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Corporate bond credit spreads and forecast dispersion ☆

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ABSTRACT

Recent research establishes a negative relation between stock returns and dispersion of analysts' earnings forecasts, arguing that asset prices more reflect the views of optimistic investors because of short-sale constraints in equity markets. In this article, we examine whether a similar effect prevails in corporate bond markets. After controlling for common bond-level, firm-level, and macroeconomic variables, we find evidence that bonds of firms with higher dispersion demand significantly higher credit spreads than otherwise similar bonds and that changes in dispersion reliably predict changes in credit spreads. This evidence suggests a limited role of short-sale constraints in our corporate bond data sets. Consistent with a rational explanation, dispersion appears to proxy largely for future cash flow uncertainty in corporate bond markets.

1. Introduction

Do analysts' earnings forecasts play a role in corporate bond markets similar to the one they play in equity markets? Previous work has demonstrated that much of the variation in credit spreads on corporate bonds is explained by bond characteristics, credit quality, and market conditions (e.g., duration, credit rating, and default premium). However, the relevance of equity analyst data on firm characteristics, which is largely catered to equity markets, has not been explored nearly as thoroughly for corporate bond markets.

Our study is the first to provide empirical evidence on the role of earnings uncertainty and especially dispersion in analysts' earnings forecasts (*forecast dispersion*) on levels and changes of credit spreads. The objective of this paper is to analyze whether forecast dispersion plays a role in corporate bond markets similar to the one it plays in equity markets. To do so, we explore how credit spreads and bond returns reflect disagreement among equity analysts and how this effect differs across firms and across time. In addition, our study provides a gauge for the functioning of bond and equity markets. Before discussing and interpreting our findings, we develop two competing hypotheses about the relation between credit spreads and forecast dispersion.[2]

The first hypothesis, motivated by Miller (1977), views forecast dispersion as a measure of divergence of opinion and claims that, in the presence of short-sale constraints, bond prices should more reflect the views of optimistic investors. Miller argues that when investor biases differ and short-sale constraints bind, investors with pessimistic views cannot sell (unless they own the asset), while investors with optimistic views are able to purchase and raise prices. As a result, negative views are not completely incorporated, and bond prices are upwardly biased, giving rise to lower

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[2] We formalize these ideas in the Appendix A within a simple model, in which analyst-specific forecast variances have a behavioral (divergence of opinion) and a rational (cash flow uncertainty) component.

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credit spreads. Thus, according to this behavioral view, higher forecast dispersion leads to higher firm values and hence lower credit spreads.

The second hypothesis contends that, in corporate bond markets, forecast dispersion proxies for future cash flow uncertainty. In structural models of credit risk, such as Merton (1974) model, corporate debt is a riskfree bond less a put option on the value of the firm's assets. The strike price equals the par value of debt and reflects the limited liability of equity in the event of default. Default, the event where a firm is unable to meet its obligations, occurs when the value of the firm's assets falls below the strike price. The volatility that is relevant for option value, and thus for corporate debt, is total asset volatility, including both idiosyncratic volatility and systematic volatility. A firm with more volatile operating income (or asset returns) is more likely to reach the default boundary. When volatility increases, the value of the put option increases, benefiting equityholders at the expense of bondholders. According to this rational explanation of the spread–dispersion relation, higher forecast dispersion leads to higher credit spreads. In addition to contractual differences, the second hypothesis relates to institutional differences between bond and equity markets and, in particular, to the relative lack of short-sale constraints for corporate bonds.[3]

Consistent with the second hypothesis, we find that corporate bonds with higher forecast dispersion demand higher credit spreads. This reliably positive spread–dispersion relation is, however, difficult to reconcile with the first hypothesis. In a univariate regression, dispersion accounts for about 23% of the cross-sectional variation of credit spreads. Moreover, a one-standard deviation increase in dispersion increases credit spreads by 19 basis points, with the sample average credit spread being 100 basis points. This effect is more pronounced for bonds of lower credit quality, longer maturities, smaller firms, and more levered firms. Multivariate regressions with other control variables (such as credit rating, duration, bond liquidity, earnings volatility, firm leverage, firm size, book-to-market, profitability, stock return volatility, and macroeconomic variables) explain up to 81% of the cross-sectional variation in the levels of credit spreads, while coefficient estimates corresponding to forecast dispersion are positive and typically significant at better than 1%.[4]

Furthermore, we find that corporate bonds with higher forecast dispersion earn higher future returns. In particular, we document that changes in forecast dispersion also significantly predict changes in credit spreads after including common control variables such as changes in term structure factors and in credit ratings, option-implied volatilities, and stock index returns (see, e.g., Collin-Dufresne et al., 2001). Moreover, applying the sorting procedure of Diether et al. (2002) to corporate bonds generates an annually compounded return differential between the highest and the lowest dispersion portfolio of more than 100 basis points.[5]

[3] Corporate bonds are primarily held and traded by large financial institutions rather than individual investors. To this end, Nagel (2005) reports a negative effect of institutional ownership on short-sale constraints. It has also been argued that institutional investors are less prone to behavioral biases. Several institutional details of equity markets, which appear to be absent from corporate bond markets, can make shorting stocks difficult (see, e.g., Jones, 2003). Finally, Longstaff et al. (2005) report relatively low costs for shorting investment-grade corporate bonds.

[4] Consistent with our results, Cremers et al. (2008) find a positive relation between individual option-implied volatility and credit spreads for the 1996–2002 period. Similarly, Tang and Yan (2010) report that firm-level implied volatility explains the cross-sectional variation in credit default swap spreads.

[5] Each month, we assign bonds into five quintiles based on dispersion in the previous month. We then calculate monthly returns from equally weighted average returns of all bonds in a given dispersion portfolio. This methodology was originated to reduce return variability (see, e.g., Jegadeesh and Titman, 1993).

In the light of these findings, forecast dispersion appears to proxy largely for future cash flow uncertainty in our sample of corporate bonds. To confirm our baseline results, we adopt various robustness checks. First, we estimate the baseline model in different specifications with year, quarter, firm, industry, and bond-level fixed effects to verify that our results are not the outcome of spurious time-series or cross-sectional correlation. We also control for time-series correlation in errors by computing Fama and MacBeth (1973); Newey and West (1987), and two-way-clustered standard errors as well as estimating pure cross-sectional regressions. The economic and statistical significance of our findings does not change under these more restrictive, econometric specifications. Second, we show that other firm-level uncertainty proxies, such as earnings volatility, earnings forecast errors, or excess stock returns, do not subsume dispersion. Third, we follow recent studies by Livingston et al. (2007, 2008) to see whether our findings are influenced by corporate bonds with notch-level or letter-level split ratings. Fourth, given changes in accounting transparency (e.g., Regulation Fair Disclosure in 2000) and bond market transparency (e.g., SEC regulation on the reporting and dissemination of fixed income transactions in 2001), we provide evidence for a reliably positive spread–dispersion relation during the post-2000 period.

Due to accounting conventions, dispersion is based on forecasts of earnings after interest and taxes. Another concern is therefore the possibility that, like earnings per share, dispersion captures the variation in firms' interest expenses and their marginal corporate tax rates. To cancel out interest and tax differentials across firms, we multiply dispersion by the ratio of operating cash flow over net income. Our main result also holds in this estimation with a dispersion measure that is based on operating cash flows instead of earnings (the difference being interest expenses and taxes). Second, we stratify the panel into subsamples based on time period, credit rating, firm size, bond maturity, and firm leverage. In all subsample tests, the dispersion result remains unexpectedly robust with significance mostly at the 0.1% level. In a third robustness test of this critique, we examine the significance of the interaction term of dispersion multiplied by leverage together with leverage alone.

We also implement various tests to study the validity of the second hypothesis relative to alternate explanations. First, Johnson (2004) suggests that, if firm fundamentals are unobservable, forecast dispersion may proxy for idiosyncratic risk, that is, unpriced parameter uncertainty. To examine this alternative, we include forecast dispersion and market-risk-adjusted equity return volatility (i.e., the idiosyncratic risk proxy of Campbell and Taksler (2003)) in the same regression specification. Their measure of idiosyncratic risk affects neither the economic nor the statistical significance level of forecast dispersion. If dispersion mostly captured unpriced parameter uncertainty in corporate bond markets, one would expect these variables to interact with each other. Second, we test whether forecast dispersion predicts future earnings volatility. We estimate current levels (or changes) of earnings volatility as a function of lagged levels (or changes) of earnings volatility and lagged levels (or changes) of dispersion. Third, we analyze the link between forecast dispersion and squared changes in earnings or squared earnings surprises.

The paper proceeds as follows. Section 2 discusses the data sources, variables, and summary statistics. Section 3 contains the main results, while Section 4 presents robustness checks. Section 5 concludes. A simple model of credit spreads and forecast dispersion is developed in the Appendix A.

2. Data and summary statistics

Before testing the predictions, we discuss the data for credit spreads, forecast dispersion, and control variables.

2.1. Sample construction

The quarterly panel data originate from four sources:

1. Corporate bond prices from Lehman Fixed Income Database.
2. Earnings forecasts from Institutional Brokers Estimates System database.
3. Firms' accounting information from Standard & Poor's COMPUSTAT database.
4. Stock prices and returns from Center for Research in Security Prices database.

We start with all monthly trader quotes for fixed-rate corporate bonds issued by US firms as reported in the Lehman Fixed Income Database (LFID, henceforth) between January 1987 and March 1998 (505,367 monthly observations).[6] The sample starts in January 1987 since analyst forecast data is largely unavailable for our sample firms prior to 1987. The sample ends in March 1998 as Lehman Brothers stopped reporting the bond trades after this date. We do not include bond prices with matrix quotes because traders' quotes are more likely to reflect information on bond prices than matrix quotes. Quoted prices are the ones established by traders. When a bond has not traded recently and traders are unwilling to make quotes, a matrix price is computed based on a proprietary algorithm.

We exclude financial services firms (152,526 bond-months) similar to previous bond pricing studies (see, e.g., Collin-Dufresne et al., 2001 or Eom et al., 2004). Our goal is to ensure that payout characteristics of bonds in our sample are similar; hence we drop bonds with option-like features such as callability, putability, convertibility, and sinking fund provisions (222,494 bond-months). Following Collin-Dufresne et al. (2001), we omit bond observations with less than 4 years of maturity and bonds in default because they are illiquid (29,395 bond-months).[7] To ensure that each issuer has significant variation in the time-series of yields, we exclude firms with less than 25 monthly observations (3933 bond-months). Based on these preliminary filters, we identify 97,019 monthly observations of 2618 bonds by 703 firms for our study.

