percent of corporate bond trades." Available at https://www.finra.org/media-center/news-releases/2005/nasds-fully-implemented-trace-brings-unprecedented-transparency.

stated credit ratings, we show a strong relation between the cross-sectional variation in credit spreads and differential credit risks. In particular, we explore two aspects of the manifestation of credit risk: future downgrades and downside performance. Bonds with meaningfully wider credit spreads than same-rated bonds are more likely to be downgraded in the future and behave more like lower-rated bonds.

Our results not only confirm the important role markets play in efficiently aggregating information, but also suggest a tangible way to improve credit risk monitoring through the use of up-to-date market prices. A market-informed credit assessment combined with other information, such as stated credit ratings, can provide a more complete picture of a bond's credit quality. This approach is highly practical given the evolution of the fixed income markets towards greater price transparency, especially in the last decade. Besides dealer quotes and index prices, one can now observe transaction prices disseminated through TRACE and other similar systems. Because of these favorable developments, we believe the credit risk management methodology we have laid out can be implemented in a systematic and cost-effective way. While we have focused on corporate bonds in this paper, the implication that investors can use information contained in market prices to help monitor credit risk could apply similarly to the credit monitoring of other fixed income securities or credit risk management in other settings.

Tables

TABLE 1

Data Summary, 1999-2018

This table presents the time-series averages of the monthly number of issues, number of issuers, and market value of the corporate bond sample by credit rating (Panel A) and by maturity (Panel B) from January 1999 to December 2018. The sample consists of US-issued fixed-coupon corporate bonds in the Bloomberg/Barclays US Aggregate Bond Index and US High Yield Bond Index with no optionality except for make-wholes, with maturities of less than 35 years and S&P ratings between AAA and B.

PANEL A: BY CREDIT RATING

	AAA	AA	A	BBB	BB	B	All
Average # of Issues	50	234	1,067	1,004	213	96	2,665
Average # of Issuers	9	36	182	264	79	34	546
Average Market Value ($ in billions)	41	209	733	597	107	51	1,738

PANEL B: BY MATURITY

	1–3Y	3–7Y	7–10Y	10–15Y	15–20Y	20–25Y	25–30Y	30–35Y	All
Average # of Issues	589	891	444	106	134	219	273	10	2,665
Average # of Issuers	265	365	253	79	91	128	154	8	546
Average Market Value ($ in billions)	373	585	306	52	80	145	190	6	1,738

TABLE 2

Time-Series Average of Cross-Sectional Statistics for Distance to Midpoint, 1999-2018

This table reports the average of the monthly cross-sectional mean, standard deviation, minimum, 10th percentile, 25th percentile, median, 75th percentile, 90th percentile, and maximum of distance to midpoint for all bonds in the sample (AAA–BB) and bonds by credit rating from January 1999 to December 2018. Distance to midpoint is the distance of each corporate bond's credit spread to the midpoint between the spread curve of peer credit rating and the spread curve of next-lower credit rating.

(%)	Mean	Std. Dev.	Min	P10	P25	P50 (Median)	P75	P90	Max
All	-0.63	1.12	-4.76	-1.82	-1.14	-0.56	-0.17	0.25	13.37
AAA	-0.13	0.20	-0.54	-0.34	-0.24	-0.14	-0.04	0.07	0.53
AA	-0.15	0.34	-0.88	-0.53	-0.36	-0.18	0.01	0.23	1.43
A	-0.36	0.57	-1.51	-0.89	-0.70	-0.44	-0.14	0.25	4.58
BBB	-1.00	1.22	-3.16	-2.20	-1.70	-1.17	-0.54	0.21	9.25
BB	-1.08	1.89	-4.50	-3.00	-2.18	-1.26	-0.32	0.82	9.99

TABLE 3

Percentage of Bonds above the Midpoint, 1999-2018

This table summarizes the distribution of monthly percentage of bonds above the midpoint threshold by count (Panel A) and by market value (Panel B) from January 1999 to December 2018. Each month, we calculate the percentage of bonds in each credit rating group with credit spread above the midpoint threshold (the midpoint between the spread curve of peer credit rating and the spread curve of next-lower credit rating) and report the mean, minimum, 25th percentile, median, 75th percentile, and maximum of the monthly percentages over the sample period.

PANEL A: BY ISSUE COUNT

	AAA	AA	A	BBB	BB	All
Mean	14.8%	22.2%	15.1%	10.6%	15.1%	14.0%
Min	0.0%	0.0%	0.0%	3.5%	0.0%	7.5%
P25	4.7%	17.8%	10.3%	7.9%	10.4%	10.7%
P50 (Median)	17.2%	22.8%	13.3%	10.4%	16.5%	12.7%
P75	22.8%	26.9%	19.6%	12.7%	21.4%	17.8%
Max	48.5%	41.0%	30.1%	23.8%	33.0%	24.2%

PANEL B: BY MARKET VALUE

	AAA	AA	A	BBB	BB	All
Mean	14.3%	23.3%	17.6%	9.7%	14.0%	15.6%
Min	0.0%	0.0%	0.0%	2.6%	0.0%	6.7%
P25	3.7%	14.3%	8.6%	6.3%	7.6%	10.1%
P50 (Median)	13.4%	21.0%	12.7%	9.2%	13.2%	12.3%
P75	23.1%	32.8%	25.4%	13.2%	19.9%	22.1%
Max	63.9%	54.9%	43.4%	22.2%	49.6%	31.3%

TABLE 4

Time-Series Average Frequency of Downgrades, 1999-2018

This table summarizes the time-series average and standard deviation of downgrade frequencies over non-overlapping three-, six-, and 12-month periods from January 1999 to December 2018 for all bonds as well as bonds whose credit spreads are above or below the midpoint threshold (the midpoint between the spread curve of peer credit rating and the spread curve of next-lower credit rating). Downgrades are based on the granular S&P credit rating scale with the plus/minus modifiers.

	3-Month			6-Month			12-Month		
	All	Below Midpoint	Above Midpoint	All	Below Midpoint	Above Midpoint	All	Below Midpoint	Above Midpoint
Average	4.1%	2.7%	12.1%	7.8%	5.6%	20.1%	14.4%	11.4%	32.4%
Standard Deviation	3.5%	2.5%	10.4%	5.3%	4.0%	13.6%	6.8%	5.5%	15.6%
Difference (Above–Below)			9.4%			14.4%			21.0%
t-Statistic of Difference			*9.42*			*8.25*			*7.42*

TABLE 5

Logistic Regression of Downgrade Probability on Distance to Midpoint, 1999-2018

We run Fama-MacBeth regressions using the following logistic regression specification over non-overlapping periods with different lengths:

$$Prob\big(\Delta CR_{i,t\to t+k} < 0\big) = logit^{-1}\big(\alpha + \gamma I_{i,t}^{IG} + \beta \cdot d_{i,t}\big), \qquad k = 3, 6, or\ 12$$

where $d_{i,t}$ is the distance-to-midpoint variable, defined as the distance from bond i's credit spread to the midpoint threshold between the bond's same-rated peer spread curve and the adjacent spread curve with lower credit rating, $\Delta CR_{i,t->t+k} = CR_{i,t+k} - CR_{i,t}$ denotes bond i's rating change from month t to month $t+k$ based on numerically coded credit ratings (AAA = -1, AA+ = -2, AA = -3, AA-= -4, …, C = -21 and D = -22), and $I_{i,t}^{IG}$ is the indicator variable for whether bond i is rated investment grade or high yield in month t. The table reports the average slopes (β) across periods, t-statistics of the average slopes (in parentheses), and the average pseudo R^2 across periods.

k	β	R^2
3	0.81	0.09
	(10.27)	
6	0.88	0.09
	(9.74)	
12	0.88	0.08
	(7.02)	

TABLE 6

Linear Regression of the Magnitude of Rating Changes on Distance to Midpoint, 1999-2018