Within this preliminary sample, we identify issuers with Institutional Brokers Estimates System (I/B/E/S) coverage. We obtain a quarterly panel by merging the bond and I/B/E/S databases because we define forecast dispersion at the quarterly frequency. After merging the two databases, we keep the latest bond observation preceding the earnings announcement date of the quarter. These two restrictions lead to 19,071 quarterly observations. We drop observations whenever the issuer is covered by less than two analysts since at least two forecasts are needed to calculate forecast dispersion (152 bond-quarters). We also delete bonds not rated by S&P or Moody's (7 bond-quarters) and observations with no defined earnings volatility (311 bond-quarters) or liquidity proxy (2597 bond-quarters) since at least five preceding observations are required to define these variables.

The final sample covers 16,004 quarterly observations of 1389 bonds by 382 issuers; that is, firms have on average 3.64 bonds outstanding. The average number of quarterly quotes per bond is about 12. Finally, to avoid biases due to outliers all variables are winsorized at the 1% level (i.e., at the 0.5% and 99.5% percentiles).

2.2. Credit spreads and forecast dispersion

Our dependent variable is corporate bond credit spread, *CS*, which is the difference between the yield-to-maturity of the corporate bond and the Treasury yield of the same (remaining) maturity. To obtain Treasury yields of any maturity we construct the entire yield curve from 1, 2, 3, 5, 7, 10, and 30-year Treasuries by linear interpolation. The Treasury yields come from the H.15 release of the Federal Reserve System.

The main independent variable is dispersion in equity analysts' quarterly earnings per share forecasts (or *forecast dispersion*), denoted by *DISP*. Quarterly earnings forecasts come from the I/B/E/S Detail File. For every (fiscal) quarter q, we define a benchmark date, t_q, which is the last day of the calendar month preceding the month earnings are announced. We measure raw dispersion as the standard deviation of the most recently revised forecasts by all analysts within the period from t_{q-1} to t_q. This procedure ensures that (1) quarterly forecast dispersion is calculated using non-overlapping periods and (2) forecast data always precedes bond data since the LFID reports bond prices at the end of the month. To make dispersion magnitudes comparable across firms, we follow Thomas (2002) and Zhang (2006) and deflate raw dispersion by end-of-quarter stock price measured at t_q, which is about thirty days before the earnings announcement date.[8]

2.3. Control variables

We include a large number of control variables to verify that known determinants of credit spreads do not drive our results. Firms with higher default probability and/or lower expected recovery rate have higher default risk and hence higher credit spreads. We thus use various firm-specific and bond-specific proxies to control for common default risk factors. In addition, we control for bond liquidity and analyst coverage. Table 1 provides an index of all variables with brief descriptions.

The main control variables are defined as follows:

1. *Earnings volatility.* The first control variable in this study is (historical) earnings volatility, *VOLEARN*, which is the time-series standard deviation of quarterly earnings per share over the last eight quarters divided by the stock price.
2. *Number of analysts.* The number of analysts who post forecasts during a given quarter is assigned the variable *N*. We drop bond-quarter observations if $N < 2$.
3. *Credit rating.* Rating is our main credit risk proxy. It captures both default and recovery risk. The ordinal S&P rating of a bond is given by AAA = 1, AA = 2, A = 3, BBB = 4, BB = 5, and B = 6. We define *RATINGSQ* as the square of these broad ratings, following Hoven Stohs and Mauer (1996).[9] By squaring ratings we capture the nonlinear increase in credit risk between consecutive rating groups. Whenever the S&P rating is unavailable, we use the corresponding Moody's rating.
4. *Subordination.* For subordinated bonds, we include a dummy variable (*SUBORD*).

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6 Other recent studies by, for example, Elton et al. (2001), Eom et al. (2004) and Gebhardt et al. (2005) also rely on the LFID.

7 In unreported regressions, we find that dropping bonds with less than 2 years of maturity does not alter our main results. Chen et al. (2007) provide a thorough study of bond-level liquidity.

8 Alternatively, we have normalized raw dispersion by the absolute value of earnings (see, e.g., Diether et al., 2002) or by the book value of assets (see, e.g., Johnson, 2004). We have verified that our results are robust to different scaling procedures (details are available upon request). Moreover, we use the dispersion definition of Diether et al. (2002) in Section 4.4 to analyze a matched sample of bond and stock returns.

9 In robustness tests, we refine these broad rating groups by using their historical default probabilities or by using finer notch ratings, which convey information about potential upgrades and downgrades.

Table 1
Variable descriptions. This table defines and summarizes the variables we use in our analysis. We obtain bond yields and indexes from the Fixed Income Database, earnings data from I/B/E/S, stock price data from CRSP, and accounting information from COMPUSTAT (CS).

Abbreviation	Name of variable	Variable description
CS	Credit spread	The yield-to-maturity of the bond less the Treasury yield of closest maturity
DISP	Forecast dispersion	Ratio of raw dispersion divided by the firm's stock price measured at the quarter's benchmark date t_q. Raw dispersion is equal to the cross-sectional standard deviation of the most recently revised quarterly earnings per share estimates preceding the quarter's benchmark date. The quarter's benchmark date is the last day of the calendar month preceding the month earnings are announced
VOLEARN	Volatility of earnings	Ratio of raw earnings volatility divided by the firm's stock price measured at the quarter's benchmark date t_q. Raw earnings volatility is equal to the time-series standard deviation of quarterly earnings per share over the last eight quarters
N	Number of analysts	Number of analysts who post earnings estimates for a given firm during a given quarter
RATINGSQ	Ratings squared	Square of the ordinal S&P rating. The broad rating of a bond is given by the following transformation: AAA = 1, AA = 2, A = 3, BBB = 4 , BB = 5, B = 6, and below B = 7. When the S&P rating is unavailable, we use the corresponding Moody's rating groups
SUBORD	Subordination	Equals one if the bond is subordinated, zero if senior
DURATION	Duration	Macaulay duration as reported by the Lehman Fixed Income Database
LIQUIDITY	Bond liquidity	Number of months a bond is assigned a market quote during the past 12 months divided by 12
LEVER	Firm leverage	Long-term debt (CS item #9) divided by total assets (CS item #6)
SIZE	Firm size	Natural logarithm of long-term debt (CS item #9) plus common equity (CS item #60)
B/M	Book-to-market ratio	Book value of equity (CS item #60) divided by market value of equity (CS item #24 * CS item #25)
PROFIT	Operating profitability	Earnings before tax and depreciation (CS item #13) divided by total assets (CS item #6)
R	Risk-free rate	Yield on 10-year Treasury bonds, $R(10yr)$
SLOPE	Slope of term structure	Yield on 10-year Treasury bonds minus yield on 2-year Treasury bonds, $SLOPE = R(10yr) - R(2yr)$
RETSP	S&P 500 index return	Return on the S&P 500 stock index return over the last quarter
VIX	Volatility index	Average implied volatility of eight near-the-money options on the S&P 100 index
JUMP	Probability of jump	Probability of a large size jump on S&P 100 index, calculated using out-of-the money puts as well as at- and in-the-money call options (see Section 4.4 or Collin-Dufresne et al. (2001) for estimation details)
CORP	Corporate bond yield spread	Difference between the yields of long-term Aaa bond index and long-term government bond index
DEF	Default risk spread	Difference between the yields of long-term Baa bond index and long-term Aaa bond index
VOLRET	Idiosyncratic volatility	Time-series standard deviation of daily excess stock returns over the last 180 days preceding the day of the observation. Excess stock return is defined as the stock return including the dividend payments less the return on the CRSP value-weighted market portfolio
TURNOVER	Stock turnover	Total number of shares traded during the last 180 days divided by number of shares outstanding
VOLERR	Volatility of forecast errors	Standard deviation of average forecast errors over the last eight quarters preceding the observation date. Average forecast error is defined as consensus forecast minus realized earnings per share
VOLOPER	Volatility of operating profit	Time-series sample standard deviation of quarterly earning before interest taxes and depreciation (CS quarterly item #21) over the last eight quarters preceding the observation (i.e., current) date
SPLIT	Split bond ratings	*SPLIT*1 (*SPLIT*2) equals one if S&P and Moody's disagree on a rating at the notch-level (letter-level)
EARN	Earnings per share	Realized quarterly earnings per share divided by the firm's stock price
SURPEARN	Surprise in earnings per share	Realized quarterly earnings per share minus the average of most recent analyst forecasts over stock price

5. *Duration.* We use the bond's Macaulay duration (*DURATION*). Duration is a default risk proxy because bonds with longer duration compound more default risk.
6. *Liquidity*. This is a bond-level proxy for liquidity. We count the number of months a bond is assigned a market quote during the past 12 months. To calculate it LIQUIDITY, we then divide this count by 12, which normalizes this measure to the unit interval.
7. *Firm leverage.* The firm's debt-to-firm value ratio is another common distress proxy. We employ a book value-based definition of firm leverage. That is, *LEVER* equals long-term debt (CS item #9) divided by total assets (CS item #6).
8. *Firm size.* Firm size has also a book value-based definition. *SIZE* is the natural logarithm of long-term debt (CS item #9) plus common equity (CS item #60).
9. *Book-to-market.* The book-to-market (B/M) ratio is often viewed as a distress proxy (see, e.g., Fama and French, 1993). We compute B/M as the book value of equity (CS item #60) divided by market value of equity (CS item #24 * CS item #25).
10. *Profitability.* Firms with higher operational income are less likely to default in the near future. *PROFIT* equals earnings before tax and depreciation (CS item #13) divided by book value of total assets (CS item #6) .

2.4. Summary statistics

To gauge first insights into the association of credit spreads and forecast dispersion, we examine their univariate relation in the cross-section and over time. In Fig. 1, we chart the average credit spread of each bond versus average forecast dispersion of each firm. It shows a positive univariate relation. The correlation between the two series is 0.54. Fig. 2 depicts the time-series correlation between the quarterly averages of the credit spreads of all firms in the sample and average firm-level forecast dispersion between January 1987 and March 1998. As shown by the graph, the two series display common trends, and forecast dispersion closely tracks contemporaneous movements in average credit spreads. The correlation of the two series is 0.79. From the two figures, we see that forecast dispersion captures much of the variation in credits spreads both across firms and through time.