We run Fama-MacBeth regressions using the following linear regression specification over non-overlapping periods with different lengths:

$$\Delta CR_{i,t\to t+k} = \alpha + \gamma I_{i,t}^{IG} + \beta \cdot d_{i,t} + \epsilon_{i,t+k}, \quad k = 3, 6, or\ 12$$

where $d_{i,t}$ is the distance-to-midpoint variable, defined as the distance from bond i's credit spread to the midpoint threshold between the bond's same-rated peer spread curve and the adjacent spread curve with lower credit rating, $\Delta CR_{i,t->t+k} = CR_{i,t+k} - CR_{i,t}$ denotes bond i's rating change from month t to month $t+k$ based on numerically coded credit ratings (AAA = -1, AA+ = -2, AA = -3, AA- = -4, …, C = -21, and D = -22), $I_{i,t}^{IG}$ is the indicator variable for whether bond i is rated investment grade or high yield in month t, and $\epsilon_{i,t+k}$ is the error term. The table reports the average slopes (β) across periods, t-statistics of the average slopes (in parentheses), and the average adjusted R^2 across periods.

k	β	R^2
3	-0.10	0.06
	(-10.42)	
6	-0.19	0.09
	(-10.01)	
12	-0.34	0.11
	(-7.45)	

TABLE 7

Performance Summary, February 1999-December 2018

This table summarizes the characteristics and performance of BBB rated bonds with different distances to midpoint, BB rated bonds and BB/B rated bonds from February 1999 to December 2018. Each month, we form portfolios of bonds rated BBB, BB, and BB/B based on their stated S&P ratings. For BBB rated bonds, we form two additional portfolios: one consists of BBB rated bonds below the midpoint threshold and the other consists of those above the midpoint threshold. We calculate the market value-weighted returns each month and report the annualized compound return, standard deviation, and downside-performance measures, such as maximum drawdown and worst rolling one-, three-, and five-year annualized returns over the full sample period. The table also reports the average monthly returns of different portfolios as well as the t-statistics of monthly return differences between the above-midpoint and the below-midpoint BBB rated portfolios when the average BB-minus-BBB spread widens by at least 0 bps, 10 bps, and 20 bps.

	BBB rated				
	All	Below BBB/BB Midpoint (1)	Above BBB/BB Midpoint (2)	BB rated	BB/B rated
Avg. Yield-to-Worst (YTW)	5.27	4.89	7.34	7.05	7.64
Avg. Option-Adjusted-Duration (OAD)	6.58	5.71	6.82	5.31	5.16
Annualized Compounded Return	5.51	5.23	6.41	5.82	6.36
Annualized Standard Deviation	5.62	4.78	10.81	8.52	9.25
Maximum Drawdown	16.03	12.93	32.37	25.05	30.02
Worst Rolling 1Y Return	-15.35	-11.55	-30.27	-23.57	-28.45
Worst Rolling 3Y Return, Annualized	-2.26	-0.69	-9.30	-5.08	-6.60
Worst Rolling 5Y Return, Annualized	0.03	1.12	-4.12	-0.85	-1.47
Average Monthly Return When BB–BBB Spread Widens by					
$\geq$ 0 bps	0.37	0.41	-0.05	-0.32	-0.44
t-Statistic, (1) vs. (2)		*1.90*			
$\geq$ 10 bps	0.27	0.33	-0.40	-0.80	-0.96
t-Statistic, (1) vs. (2)		*2.23*			
$\geq$ 20 bps	0.12	0.19	-0.65	-1.05	-1.25
t-Statistic, (1) vs. (2)		*2.14*			

(Total number of the months = 239; Percent of the months = 47%, 32% & 26%, when BB-BBB spread widens by at least 0, 10, & 20 bps, respectively)

TABLE 8

Summary Statistics of Corporate Bond Samples for Main Results and Robustness Checks

This table reports the time-series average of characteristics (number of issues, number of issuers, total market value, yield to worst, and option-adjusted duration) of corporate bond data used in our main downgrade frequency analysis in Section 4.1 and robustness checks. Sample period is from 1999 to 2018 unless otherwise stated.