Table 2 presents sample characteristics at the bond-level (and at the firm-level in parentheses) for different time periods, industries, credit ratings, bond maturities, and firm sizes. For each category, we report the number of bonds, the percentage of bonds in the category, and the mean and the median credit spreads.

2.4.1. Industries

We classify issuers into 10 industries using the sector codes provided by LFID: Basic Industry, Capital Goods, Consumer Cyclical,

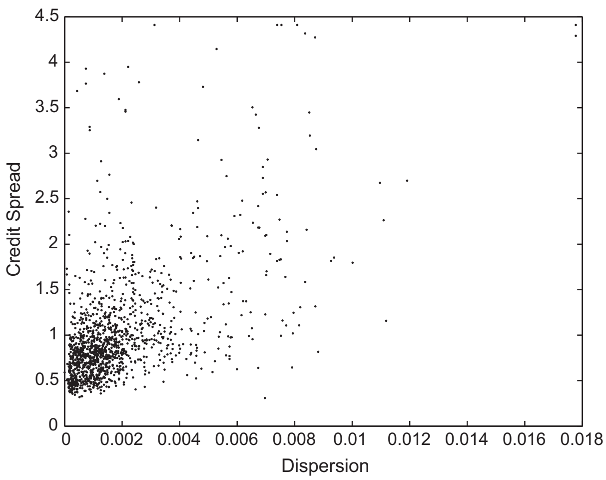

Fig. 1. Cross-sectional relation between credit spreads and forecast dispersion. This figure plots the relation between average bond-level credit spreads and average firm-level forecast dispersion. Credit spread is the yield-to-maturity of the bond less the Treasury yield of closest maturity. Forecast dispersion is the standard deviation of earnings forecasts divided by the end-of-quarter stock price.

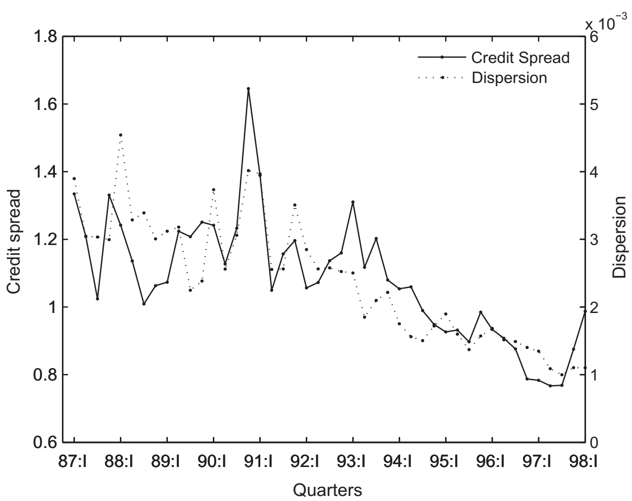

Fig. 2. Time-series relation between credit spreads and forecast dispersion. This figure charts quarterly averages of credit spreads and forecast dispersion for the sample from 1987:01 to 1998:03. Credit spread is the yield-to-maturity of the bond less the Treasury yield of closest maturity. Forecast dispersion is the standard deviation of earnings forecasts divided by the end-of-quarter stock price.

Consumer Non-cyclical, Electric, Energy, Natural Gas & Water, Technology, Transportation, and Telecommunications. For different industries, average bond-level credit spreads vary between 71 and 117 basis points except for Transportation, which has the highest industry-wide average spread of 136 basis points.

2.4.2. Time periods

Before 1991, there are fewer bonds contained in the sample; analyst coverage is also much lower on average. We therefore divide our data only into six (instead of 12) subgroups consisting of non-overlapping, 2-year periods, that is, 87–88, 89–90, 91–92, 93–94, 95–96, and 97–98. During our sample period, mean (median) credit spreads decline from about 116.0 (93.4) basis points to 83.7 (75.8) basis points at the bond-level.

2.4.3. Credit ratings

We split the sample into three rating categories: High rated issues are AAA and AA; Medium rated firms are A and BBB; and Low rated firms are rated BB to C. Seventy-six percent of our observations are Medium rated, while junk bonds only constitute about 8% of the sample. Hence, more than 90% of the firms in our sample are rated investment grade. Rating has a significant, negative association with spreads. As credit ratings deteriorate from High to Medium (Low), average bond-level credit spreads gradually increase from 59.4 to 96.2 (226.4) basis points.

2.4.4. Firm size

For investigating firm size effects, we stratify our sample into three size categories: Small, Medium, and Large, based on 33% percentiles with respect to sample firm size. Table 2 reveals a negative relationship between firm size and credit spreads. The difference in average spreads between Small and Large firms is 44 basis points.

2.4.5. Bond maturity

The sample is divided into three categories with respect to the time-to-maturity of each bond: Short maturity issues are defined as less than 7 years, Medium maturity is between 7 and 12 years, Long maturity issues have a maturity of more than 12 years. Notably, the three maturity subsamples are well-balanced. The difference in credit spreads between Short and Long maturity bonds is 22 basis points on average.

2.4.6. Firm leverage

We split the sample into firms with low, medium, and high financial leverage. The median bond-level credit spread increases from the bottom to the top 33-percentile by about 30 basis points.

Table 3 reports the sample size, mean, median, standard deviation, minimum, and maximum of the variables we use in our analysis. Panel A and B, respectively, tabulate bond-level and firm-level statistics. The sample properties of credit spreads are in line with other studies, such as Duffee (1998) or Elton et al. (2001), the mean spread is 100 basis points with a standard deviation of 60.9 basis points. Our data contain credit spreads ranging from 30.8 to 441 basis points. Forecast dispersion and earnings volatility exhibit relatively high variation. For both variables, standard deviations exceed sample means. The number of analysts per firm varies between 2 and 33, with an average of 10 analysts.

All other determinants of credit spreads fall into reasonable ranges too. For example, the median bond in our sample has a credit rating of A and about 9 (6.38) years to maturity (duration). Only 1.4% of the bonds are subordinated, and hence most sample bonds are senior and unsecured. Every bond on average trades every month during a 12-month window (i.e., our liquidity ratio equals on average 98.7%). This feature of the data indicates a fairly liquid environment and hence dissolves concerns about substantial liquidity premia being impounded into credit spreads. The average firm has log(assets) worth \$7.8 million, and return on assets of 15.2%. The average firm's book-to-market of 0.477 and 26.4% leverage indicate that our sample is, on average, comprised of moderately-levered firms that appear to reside far from financial distress.

Table 4 reports the correlation matrix for bond-level observations of our variables. Based on this table, we make three observations. First and, consistent with the second hypothesis, forecast dispersion is positively and significantly associated with credit spreads (i.e., a correlation of 0.48 is estimated). This reliable statistical relation complements the observations from Figs. 1 and 2 that dispersion is important in explaining levels of credit spreads. Second, analyst coverage is inversely related to credit spreads, that is, a higher number of equity analysts following any given firm tends to result in lower credit spreads on corporate bonds. Third, correlation coefficients between credit spreads and other control variables are also statistically significant at the 1% level and exhibit the expected signs. Although we carry out more careful robustness checks later, based on Table 4, there is no meaningful association

Table 2
Mean and median credit spreads on corporate bonds. Using panel data from 1987 to 1998, the table reports mean and median credit spreads, in percentage points, for bond-level (and firm-level) observations (in parentheses). The table also provides breakdowns by industries, 2-year time periods, credit rating groups, bond maturity groups, as well as terciles of firm leverage and firm size. All variables are winsorized at the 1% level.

	Observations	Mean spread	Median spread
All	16,004 (382)	1.000 (1.092)	0.845 (0.873)
Industries			
Basic	2405 (54)	1.040 (1.256)	0.874 (0.956)
Capital	2211 (61)	0.968 (1.079)	0.853 (0.873)
Consumer cyclical	3208 (77)	1.064 (1.275)	0.903 (0.953)
Consumer noncyclical	2591 (66)	0.818 (0.896)	0.729 (0.771)
Electric	1624 (40)	0.903 (0.946)	0.726 (0.766)
Energy	1243 (26)	0.990 (1.153)	0.870 (0.873)
Natural Gas & Water	830 (16)	1.167 (1.090)	0.950 (0.888)
Technology	469 (14)	0.935 (0.991)	0.682 (0.735)
Telecommunications	315 (11)	0.708 (0.764)	0.670 (0.671)
Transportation	1108 (17)	1.355 (1.194)	1.135 (1.138)
Time periods			
87–88	666 (99)	1.160 (1.133)	0.934 (0.922)
89–90	711 (109)	1.253 (1.330)	1.080 (1.146)
91–92	2126 (190)	1.139 (1.131)	0.955 (0.946)
93–94	4398 (261)	1.092 (1.109)	0.898 (0.912)
95–96	4883 (305)	0.905 (0.947)	0.750 (0.774)
97–98	3220 (271)	0.837 (0.853)	0.758 (0.768)
Credit rating groups			
High (AAA–AA)	2599 (40)	0.594 (0.555)	0.553 (0.519)
Medium (A–BBB)	12,203 (256)	0.962 (0.974)	0.869 (0.880)
Low (BB–C)	1202 (86)	2.264 (2.926)	2.093 (2.838)
Firm size terciles			
Small (below 7.94)	3650 (151)	1.106 (1.241)	0.896 (0.950)
Medium (7.94–8.90)	3720 (74)	0.972 (0.954)	0.818 (0.816)
Large (above 8.90)	3749 (48)	0.845 (0.801)	0.771 (0.762)
Bond maturity groups			
Short (<7 years)	4953 (87)	0.902 (1.267)	0.697 (0.849)
Medium (7–12 years)	5494 (166)	0.965 (1.065)	0.805 (0.864)
Long (>12 years)	5557 (129)	1.122 (1.008)	0.968 (0.890)
Firm leverage terciles			
Low (below 20.7%)	3678 (96)	0.797 (0.847)	0.700 (0.736)
Medium (20.7–29.6%)	3748 (85)	0.883 (0.950)	0.798 (0.830)
Large (above 29.6%)	3693 (92)	1.241 (1.460)	1.003 (1.144)

between dispersion and firm size. This finding counters concerns that dispersion might latently pick up size effects in explaining credit spreads. To substantiate these univariate results, we perform multivariate estimations that include control variables and, in addition, impose further econometric restrictions in Section 3.

3. Empirical results

As discussed in Section 1, the two conflicting theories predict different signs for the spread–dispersion relation. Linear regressions of credit spreads on forecast dispersion and common control variables therefore suffice.[10] We begin in Section 3.1 by examining the full sample over the 1987–1998 period and run a series of pooled OLS regressions. In Section 3.2, we stratify the sample into subsets of firms and reestimate the baseline regression from Section 3.1 on subsamples. In the alternative econometric tests of Section 3.3, we estimate the baseline model with different fixed effects in OLS regressions, OLS with Newey and West (1987) standard errors, OLS with standard errors clustered simultaneously by firm and quarter, Fama and MacBeth (1973) regressions, and pure cross-sectional regressions. In addition to these results on levels, changes in credit spreads as a function of changes in forecast dispersion are examined in Section 3.4.

3.1. Findings for levels of credit spreads in the full sample

As a next step, we study several structural determinants of credit spreads. For each bond i trading in month t, we denote credit spread by $CS_{i,t}$ and estimate the following linear model:

$$CS_{i,t} = \beta_0 + \beta_1 \, DISP_{i,t} + \beta_2 \, VOLEARN_{i,t} + \sum_{j=3}^{J} \beta_j \, CONTROL(j)_{i,t} + \epsilon_{i,t}, \tag{1}$$

which explains credit spreads using forecast dispersion, earnings volatility, and various control variables. The results for pooled OLS regressions with standard errors clustered at the firm-level are gathered in Table 5.[11] Consistent with the second hypothesis, credit spreads are reliably increasing with dispersion, as displayed in column 1. The regression coefficient corresponding to forecast dispersion is positive and statistically significant at better than 0.1% (t-value = 7.68). Moreover, the coefficient estimate corresponding to earnings volatility is also positive and statistically significant at better than 0.1% (t-value = 5.79). Thus, like higher forecast dispersion, higher earnings volatility predicts, all else equal, higher credit spreads. Column 1 reveals a negative and better than 0.1% significant relation between credit spreads and analyst coverage.

In column 2, we investigate whether the effect of forecast dispersion and earnings volatility on credit spreads is invariant to the inclusion of additional bond- and firm-level variables that are known to explain credit spreads in the cross-section. We add as control variables credit rating squared, subordination, duration, and liquidity. We refer to this specification as our *baseline regression model*, which we continue to analyze from different angles throughout the remainder of Section 3. The results of the baseline specification remain consistent with our conjectures. Forecast dispersion and earnings volatility continue to be statistically significant after including these controls. However, the number of analysts loses significance, possibly due to the correlation with rating squared. The coefficient estimates of all control variables are statistically significant and have the expected signs.[12] Compared to column 1, the adjusted R-squared of 58% is almost twice as high, which is largely due to inclusion of rating squared.[13]

The baseline results are also economically meaningful in supporting the implications of the modeling framework in the Appendix A. For example, the estimates in column 2 suggest that for two otherwise identical firms, the firm with a one standard deviation higher dispersion should have a credit spread that is $0.0024 * 57.417 \approx 13.78$ basis points higher. Economically, earn-

[10] We also examine the possibility of nonlinearity between credit spreads and forecast dispersion. First, we estimate the bivariate kernel density of CS and $DISP$ to obtain a nonparametric plot, in which their association appears approximately linear. Second, we regress CS on $DISP$, $DISP^2$, $DISP^3$, and $DISP^4$. The linear regression coefficient continues to be 0.1% significant, but none of the higher-order (i.e., nonlinear) terms have statistical significance. These tests thus support the view of a linear spread–dispersion relation.

[11] Column 7 of Table 7 shows a pooled OLS regression with standard errors clustered across both firms and years.

[12] In untabulated estimations, similar results prevail when we suppress the influence of outliers by winsorizing credit spreads, dispersion and earnings volatility at the 5% or 10% level. Some additional cluster analysis reveals that the results are robust in the main cluster but weaker in clusters with more extreme observations.

[13] It is well known that default risk does not change linearly between consecutive rating categories. Thus, squaring ordinal ratings aims at picking up this nonlinear effect. To better control for this nonlinearity, we replace squared ratings ($RATINGSQ$) in column (2) of Table 5 with historical default probabilities of each rating cohort. Specifically, we select 5-year cumulative default frequencies provided by Moody's Investors Service (2004) for the 1987–2003 time period. The coefficient estimate (t-value) of $DISP$ is 61.133 (7.72) and hence the baseline result remains robust after replacing rating groups by their default probabilities.

Table 3
Summary statistics. Using panel data from 1987 to 1998, this table summarizes the sample properties of credit spreads on corporate bonds and forecast dispersion for all bond-level observations in Panel A and for firm-level observations in Panel B. In addition, it reports summary statistics of the main control variables for e.g. bond characteristics and firm characteristics. All variables are winsorized at the 1% level.

	Obs.	Mean	Median	St. Dev.	Min.	Max.
Panel A: Bond-level observations						
Credit spread (*CS*)	16,004	1.000	0.845	0.609	0.308	4.410
Forecast dispersion (*DISP*)	16,004	0.002	0.001	0.002	0.000	0.018
St. Dev. of earnings (*VOLEARN*)	16,004	0.009	0.005	0.009	0.001	0.056
Number of analysts (*N*)	16,004	10.032	9.000	5.041	2.000	33.000
Rating squared (*RATINGSQ*)	16,004	11.822	9.000	6.224	1.000	36.000
Subordination (*SUBORD*)	16,004	0.014	0.000	0.116	0.000	1.000
Duration (*DURATION*)	16,004	7.089	6.383	2.621	3.364	13.874
Book-to-market ratio (*B*/*M*)	11,090	0.502	0.453	0.278	−0.237	1.646
Firm leverage (*LEVER*)	11,119	0.258	0.252	0.117	0.011	0.896
Firm size (*SIZE*)	11,119	8.423	8.460	1.041	5.944	11.496
Profitability (*PROFIT*)	10,991	0.142	0.140	0.057	−0.004	0.337
Liquidity (*LIQUIDITY*)	16,004	0.987	1.000	0.081	0.000	1.000
Panel B: Firm-level observations						
Credit spread (*CS*)	382	1.092	0.873	0.700	0.377	4.410
Forecast dispersion (*DISP*)	382	0.002	0.001	0.002	0.000	0.018
St. Dev. of earnings (*VOLEARN*)	382	0.008	0.005	0.009	0.001	0.056
Number of analysts (*N*)	382	8.245	7.500	4.323	2.000	24.300
Number of bonds issued (*n*)	382	3.636	2.000	3.335	1.000	30.000
Rating squared (*RATINGSQ*)	382	12.894	12.714	6.555	1.000	36.000
Subordination (*SUBORD*)	382	0.028	0.000	0.152	0.000	1.000
Duration (*DURATION*)	382	6.635	6.232	1.906	3.364	12.917
Book-to-market ratio (*B*/*M*)	273	0.477	0.449	0.252	−0.237	1.432
Firm leverage (*LEVER*)	273	0.264	0.248	0.137	0.028	0.896
Firm size (*SIZE*)	273	7.795	7.751	1.059	5.944	11.350
Profitability (*PROFIT*)	272	0.152	0.146	0.056	0.015	0.337
Liquidity (*LIQUIDITY*)	382	0.972	1.000	0.076	0.188	1.000

Table 4
Correlation matrix. Using panel data between 1987 and 1998, this table reports the Pearson correlation matrix for credit spreads, forecast dispersion, and main control variables for bond-level observations. All variables are winsorized at the 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) *CS*	1											
(2) *DISP*	0.4810*	1										
(3) *VOLEARN*	0.4694*	0.5764*	1									
(4) *N*	−0.1285*	0.002	−0.0485*	1								
(5) *RATINGSQ*	0.6796*	0.3287*	0.3880*	−0.2051*	1							
(6) *SUBORD*	0.1181*	−0.0315*	−0.0513*	−0.0449*	0.1379*	1						
(7) *DURATION*	0.0767*	−0.0477*	−0.0755*	0.1487*	−0.1173*	0.0001	1					
(8) *LIQUIDITY*	−0.0721*	−0.0612*	−0.0573*	0.0612*	−0.008	−0.0686*	0.0427*	1				
(9) *B*/*M*	0.3479*	0.4569*	0.4850*	−0.0981*	0.2679*	−0.0504*	−0.0553*	−0.0627*	1			
(10) *LEVER*	0.3839*	0.1113*	0.1339*	−0.1460*	0.4580*	0.0362*	−0.0645*	−0.0195	0.0354*	1		
(11) *SIZE*	−0.2057*	0.0398*	0.0106	0.4525*	−0.2767*	−0.0929*	0.1565*	0.0646*	0.0697*	−0.1142*	1	
(12) *PROFIT*	−0.3297*	−0.3346*	−0.3182*	0.1030*	−0.3389*	−0.023	−0.0094	0.0013	−0.5162*	−0.1294*	−0.1656*	1

* Significance at the 0.1% level.

ings volatility is slightly less important than forecast dispersion. That is, a firm with a one standard deviation higher earnings volatility is expected to have a $0.0088 * 9.141 \approx 8.04$ basis points higher credit spread.

Rating squared is a nonlinear, ordinal variable, and it is correlated with forecast dispersion and earnings volatility. Since the functional relation between credit spreads and ratings is difficult to determine theoretically, it is perhaps not surprising that other measures of cash flow uncertainty can explain credit spreads even after controlling for ratings. To fully estimate the potential effect of variation in ratings, column 3 employs dummies for each broad rating category instead of squared ratings. The coefficient estimates of the rating dummies reflect the additional premium that borrowers of lower rating quality have to pay. That is, relative to the baseline rating of AAA, a bond issue rated AA, A, BBB, BB, or B requires a credit risk premium of 10, 26, 55, 127, or 228 basis points, respectively. With the exception that the coefficient estimate of analyst coverage becomes 5%-significant, the baseline estimation results do not change after including rating dummies.[14]

In the fourth specification, we control for leverage and other firm-level distress proxies. Since earnings forecasts are based on net income, rather than EBIT, forecast dispersion could merely be capturing a leverage effect in the cross-section of credit spreads. In other words, different debt structures would mechanically create a variation in forecast dispersion that is not attributable to future cash flow risk. For performing this test, we drop rating squared in the fourth column of Table 5 and use another set of alternative default risk proxies, that is, firm leverage, firm

[14] When we replace broad ratings by notch ratings, which convey information about potential upgrades and downgrades, our results do not materially change either. That is, if we use notch rating dummies instead of letter rating dummies in Table 5 (3), the coefficient estimate (t-value) for *DISP* is 52.54 (7.87).