	Full Sample (Section 4.1)	IG Only (AAA–BBB)	High Yield Only (BB)	More Liquid (Mar 2005–Dec 2018)	Less Liquid (Mar 2005–Dec 2018)	Intermediate-Term Bonds	Long-Term Bonds
Average # of Issues	2,569	2,355	213	2,094	442	1,851	718
Average # of Issuers	518	451	79	440	235	476	265
Average Total Market Value ($ in billions)	1,687	1,580	107	1,737	190	1,223	464
Avg. YTW	4.88	4.74	7.05	4.30	4.77	4.46	6.00
Avg. OAD	6.26	6.32	5.31	6.42	8.11	4.14	12.00

TABLE 9

Time Series Average Frequency of Downgrades, 1999-2018 (Based on Yield Curve Method)

This table summarizes the time-series average and standard deviation of downgrade frequencies over non-overlapping three-, six-, and 12-month periods from January 1999 to December 2018 for all bonds as well as bonds whose yields are above or below the midpoint threshold (the midpoint between the yield curve of peer credit rating and the yield curve of next-lower credit rating). Downgrades are based on the granular S&P credit rating scale with the plus/minus modifiers.

	3-Month			6-Month			12-Month		
	All	Below Midpoint	Above Midpoint	All	Below Midpoint	Above Midpoint	All	Below Midpoint	Above Midpoint
Average	4.4%	2.8%	12.3%	8.2%	5.8%	20.5%	14.8%	11.4%	33.3%
Standard Deviation	3.5%	2.6%	10.2%	5.3%	3.9%	13.0%	6.7%	5.6%	15.3%
Difference (Above–Below)			9.6%			14.7%			21.9%
t-Statistic of Difference			*10.02*			*9.05*			*8.18*

TABLE 10

Time-Series Average Frequency of Downgrades, 1999-2018 (Threshold = Spread Curve of Next-lower Credit Rating)

This table summarizes the time-series average and standard deviation of downgrade frequencies over non-overlapping three-, six-, and 12-month periods from January 1999 to December 2018 for all bonds as well as bonds whose spreads are above or below the spread curve of next-lower credit rating. Downgrades are based on the granular S&P credit rating scale with the plus/minus modifiers.

	3-Month			6-Month			12-Month		
	All	Below Lower Credit	Above Lower Credit	All	Below Lower Credit	Above Lower Credit	All	Below Lower Credit	Above Lower Credit
Average	4.1%	3.2%	16.4%	7.8%	6.5%	25.9%	14.4%	12.6%	40.2%
Standard Deviation	3.5%	2.8%	14.3%	5.3%	4.4%	17.6%	6.8%	6.0%	18.7%
Difference (Above–Below)			13.2%			19.4%			27.6%
t-Statistic of Difference			*9.16*			*8.04*			*7.77*

TABLE 11

Time-Series Average Frequency of Downgrades, 1999 – 2018 (Investment Grade vs. High Yield)

Panels A and B summarize the time-series average and standard deviation of downgrade frequencies for investment grade bonds and high yield BB rated bonds, respectively. The downgrade frequencies are over non-overlapping three-, six-, and 12-month periods from January 1999 to December 2018 for all bonds as well as bonds whose credit spreads are above or below the midpoint threshold (the midpoint between the spread curve of peer credit rating and the spread curve of next-lower credit rating). Downgrades are based on the granular S&P credit rating scale with the plus/minus modifiers.

PANEL A: INVESTMENT GRADE ONLY

	3-Month			6-Month			12-Month		
	All	Below Midpoint	Above Midpoint	All	Below Midpoint	Above Midpoint	All	Below Midpoint	Above Midpoint
Average	3.8%	2.6%	11.2%	7.3%	5.5%	18.3%	13.6%	11.1%	30.3%
Standard Deviation	3.5%	2.5%	10.6%	5.4%	4.0%	13.8%	6.9%	5.6%	16.6%
Difference (Above–Below)			8.6%			12.8%			19.2%
t-Statistic of Difference			*8.46*			*7.22*			*6.35*

PANEL B: HIGH YIELD (BB RATED ONLY)

	3-Month			6-Month			12-Month		
	All	Below Midpoint	Above Midpoint	All	Below Midpoint	Above Midpoint	All	Below Midpoint	Above Midpoint
Average	7.5%	3.4%	18.9%	13.6%	7.6%	33.6%	22.6%	13.3%	45.4%
Standard Deviation	5.9%	3.2%	17.3%	8.2%	5.7%	21.7%	10.2%	7.7%	26.5%
Difference (Above–Below)			15.5%			26.0%			32.1%
t-Statistic of Difference			*7.83*			*7.59*			*4.70*

TABLE 12

Time-Series Average Frequency of Downgrades, March 2005-December 2018 (With TRACE Filter)

Panels A and B summarize the time-series average and standard deviation of downgrade frequencies for more liquid bonds and less liquid bonds, respectively. Bonds are labeled “more liquid” near month-end if the average trade quantity recorded in TRACE is at least $10,000 (in par value) in the last five business days in the month and “less liquid” otherwise. The downgrade frequencies are over non-overlapping three-, six-, and 12-month periods from March 2005 to December 2018, when almost all corporate bond trades were disseminated since Phase 3B of TRACE regulatory changes. The frequencies are calculated for all bonds as well as bonds whose credit spreads are above or below the midpoint threshold (the midpoint between the spread curve of peer credit rating and the spread curve of next-lower credit rating). Downgrades are based on the granular S&P credit rating scale with the plus/minus modifiers.

PANEL A: MORE LIQUID BONDS IN THE LAST FIVE BUSINESS DAYS EACH MONTH

	3-Month			6-Month			12-Month		
	All	Below Midpoint	Above Midpoint	All	Below Midpoint	Above Midpoint	All	Below Midpoint	Above Midpoint
Average	4.0%	2.7%	10.8%	7.6%	5.3%	18.6%	14.5%	10.9%	31.8%
Standard Deviation	4.2%	3.3%	11.4%	6.4%	4.6%	15.5%	8.5%	6.4%	18.7%
Difference (Above–Below)			8.1%			13.2%			20.9%
t-Statistic of Difference			*6.37*			*5.47*			*5.16*

PANEL B: LESS LIQUID BONDS IN THE LAST FIVE BUSINESS DAYS EACH MONTH

	3-Month			6-Month			12-Month		
	All	Below Midpoint	Above Midpoint	All	Below Midpoint	Above Midpoint	All	Below Midpoint	Above Midpoint
Average	2.9%	1.9%	7.2%	5.2%	4.0%	12.4%	9.2%	7.6%	21.5%
Standard Deviation	2.8%	1.9%	7.5%	4.4%	3.3%	11.4%	5.6%	4.2%	15.4%
Difference (Above–Below)			5.2%			8.5%			14.0%
t-Statistic of Difference			*5.89*			*4.70*			*4.05*

TABLE 13

Time-Series Average Frequency of Downgrades, 1999-2018 (Intermediate-Term Bonds vs. Long-Term Bonds)

Panels A and B summarize the time-series average and standard deviation of downgrade frequencies for intermediate-term bonds and long-term bonds, respectively. The downgrade frequencies are over non-overlapping three-, six-, and 12-month periods from January 1999 to December 2018 for all bonds as well as bonds whose credit spreads are above or below the midpoint threshold (the midpoint between the spread curve of peer credit rating and the spread curve of next-lower credit rating). Downgrades are based on the granular S&P credit rating scale with the plus/minus modifiers.

PANEL A: INTERMEDIATE-TERM BONDS

	3-Month			6-Month			12-Month		
	All	Below Midpoint	Above Midpoint	All	Below Midpoint	Above Midpoint	All	Below Midpoint	Above Midpoint
Average	4.2%	2.9%	12.9%	8.0%	5.9%	20.8%	14.8%	11.9%	33.1%
Standard Deviation	3.9%	2.7%	12.4%	6.0%	4.2%	16.2%	7.6%	5.8%	18.5%
Difference (Above–Below)			10.1%			14.9%			21.2%
t-Statistic of Difference			*8.49*			*7.08*			*6.27*