Table 5
Structural determinants of credit spreads (baseline regressions). Using panel data between 1987 and 1998, we regress credit spreads on corporate bonds against the variables listed below. Specifications (1)–(6) are OLS models. All variables are winsorized at the 1% level. *t*-Statistics (absolute values in parentheses) are based on robust standard errors clustered at the firm-level. Subsequently, specification (2) becomes our baseline regression model.

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.826***	0.272***	0.504***	1.472***	0.329***	0.575***
	(16.65)	(2.70)	(5.27)	(6.55)	(2.97)	(3.18)
DISP	78.820***	57.417***	56.512***	67.373***		54.679***
	(7.68)	(8.50)	(8.11)	(7.36)		(8.01)
(*VOLOPER*/*VOLEARN*) × *DISP*					24.980***	
					(6.92)	
VOLEARN	18.318***	9.141***	8.250***	18.465***	17.522***	10.192***
	(5.79)	(4.23)	(4.18)	(4.67)	(7.17)	(3.70)
N	−0.013***	−0.003	−0.005**	−0.002	−0.008***	−0.001
	(3.84)	(1.54)	(2.33)	(0.70)	(3.20)	(0.50)
RATINGSQ		0.055***			0.051***	0.047***
		(17.14)			(14.05)	(13.70)
SUBORD		0.264**	0.262**	0.462***	0.122	0.121
		(2.02)	(2.16)	(3.29)	(1.04)	(1.18)
DURATION		0.039***	0.040***	0.036***	0.039***	0.041***
		(12.64)	(13.00)	(8.96)	(12.50)	(13.89)
LIQUIDITY		−0.360***	−0.346***	−0.235**	−0.484***	−0.363***
		(4.11)	(3.88)	(2.20)	(4.43)	(3.65)
AA Rated			0.095***			
			(3.64)			
A Rated			0.264***			
			(9.36)			
BBB Rated			0.552***			
			(14.68)			
BB Rated			1.270***			
			(10.60)			
B Rated			2.283***			
			(16.44)			
LEVER				1.506***		0.588***
				(6.98)		(3.55)
SIZE				−0.124***		−0.051***
				(6.42)		(3.50)
B/M				0.086		0.082
				(0.88)		(0.96)
PROFIT				−1.217***		−0.107
				(2.92)		(0.31)
Observations	18,364	16,004	16,004	10,966	10,796	10,966
Adjusted *R*-squared	0.287	0.578	0.605	0.524	0.660	0.654

* Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.

size, book-to-market ratio, and operating profitability. The coefficient estimates of the new variables have the expected economic impact on credit spreads and, except for the book-to-market ratio, all of them are statistically significant, at better than 0.1%. Notably, the inclusion of firm leverage (t-value = 6.98) does not adversely impact the role of forecast dispersion (t-value = 7.36) in the regression model. Therefore, these alternative regression results are consistent with our predictions that, all else equal, higher earnings volatility and higher forecast dispersion lead to higher credit spreads on corporate bonds. However, after including these firm-level default risk proxies, the significance of analyst coverage declines sharply, possibly due to interaction with firm size.

In column 5, we analyze the possibility that dispersion is merely capturing the variation in firms' interest and depreciation expenses and their marginal tax rates. Recall that our empirical measure of forecast dispersion is based on forecasts of earnings after interest, depreciation expense, and taxes, while our hypotheses are based on the dispersion of operating cash flow forecasts. For this purpose, we multiply dispersion (*DISP*) with the volatility of operating cash flow per share (*VOLOPER*) over volatility of earnings per share (*VOLEARN*). When we rerun our baseline regressions with the adjusted dispersion measure, the coefficient estimate on this variable is significant at the 0.1% level. Thus, we find similarly strong support for the second hypothesis using a dispersion measure based on operating cash flows instead of earnings.

Another potentially important specification for testing the conflicting theories is naturally the one that contains all independent variables (except for the credit rating dummies and adjusted dispersion). Column 6 of Table 5 studies if and how this specification changes coefficient estimates on forecast dispersion and earnings volatility. As in all preceding specifications, forecast dispersion and earnings volatility are highly significant, with approximately the same economic magnitude as in the other specifications. Finally, notice that specification 6 explains 65% of the variation in the levels of credit spreads.

3.2. Findings for levels of credit spreads in various subsamples

We next create various subsamples based on time periods as well as credit rating, firm size, bond maturity, and firm leverage. The purpose of the tests on the stratified data, summarized in Table 6, is twofold. First, we check whether the empirical predictions continue to hold within subsamples and also ensure that they are not driven by any specific subset of firms or firm characteristics. Second, we examine whether variations of slope coefficients for forecast dispersion and earnings volatility across subsamples consistently support one of our hypotheses.

3.2.1. Time periods

Panel A reports the estimates for 2-year periods from 1987 to 1998.[15] The regression results for the six subperiods are in line with the baseline results in Table 5. Except for the 1987–1988 subperiod, all coefficient estimates of forecast dispersion are again statistically significant and economically of the same order of magnitude as the baseline model predicts. Earnings volatility is only statistically significant during the first, fifth and sixth subperiods. Similar to the baseline results, adjusted R^2s range from 40% to 60% across the different subsamples. Hence our results appear not to be driven by a particular subperiod.

3.2.2. Credit ratings

Panel B reports subsample tests for three rating categories: High (issuers rated AAA and AA); Medium (issuers rated A and BBB); and Low (issuers rated BB to C). As mentioned in Section 2, the lion's share of the firms in the sample fall into the second rating group. These subsample regressions reveal that the coefficient estimates of forecast dispersion increase when credit quality declines, with significance at better than 0.1% across the three rating groups. These differences in coefficient estimates (i.e., for High vs. Medium and High vs. Low) are significant at better than 0.1% (i.e., *t*-statistics of 3.74 and 5.81, respectively). For higher rated firms, the sensitivity of debt values to future cash flow uncertainty is lower, which is attributable to the concave payoff structure of corporate debt. Hence the explanatory power of dispersion is expected to be low for this group. For lower rated firms, risky debt values tend to covary more with future cash flow uncertainty. Therefore, forecast dispersion appears to be economically more important for firms closer to financial distress. However, the statistical significance of the dispersion coefficients across subsamples corroborates the view that the association of forecast dispersion and credit spreads is not likely to be driven only by distressed firms. In a recent paper, Longstaff et al. (2005) mention that shorting corporate bonds typically costs about five basis points, while this cost can rise to 50–75 basis points for the bonds of financially distressed firms. Hence if the first hypothesis involving short-sale constraints captured the dominating effect of the spread–dispersion relation, then it should be negative (or at least insignificant) for the bonds of lowest credit quality.

3.2.3. Firm size

The size subgroups in Panel C are constructed as in Table 2. The coefficient estimates for dispersion are significant, at higher than the 0.1% level in each subsample, whereas earnings volatility is only marginally significant for small and large size groups. Considering the change in slope coefficients from small to large size groups, forecast dispersion and earnings volatility both exhibit a hump-shaped behavior. However, the difference in slope coefficients in the Small and Medium groups is not statistically significant (*t*-value = 1.10), whereas the difference is significant for the Small vs. Large groups (*t*-value = −2.94). As a result, the non-monotonic behavior does not contradict the conjecture that forecast dispersion should be economically more important for smaller firms. The dispersion coefficients' statistical significance across subsamples dissolves concerns that the spread–dispersion relation is largely attributable to small firms with higher cash flow volatility.

3.2.4. Bond maturity

In Panel D, coefficient estimates of forecast dispersion and earnings volatility remain significant within the time-to-maturity subsamples, and their economic magnitude does not vary too much across groups. Running again a *t*-test reveals that the difference in coefficient estimates between Short (Medium) and Long is different from zero with *t*-statistics of −0.15 (−1.42).

3.2.5. Firm leverage

To detect leverage-induced biases in our baseline regressions, we split the sample, as in Table 2, into three groups based on low (below 33-percentile), medium (between 33- and 67-percentile) and high (above 67-percentile) leverage. Panel E contains the findings for these leverage subsamples. Most importantly, the regression coefficients for forecast dispersion are as precisely measured as in the baseline regression for all subgroups (i.e., significant at better than 0.1%). The difference in coefficient estimates in the subsamples are also significantly different from zero (i.e., *t*-value = 3.46 for Low vs. Medium and *t*-value = 4.94 for Low vs. High). Finally, it is worth noting that we continue to control for cross-sectional variation in default risk by including credit rating, which is likely to be a more restrictive model within the subsamples. Consistent with the second hypothesis, forecast dispersion's coefficient estimates are still reliable determinants of credit spreads, with increasing economic importance from Low to Medium to High leverage.

3.3. Findings for levels of credit spreads under different specifications

In this section, we consider more restrictive tests to examine the significance of the baseline results. Put differently, we examine alternative specifications to ensure that our findings are not due to spurious correlations in the cross-section and the time-series of credit spreads. The results of these robustness checks are located in Table 7. To examine estimation biases in the time-series, we experiment with time-series fixed effects. Columns 1 and 2 augment the baseline model (see column 2 in Table 5) with yearly and quarterly dummies, respectively.[16] Our results remain intact after extending the baseline model to different specifications of time dummies.

Furthermore, we seek to verify that our baseline results regarding the effect of forecast dispersion on credit spreads is not largely due to spurious cross-sectional correlations between credit spreads and other bond and firm characteristics. In different specifications, we extend the baseline regression by industry-level, firm-level, and bond-level dummies, respectively. These results are reported in columns 3, 4, and 5 of Panel A. The inclusion of these fixed effects does not change the statistical significance of the relation between forecast dispersion, earning volatility, and credit spreads. With bond-level fixed effects, the bond-level control variables duration and liquidity are, as expected, statistically insignificant. Note that the adjusted *R*-squared of the fifth specification exceeds 81%.