PANEL B: LONG-TERM BONDS

	3-Month			6-Month			12-Month		
	All	Below Midpoint	Above Midpoint	All	Below Midpoint	Above Midpoint	All	Below Midpoint	Above Midpoint
Average	3.9%	2.1%	11.0%	7.4%	4.7%	19.0%	13.7%	9.7%	31.3%
Standard Deviation	2.8%	2.1%	8.8%	4.5%	3.7%	11.6%	6.0%	5.4%	14.1%
Difference (Above–Below)			8.9%			14.3%			21.7%
t-Statistic of Difference			*9.58*			*8.39*			*7.48*

TABLE 14

Monthly Fama-MacBeth Logistic Regression with Newey-West Correction, 1999-2018

We run monthly Fama-MacBeth regression using the following cross-sectional logistic regression specification:

$$Prob\left(\Delta CR_{i,t\to t+k} < 0\right) = logit^{-1}\left(\alpha + \gamma I_{i,t}^{IG} + \beta \cdot d_{i,t}\right), \qquad k = 3, 6, or\ 12$$

where $d_{i,t}$ is the distance-to-midpoint variable, defined as the distance from bond i's credit spread to the midpoint threshold between the bond's same-rated peer spread curve and the adjacent spread curve with lower credit rating, $\Delta CR_{i,t->t+k} = CR_{i,t+k} - CR_{i,t}$ denotes bond i's rating change from month t to month t+k based on numerically coded credit ratings (AAA = -1, AA+ = -2, AA = -3, AA- = -4, …, C = -21 and D = -22), and $I_{i,t}^{IG}$ is the indicator variable for whether bond i is rated investment grade or high yield in month t. The table reports the average slopes (β) across months, t-statistics of the average slopes (in parentheses), and the average monthly pseudo R^2. For three-, six-, and 12-month horizons, t-statistics are calculated by adjusting the standard errors of the slopes using Newey-West correction with two, five, and 11 lags, respectively.

k	β	R^2
3	0.85	0.10
	(11.84)	
6	0.93	0.09
	(9.81)	
12	0.91	0.08
	(8.15)	

TABLE 15

Monthly Fama-MacBeth Linear Regression with Newey-West Correction, 1999-2018

We run monthly Fama-MacBeth regression using the following linear regression specification:

$$\Delta CR_{i,t\to t+k} = \alpha + \gamma I_{i,t}^{IG} + \beta \cdot d_{i,t} + \epsilon_{i,t+k}, \quad k = 3, 6, or\ 12$$

where $d_{i,t}$ is the distance-to-midpoint variable, defined as the distance from bond i's credit spread to the midpoint threshold between the bond's same-rated peer spread curve and the adjacent spread curve with lower credit rating, $\Delta CR_{i,t->t+k} = CR_{i,t+k} - CR_{i,t}$ denotes bond i's rating change from month t to month $t+k$ based on numerically coded credit ratings (AAA = -1, AA+ = -2, AA = -3, AA- = -4, …, C = -21 and D = -22), $I_{i,t}^{IG}$ is the indicator variable for whether bond i is rated investment grade or high yield in month t, and $\epsilon_{i,t+k}$ is the error term. The table reports the average slopes (β) across months, t-statistics of the average slopes (in parentheses), and the average monthly adjusted R^2. For three-, six-, and 12-month horizons, t-statistics are calculated by adjusting the standard errors of the slopes using Newey-West correction with two, five, and 11 lags, respectively.

k	β	R^2
3	-0.11	0.07
	(-12.76)	
6	-0.20	0.09
	(-11.56)	
12	-0.35	0.11
	(-7.48)	

References

Altman, Edward I. and Herbert A. Rijken. 2004 “How Rating Agencies Achieve Rating.” *Journal of Banking & Finance* 28.11: 2679–2714.

Badoer, Dominique C., Cem Demiroglu and Christopher M. James. 2019. “Ratings Quality and Borrowing Choice.” *Journal of Finance*, 71.5: 2619–2665.

Barclays. 2014. “Barclays Index Methodology.” *Barclays Index, Portfolio & Risk Solutions.* (2014).

Black, Fischer and Myron Scholes. 1973. “The Pricing of Options and Corporate Liabilities.” *Journal of Political Economy* 81.3: 637–654.

Becker, Bo and Todd Milbourn. 2011. “How Did Increased Competition Affect Credit Ratings?” *Journal of Financial Economics* 101: 493–514.

Cornaggia, Jess and Kimberly J. Cornaggia. 2013. “Estimating the Costs of Issuer-Paid Credit Ratings.” *Review of Financial Studies* 26: 2229–2269.

Covitz, Dan and Chris Downing. 2007. “Liquidity or Credit Risk? The Determinants of Very Short-Term Corporate Yield Spreads.” *Journal of Finance* 62.5: 2303–2328.

Duffee, Gregory R. 1998. “The Relation Between Treasury Yields and Corporate Bond Yield.” *Journal of Finance* 53.6: 2225–2241.

Duffie, Darrell and Kenneth J. Singleton. 1999. “Modeling Term Structures of Defaultable Bonds.” *The review of Financial Studies* 12.4: 687–720.

Duffie, Darrell and Kenneth J. Singleton. 2012. “Credit risk: Pricing, Measurement, and Management.” *Princeton University Press*.

Elton, Edwin J., Martin J. Gruber, Deepak Agrawal, and Christopher Mann. 2001. “Explaining the Rate Spread on Corporate Bonds.” *Journal of Finance* 56.1: 247–277.

Fama, Eugene F. 1986. “Term Premiums and Default Premiums in Money Markets.” *Journal of Financial Economics* 17.1: 175–196.

Fama, Eugene F. and James D. MacBeth. 1973. “Risk, Return, and Equilibrium: Empirical Tests.” *Journal of Political Economy* 81(3): 607–636.

Giesecke, Kay, Francis A. Longstaff, Stephen Schaefer, and Ilya Strebulaev. 2011. “Corporate Bond Default Risk: A 150–Year Perspective.” *Journal of Financial Economics* 102.2: 233–250.

Gilchrist, Simon, and Egon Zakrajsek. 2012. “Credit Spreads and Business Fluctuations.” *American Economic Review* 102(4): 1692–1720.

Hull, John, Mirela Predescu, and Alan White. 2004. “The Relationship Between Credit Default Swap Spreads, Bond Yields, and Credit Rating Announcements.” *Journal of Banking & Finance* 28.11: 2789–2811.

Jiang, John Xuefeng, Mary H. Stanford, and Yuan Xie. 2012. “Does it Matter Who Pays for Bond Ratings? Historical Evidence.” *Journal of Financial Economics* 105: 607–621.

Jorion, Philippe, Zhu Liu, and Charles Shi. 2005. “Informational Effects of Regulation FD: Evidence from Rating Agencies.” *Journal of Financial Economics* 76.2: 309–330.

Lee, Jongsub, Andy Naranjo, and Guner Velioglu. 2018. “When Do CDS Spreads Lead? Rating Events, Private Entities, and Firm Specific Information Flows.” *Journal of Financial Economics* 130.3: 556–578.

Longstaff, Francis A., Sanjay Mithal, and Eric Neis. 2005. “Corporate Yield Spreads: Default Risk or Liquidity? New Evidence From the Credit Default Swap.” *Journal of Finance* 60.5: 2213–2253.

Merton, Robert C. 1974. “On the Pricing of Corporate Debt: The Risk Structure of Interest Rates.” *Journal of Finance* 29.2: 449–470.

Moody's. 2018. "Cross–Sector: Annual Default Study: Corporate Default and Recovery Rates, 1920–2017." *Moody's Investors Service*.

Nozawa, Yoshio. 2017. "What Drives the Cross–Section of Credit Spreads?: A Variance Decomposition Approach." *Journal of Finance* 72.5: 2045–2072.

Standard & Poor's. 2019. "Default, Transition and Recovery: 2018 Annual Global Corporate Default and Rating Transition Study." *S&P Global Ratings*.

White, Lawrence J. 2010. "Markets: The Credit Rating Agencies." *Journal of Economic Perspectives* 24.2: 211–26.

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