In our next set of alternative econometric specifications, we control for time-series correlation in residuals in four different ways. In column 6, we first estimate an OLS regression with Newey–West standard errors.[17] Second, we follow Petersen (2009) and estimate an OLS regression with standard errors clustered on two dimensions (i.e., firm and quarter) in column 7. These specifications with alternative standard errors present further support for the

[15] Since the number of quarterly observations increases rapidly after 1990, our estimation results are then also statistically significant in 1-year subsamples. For consistency, we only report 2-year periods.

[16] Time dummies can weaken the spurious correlation between credit spreads and macroeconomic shocks arising from a relation between firm-level cash flow uncertainty and the business cycle.

[17] For the regressions with Newey–West standard errors in the paper, the optimal lag length is defined as the median of the list of lags that minimize the following statistics: Akaike's information criterion, Schwarz information criterion, Hannan–Quinn information criterion, and final prediction error.

Table 6
Regressions for stratified data. Using panel data between 1987 and 1998, we regress credit spreads on corporate bonds against the variables listed below; i.e., from the baseline regression model of Table 5 (2). We stratify the panel into subsets for different time periods, credit ratings, firm sizes, bond maturities, and firm leverage ratios. OLS t-statistics (absolute values in parentheses) are based on robust standard errors clustered at the firm-level. All variables are winsorized at the 1% level.

	Panel A: Consecutive, 2-year time periods						Panel B: Credit rating		
	87–88	89–90	91–92	93–94	95–96	97–98	High	Medium	Low
Constant	−0.183	0.025	0.475***	0.067	−0.220	−0.406	0.452***	0.384***	−0.244
	(1.05)	(0.10)	(2.71)	(0.30)	(1.01)	(1.64)	(8.00)	(3.00)	(0.37)
DISP	1.478	24.096*	47.681***	68.374***	48.148**	26.745**	33.687***	55.548***	70.855***
	(0.13)	(1.75)	(4.27)	(4.47)	(2.00)	(2.55)	(5.36)	(6.93)	(5.39)
VOLEARN	5.467*	3.884	5.913	3.241	13.776***	7.903**	2.272	6.627***	15.779***
	(1.94)	(1.13)	(1.56)	(0.85)	(3.19)	(2.39)	(1.16)	(3.14)	(2.84)
N	−0.014	0.002	−0.007	−0.004	−0.006	0.004	−0.007***	−0.002	−0.033**
	(1.53)	(0.27)	(1.61)	(1.21)	(1.50)	(0.90)	(3.01)	(0.87)	(2.34)
RATINGSQ	0.079***	0.070***	0.065***	0.067***	0.051***	0.045***	0.038***	0.043***	0.086***
	(10.09)	(6.56)	(8.45)	(13.00)	(10.07)	(13.49)	(5.12)	(9.90)	(6.04)
SUBORD	0.291	0.419	0.492	0.200	0.219**	0.100	–	0.244*	0.337
	(1.22)	(0.95)	(1.12)	(1.09)	(2.25)	(1.13)	–	(1.71)	(1.38)
DURATION	0.059***	0.067***	0.009	0.042***	0.053***	0.049***	0.038***	0.042***	0.017
	(4.12)	(4.07)	(1.14)	(7.82)	(13.89)	(17.31)	(15.92)	(11.09)	(0.88)
LIQUIDITY	0.129	−0.061	−0.229	−0.210	0.006	0.205	−0.260***	−0.376***	−0.297
	(1.03)	(0.38)	(1.50)	(1.05)	(0.03)	(0.85)	(4.97)	(3.38)	(0.72)
Observations	666	711	2126	4398	4883	3220	2599	12,203	1202
Adj. R-squared	0.629	0.423	0.603	0.673	0.593	0.628	0.406	0.341	0.393

	Panel C: Firm size			Panel D: Bond maturity			Panel E: Firm leverage		
	Small	Medium	Large	Short	Medium	Long	Low	Medium	High
Constant	0.262**	0.495*	0.308*	0.680***	0.889***	0.672***	0.339***	0.233	0.374
	(2.21)	(1.95)	(1.92)	(3.31)	(5.45)	(5.23)	(3.29)	(1.55)	(1.64)
DISP	55.415***	60.086***	42.663***	58.179***	48.659***	57.608***	41.770***	57.197***	62.105***
	(3.68)	(4.88)	(8.24)	(5.36)	(5.49)	(7.97)	(5.59)	(7.65)	(5.21)
VOLEARN	7.672*	17.643***	4.325	7.456**	10.586***	8.283***	6.429**	12.206***	8.940**
	(1.94)	(3.73)	(1.32)	(2.20)	(3.94)	(3.24)	(2.33)	(3.95)	(2.24)
N	−0.013**	−0.000	−0.005**	−0.004	−0.000	−0.006**	−0.005**	−0.005**	−0.012**
	(2.34)	(0.08)	(2.63)	(1.28)	(0.13)	(2.52)	(2.36)	(2.42)	(2.22)
RATINGSQ	0.064***	0.047***	0.047***	0.056***	0.058***	0.049***	0.048***	0.039***	0.065***
	(12.72)	(8.06)	(10.86)	(13.01)	(14.27)	(13.53)	(8.95)	(7.90)	(10.52)
SUBORD	0.095	0.049	0.098*	0.422**	0.152	0.239	0.042	0.035	0.240
	(0.71)	(0.57)	(1.91)	(2.05)	(1.31)	(1.16)	(0.48)	(0.71)	(1.08)
DURATION	0.038***	0.041***	0.042***	−0.038**	−0.068***	−0.010	0.036***	0.040***	0.046***
	(6.26)	(8.25)	(11.26)	(2.03)	(4.41)	(1.51)	(13.23)	(10.70)	(7.69)
LIQUIDITY	−0.315***	−0.628***	−0.287*	−0.450**	−0.355***	−0.110	−0.280***	−0.208	−0.545***
	(3.31)	(2.66)	(1.99)	(2.57)	(3.22)	(1.12)	(3.48)	(1.63)	(2.82)
Observations	3650	3720	3749	4953	5494	5557	3678	3748	3693
Adj. R-squared	0.608	0.675	0.675	0.558	0.591	0.610	0.616	0.614	0.623

* Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.

second hypothesis, namely that the relation between credit spreads and forecast dispersion is reliably positive.

Third, we implement the Fama and MacBeth (1973) approach by running cross-sectional regressions for each quarter and report average coefficient estimates in column 8. We find that dispersion is significant at the 0.1% level with a slightly reduced economic significance. Finally, we run a pure cross-sectional regression based on time-series averages of bond-level observations in our third time-series correlation test. These estimation results are summarized as specification 9. Observer that, under this alternative econometric specification for the cross-section, both economic and statistical importance of forecast dispersion increase relative to column 8.

3.4. Findings for changes of credit spreads

Using a quarterly panel of the level of corporate bonds credit spreads, most of our identification so far comes from the cross-section. However, the cross-sectional relation between credit spread levels and forecast dispersion may be a noisy indicator of the underlying economic relation since future cash flow uncertainty influences dispersion as well as many other firm-specific factors. While the inclusion of firm fixed effects and various firm-level credit risk factors in the previous subsections partly addresses this concern, additional identification can come from relating changes in credit spreads to changes in dispersion.[18]

Our dependent variable is the change in the credit spread between two consecutive quarters, $\Delta CS_{i,t}$. We arrive at a total of 13,193 observations over the 1987–1998 period, with 98.7% being from differences in quotes of consecutive quarters. To test our empirical predictions, we estimate the following linear model for bond i at time t:

$$\Delta CS_{i,t} = \gamma_0 + \gamma_1 \Delta DISP_{i,t} + \gamma_2 \Delta VOLEARN_{i,t} + \sum_{i=3}^{J} \gamma_j \Delta CONTROL(j)_{i,t} + \epsilon_{i,t}, \tag{2}$$

[18] Notably, changes of credit spreads are a subject of independent interest for academics and practitioners. For example, Collin-Dufresne et al. (2001) point out that hedge funds often enter highly levered positions in corporate bonds and then hedge away interest rate risk by shorting Treasury bonds. Consequently, these long-short portfolios are highly sensitive to changes rather than levels of credit spreads.

Table 7

Regressions with additional econometric restrictions. Using panel data between 1987 and 1998, we regress credit spreads on corporate bonds against the variables listed below; i.e., from the baseline regression model of Table 5 (2). Specifications (1)–(5) are pooled OLS regressions. We include either 12 year dummies in (1), (3), (4), and (5) or 48 quarter time dummies in (2). In addition, we control for industry, firm, and bond issue fixed effects in (3), (4), and (5), respectively. OLS *t*-statistics (absolute values in parentheses) are based on robust standard errors clustered at the firm-level. Specification (6) reports results of OLS estimations with *t*-statistics based on Newey–West standard errors. Specification (7) shows OLS estimations with *t*-statistics based on standard errors clustered simultaneously on two dimensions (i.e., firm and quarter). Specification (8) reports average coefficients obtained from Fama–MacBeth regressions performed on 45 calendar quarters over the sample period. Finally, we run pure cross-sectional regressions based on the time-series averages of 1389 bonds, reported in (9). All variables are winsorized at the 1% level.

	Panel A					Panel B		Panel C	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	0.120	0.158	0.277**	0.076	0.366***	0.272***	0.272	−0.025	−0.153*
	(1.25)	(1.55)	(2.35)	(0.60)	(2.75)	(3.61)	(1.44)	(0.18)	(1.67)
DISP	43.435***	55.683***	46.680***	42.407***	38.598***	57.417***	57.417***	33.856***	78.167***
	(6.26)	(7.97)	(5.97)	(5.50)	(4.85)	(15.48)	(4.24)	(6.32)	(9.93)
VOLEARN	7.720***	7.845***	8.300***	11.367***	11.400***	9.141***	9.141***	6.823***	4.183**
	(3.68)	(3.72)	(3.53)	(4.99)	(4.61)	(8.08)	(3.65)	(6.59)	(2.47)
N	−0.003	−0.004*	−0.009***	−0.008***	−0.006***	−0.003***	−0.003	−0.005***	0.000
	(1.55)	(1.88)	(3.76)	(3.91)	(2.91)	(3.47)	(1.47)	(3.57)	(0.09)
RATINGSQ	0.059***	0.056***	0.062***	0.053***	0.048***	0.055***	0.055***	0.063***	0.063***
	(18.41)	(17.53)	(20.24)	(9.08)	(6.64)	(37.07)	(14.36)	(25.14)	(34.10)
SUBORD	0.241*	0.220*	0.170	0.218**	–	0.264***	0.264**	0.241***	0.342**
	(1.93)	(1.71)	(1.39)	(2.57)	–	(3.48)	(2.29)	(4.34)	(4.39)
DURATION	0.045***	0.041***	0.045***	0.049***	−0.006	0.039***	0.039***	0.044***	0.023***
	(14.81)	(13.32)	(15.67)	(23.96)	(0.27)	(21.24)	(6.98)	(12.22)	(6.64)
LIQUIDITY	−0.086	−0.273***	−0.100	−0.080	−0.034	−0.360***	−0.360**	0.006	0.052
	(0.96)	(3.08)	(1.15)	(0.99)	(0.47)	(4.90)	(2.13)	(0.04)	(0.58)
Year dummies	Yes	–	Yes	Yes	Yes	–	–	–	–
Quarterly dummies	–	Yes	–	–	–	–	–	–	–
Industry dummies	–	–	Yes	–	–	–	–	–	–
Firm dummies	–	–	–	Yes	–	–	–	–	–
Bond dummies	–	–	–	–	Yes	–	–	–	–
Observations	16,004	16,004	16,004	16,004	16,004	16,004	16,004	16,004	16,004
Adj. *R*-squared	0.625	0.596	0.646	0.774	0.813	0.578	0.578	0.592	0.658

* Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.

where the term ΔX denotes quarterly changes in the variable X and $CONTROL(j)$ represents the jth control variable, with potential dependence on both bond i and time t. In the first specification, we follow Duffee (1998) and Collin-Dufresne et al. (2001) and include, as control variables, quarterly changes in the level of the 10-year Treasury yield, $\Delta R_t(10yr)$[19]; quarterly changes in rating squared, $\Delta RATINGSQ_{i,t}$; and quarterly changes in the slope of the yield curve, $\Delta SLOPE_t$. The slope of yield curve is defined as the differential between the 10-year and 2-year Treasury bond yields, $SLOPE_t = R_t(10yr) - R_t(2yr)$. The estimation results of pooled OLS regression given by (2) are located in Table 8. The positive sign of the coefficient estimate of $\Delta DISP$ is consistent with the second hypothesis. Column 1 also reveals that changes in credit spreads depend significantly on changes in forecast dispersion. However, changes in earnings volatility have little impact on them. As expected, the coefficient estimates for the level and the slope of the yield curve are negative and significant at better than 0.1%. Changes in squared credit ratings also explain changes in credit spreads (at better than the 5% level).

Column 2 of Table 8 includes additional control variables relative to the first specification:

1. To capture changes in the overall economy, we use quarterly S&P 500 index returns, $RETSP_t$.
2. To see if forecast dispersion proxies for idiosyncratic (i.e., unpriced parameter) risk, we include quarterly changes in firm-level idiosyncratic stock return volatility, $\Delta VOLRET_t$, in our test.
3. Option-implied volatility is also a measure for future cash flow uncertainty (see, e.g., Chiras and Manaster, 1978). However, most of our sample firms lack data on publicly traded options. We therefore resort to the best available substitute: changes in the *VIX* index, ΔVIX_t, which corresponds to a weighted average of eight implied volatilities of near-the-money options on the OEX (S&P 100) index.
4. Changes in the probability and magnitude of a large negative jump in firm value should have a significant effect on credit spreads. We therefore construct a jump risk probability, *JUMP*, which reflects the risk of a large negative stock market return. Similar to *VIX*, this measure cannot be obtained at the firm-level. We thus estimate the magnitude of a market-level negative jump. Our estimation procedure is similar to the one in Collin-Dufresne et al. (2001). We first calculate implied volatilities from 1-month out-of-the-money put options and in-the-money call options on the S&P 100 index. We then fit a linear-quadratic regression, $\sigma(K) = a + bK + cK^2$, of implied volatilities $\sigma(K)$ on strike prices K. Our estimate of *JUMP* is defined as $JUMP = \sigma(0.9S) - \sigma(S)$, where S is the current level of the S&P 100 index.

In column 2, we find that the stock and option market-based proxies do not weaken the economic and statistical significance of forecast dispersion. Specifically, the coefficient estimate of $\Delta DISP$ remains 5% significant, while the slope coefficient of the new variables *RETSP*, $\Delta VOLRET$, and $\Delta JUMP$ have the expected sign and are significant at better than 1%.

A common concern regarding specifications 1 and 2 is that a spurious correlation in the time-series of credit spread changes

[19] In an unreported regression, we add the squared level of the yield curve, $(\Delta R_t(10yr))^2$, which captures potential nonlinear effects. The results of column 1 are not affected by this modified specification.

Table 8
Structural determinants of changes in credit spreads. Using panel data between 1987 and 1998, we regress changes in credit spreads on corporate bonds against the variables listed below; i.e., the first difference of forecast dispersion, earnings volatility, and common control variables. Specifications (1)–(4) are pooled OLS regressions with additional control variables, 12 year dummies, and firm fixed effects. OLS *t*-statistics (absolute values in parentheses) are based on robust standard errors clustered at the firm-level. Specification (5) documents the results of an OLS estimation with *t*-statistics (absolute values in parentheses) based on Newey–West standard errors. All variables are winsorized at the 1% level.

	(1)	(2)	(3)	(4)	(5)
Constant	−0.007***	−0.006*	−0.006***	0.061***	−0.006**
	(2.96)	(1.96)	(3.42)	(4.15)	(2.69)
Δ*R*(10*yr*)	−0.072***	−0.083***	−0.083***	−0.093***	−0.083***
	(10.34)	(11.03)	(10.59)	(10.06)	(16.46)
Δ*SLOPE*	−0.033***	−0.037***	−0.039***	−0.045***	−0.037***
	(3.36)	(3.57)	(3.66)	(2.63)	(4.75)
Δ*DISP*	5.577**	7.904**	8.040**	7.535**	7.668***
	(2.11)	(2.49)	(2.44)	(2.34)	(3.81)
Δ*VOLEARN*	−2.477	−1.895	−1.443	−1.451	−1.846
	(0.86)	(0.58)	(0.41)	(0.45)	(0.93)
Δ*RATINGSQ*	0.013**	0.012*	0.011	0.011*	0.012***
	(2.05)	(1.90)	(1.57)	(1.67)	(3.26)
Δ*VOLRET*		8.575***	8.474***	7.920***	8.686***
		(3.50)	(3.33)	(3.03)	(5.66)
RETSP		−0.198***	−0.194***	−0.058	−0.202***
		(4.78)	(4.45)	(1.16)	(6.60)
Δ*VIX*		0.004***	0.004***	0.005***	0.004***
		(3.46)	(3.56)	(4.37)	(5.15)
Δ*JUMP*		0.020***	0.020***	0.018***	0.020***
		(3.92)	(3.52)	(3.12)	(4.95)
Year dummies	–	–	–	Yes	–
Firm dummies	–	–	Yes	Yes	–
Observations	13,197	11,981	11,981	11,981	11,981
Adj. *R*-squared	0.035	0.052	0.096	0.124	0.054

* Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.

and changes in forecast dispersion produces the results. Similarly, spurious cross-sectional correlations between credit spread changes and changes of other firm characteristics (such as credit ratings or earnings volatility) could have biased our regression results. To test for such estimation biases, we include in specification 3 (4), year (year and firm) dummies. The results with time-series and year fixed effects are similar to the ones without the fixed effects structure. That is, Δ*DISP* is significant at the 1% level. Although idiosyncratic stock return volatility is better than 0.1% significant, forecast dispersion remains nevertheless unaffected by these additional econometric restrictions.

Finally, we report OLS with *t*-statistics based on Newey–West standard errors in column 5 to control for the time-series correlation in errors. Relative to the previous specifications, the results remain robust. The coefficient estimate of changes in dispersion is roughly at the same level and is again better than 1% significant. Altogether, the evidence on changes of credit spreads is consistent with our earlier findings. In particular, risk measures, such as idiosyncratic stock return volatility or index option-implied volatility, do not diminish the role of dispersion as a measure of future cash flow uncertainty.

4. Robustness checks

So far we have found evidence showing that credit spreads on corporate bonds are positively related to forecast dispersion and earnings volatility. Notably, these variables are statistically significant and economically meaningful in explaining both levels and changes of credit spreads in the full sample as well as in subsamples. The objective of this section is to provide a series of robustness checks for the main empirical results and, in particular, for the assertion that, in the corporate bond markets, forecast dispersion is largely a measure for future cash flow uncertainty. In Section 4.1, we attempt to further disentangle the role of forecast dispersion from other risk measures, such as proxies for corporate bond market characteristics, idiosyncratic risk, differences of opinion, or split credit ratings. Section 4.2 extends our analysis in Table 5 to the post-2000 period using the TRACE and Mergent corporate bond databases. Section 4.3 examines the explanatory power of forecast dispersion with respect to proxies for future cash flow uncertainty in lagged time-series regressions. Finally, Section 4.4 analyzes the relation between forecast dispersion, bond returns, and stock returns for the firms in our sample with publicly traded stocks.

4.1. Is forecast dispersion subsumed in other risk factors?

We next seek to study the robustness of our findings, with particular attention to interactions between forecast dispersion and other risk proxies. To this end, we perform tests to identify the relative merits of seven alternative explanations. We do so by augmenting our baseline model from column 2 in Table 5 each time by adding one of the following variables:

1. aggregate risk premiums of the corporate bond market (*CORP* and *DEF*);
2. interaction between dispersion and leverage (*DISP* vs. *DISP* × *LEVER*);
3. idiosyncratic stock return volatility (*VOLRET*);
4. differences of opinion (*TURNOVER*);
5. firm-level reporting noise (*VOLERR*);
6. operating profit volatility (VOLOPER); and
7. split notch- or letter-level ratings (*SPLIT*1 or *SPLIT*2).

We first check whether the impact of forecast dispersion on credit spreads is due to its correlation with aggregate risk factors of the corporate bond market. For example, the systematic (market) risk factor has empirically almost no explanatory power for corporate bonds in the presence of default and term factors (see, e.g., Fama and French, 1993). The corporate bond market yield spread, *CORP*, is defined as the difference between the yields of a long-term Aaa corporate bond index and a long-term government bond index. This variable captures the state of the corporate bond market and, in particular, tax and liquidity effects in the corporate bond market relative to the Treasury market. On the other hand, the difference between the yields of a long-term Baa bond index and long-term Aaa bond index, *DEF*, measures the default risk spread. It is a proxy for the default risk premium in the corporate bond market. By introducing *CORP* and *DEF* as independent variables, we address concerns regarding risk factors that are unique to the corporate bond market. The results, reported in column 1 of Table 9, indicate that the slope coefficient of *CORP* is insignificant, and the coefficient estimate of *DEF* is positive and significant at better than 1%. However, both variables have a minimal impact on dispersion. We thus conclude that dispersion is not subsumed by aggregate risk factors that are unique to corporate bonds.

Second, turning from the market-wide level to the firm-level, we revisit the role of firm leverage for the importance of forecast dispersion. Our goal is to investigate whether forecast dispersion is priced as a type of cash flow risk by employing a leverage test in the spirit of Johnson (2004). This test is based on an implication of structural credit risk models, which asserts that the sensitivity of credit spreads to asset volatility (or cash flow volatility) should increase with firm leverage. Hence, if dispersion proxies for future cash flow volatility firm leverage is "gearing factor" for the spread–dispersion relation. To test this hypothesis, we add two

Table 9
Regressions with additional uncertainty proxies. Using panel data between 1987 and 1998, we regress credit spreads on corporate bonds against the variables listed below. Columns (1)–(8) contain pooled OLS estimates, adding one additional uncertainty proxy to the baseline regression in column (2) of Table 5: (1) corporate bond yield spread *CORP* and default risk spread *DEF*, (2) the interaction term *DISP* * *LEVER* and firm leverage *LEVER* on its own, (3) idiosyncratic volatility of stock returns (*VOLRET*), (4) stock turnover (*TURNOVER*), (5) volatility of analyst errors (*VOLERR*), (6) volatility of operating cash flows (*VOLOPER*), (7) split-rating at the notch-level (*SPLIT*1) and (8) split-rating at the letter-level (*SPLIT*2). OLS *t*-statistics (absolute values in parentheses) are based on robust standard errors clustered at the firm-level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	−0.586***	0.342***	−0.039	0.269***	0.212**	0.316***	0.250**	0.257***
	(4.37)	(3.08)	(0.34)	(2.63)	(1.99)	(3.04)	(2.13)	(2.59)
DISP	45.732***	15.494	51.241***	58.013***	53.402***	52.405***	57.460***	56.756***
	(6.78)	(1.09)	(8.15)	(8.08)	(7.52)	(7.14)	(8.47)	(8.34)
CORP	0.079							
	(1.22)							
DEF	0.666***							
	(11.07)							
DISP × *LEVER*		146.649***						
		(2.66)						
LEVER		0.189						
		(1.06)						
VOLRET			26.549***					
			(7.29)					
TURNOVER				0.047				
				(0.64)				
VOLERR					15.493***			
					(3.35)			
VOLOPER						1.954**		
						(2.35)		
*SPLIT*1							0.050**	
							(2.13)	
*SPLIT*2								0.086**
								(2.05)
VOLEARN	7.821***	10.191***	8.848***	8.505***	2.576	9.913***	9.065***	9.298***
	(3.76)	(4.14)	(4.20)	(3.89)	(0.82)	(3.81)	(4.19)	(4.32)
N	−0.003	−0.006***	−0.007***	−0.004*	−0.002	−0.007***	−0.003	−0.003
	(1.56)	(2.86)	(3.24)	(1.76)	(1.06)	(3.13)	(1.61)	(1.42)
RATINGSQ	0.058***	0.050***	0.048***	0.054***	0.055***	0.053***	0.055***	0.054***
	(18.07)	(14.16)	(17.12)	(15.52)	(16.87)	(15.62)	(17.12)	(17.05)
SUBORD	0.234*	0.123	0.231**	0.263**	0.266**	0.117	0.263**	0.276**
	(1.90)	(1.10)	(2.04)	(2.05)	(2.07)	(1.02)	(2.02)	(2.12)
DURATION	0.045***	0.039***	0.040***	0.039***	0.040***	0.038***	0.039***	0.039***
	(14.90)	(14.36)	(13.65)	(12.63)	(12.79)	(13.42)	(12.50)	(12.45)
LIQUIDITY	−0.132	−0.399***	−0.319***	−0.357***	−0.307***	−0.402***	−0.357***	−0.354***
	(1.42)	(4.33)	(3.62)	(4.02)	(3.33)	(4.30)	(4.12)	(4.14)
Observations	16,004	11,123	15,791	15,791	16,004	10,796	16,004	16,004
Adj. *R*-squared	0.615	0.649	0.599	0.566	0.585	0.646	0.5799	0.5810

* Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.

variables to the baseline regression: (1) firm leverage, *LEVER*, and (2) the dispersion–leverage interaction term, *DISP* * *LEVER*. In column 2 of Table 9, the interaction term is significant, whereas forecast dispersion alone loses significance.[20] As a consequence, the sensitivity of credit spreads to forecast dispersion is a monotonically increasing function of firm leverage. This finding supports the view that dispersion largely proxies for firm-level cash flow uncertainty in corporate bond markets.

Third, we explore the type of risk dispersion conveys to the corporate bond markets. For example, Johnson (2004) argues that forecast dispersion represents idiosyncratic (i.e., unpriced parameter) risk in equity markets and reconciles the negative relation between dispersion and future stock returns in a dynamically consistent, rational model. With this in mind, we intend to evaluate his theory in the context of the corporate bond market. Thus, we rerun our baseline test with idiosyncratic stock return volatility, *VOLRET*, to determine whether it subsumes dispersion. Following Campbell and Taksler (2003), *VOLRET* is the time-series sample standard deviation of daily market-adjusted stock returns 180 days preceding the observation. As observed in column 3, the coefficient estimate of idiosyncratic risk is significant and, as expected, has a positive sign. This is in line with Campbell and Taksler (2003), who demonstrate that idiosyncratic stock return volatility meaningfully affects credit spreads in the cross-section. However, including idiosyncratic risk in column 3 does not materially affect the role played by dispersion. This robustness test provides little support for the conjecture that dispersion captures idiosyncratic risk in our sample.

Fourth, another alternative explanation is that dispersion may measure disagreement among investors (e.g., Diether et al., 2002). Harris and Raviv (1993) and Lee and Swaminathan (2000) argue that turnover represents a measure for differences of opinion. To test this hypothesis for the corporate bond markets, we need to construct a turnover measure. However, the Lehman Fixed Income Database reports neither turnover nor trading volume for corporate bonds. We therefore rely on stock market turnover, *TURNOVER*. Our procedure for using turnover rather than trading volume follows from the possibility that the arrival of public information can perpetrate trading among investors (e.g., Harris and Raviv, 1993 or Kandel and Pearson, 1995). If turnover represents differences of opinion among investors, then turnover measures

[20] In an unreported regression, we have obtained essentially the same result when interacting credit rating with leverage. The interaction term dominates leverage alone, but does not subsume forecast dispersion.

in stock and bond markets should be positively correlated. In column 4, we include this variable in our baseline regression to check whether turnover subsumes forecast dispersion. We find that the coefficient estimate of turnover neither explains the level of credit spreads, nor has an effect on the relation between forecast dispersion and credit spreads.[21] Though this presents only an indirect test of disagreement among bond market investors, it indicates that dispersion is unlikely to capture differences of opinion.

We also consider the volatility of past analyst forecast errors, *VOLERR*, which is a proxy for the forecast precision of equity analysts (and perhaps historical cash flow volatility), and the volatility of operating profits, *VOLOPER*, during the preceding eight quarters. Notice that, in contrast to *VOLEARN*, *VOLOPER* is not affected by interest expenses and taxes. Both risk proxies enter significantly at better than 1% into specifications 5 and 6, respectively. However, they do not impact the explanatory power of dispersion for credit spreads. Thus, neither forecast precision nor historical cash flow volatility appear to explain our main findings.

Finally, we follow recent studies by Livingston et al. (2007, 2008) to verify that our results are not explained by corporate bonds with different ratings from Moody's and S&P. These split ratings are a proxy for asset opaqueness, which in turn may correlate with dispersion and hence credit spreads. To do so, we add in specifications 7 and 8 the dummy variables *SPLIT*1 and *SPLIT*2, respectively, which indicate split ratings at the notch-level and letter-level. The results of the last two columns in Table 9 show that split ratings reliably lead to higher credit spreads, which supports the view that asset opaqueness is a credit risk factor. Yet split credit ratings do not undermine the economic or statistical significance of dispersion for credit spreads in our sample.

4.2. Findings for the post-2000 period

As mentioned earlier, our primary sample ends in March 1998 since Lehman Brothers stopped reporting the bond quotes after this date. Testing the spread–dispersion relation during the post-2000 period is an important robustness check for two reasons. First, it provides results for a different time period and a different corporate bond database. Second, the US Securities and Exchange Commission (SEC) imposed two key regulations to improve the accounting and market transparency, which might impact the informativeness of forecast dispersion and credit spreads.[22] The first regulation is called "Regulation Fair Disclosure" and was implemented in October 2000. It mandates that publicly traded companies must disclose material information to all investors at the same time. The second regulation, again proposed by the SEC in January 2001, requires all members of the Financial Industry Regulatory Authority (FINRA) to publicly report their transactions in fixed income securities. As of 2008 nearly 4800 brokerage firms with 173,000 branch offices and 647,000 securities representatives report their transactions to FINRA. As a result, to gather bond prices and yields for the post-2000 period, we use the Trade Reporting and Compliance Engine (TRACE) database, which is a compilation of the transactions of FINRA member institutions.

In constructing the post-2000 sample, we mimic the methodology in Section 3 as closely as possible, although there are two main differences between LFID and TRACE. First, LFID reports the market quotes of only Lehman Brothers, while TRACE reports all corporate bond transactions of various dealers which are FINRA member institutions. Second, TRACE reports only the time, price, and volume of a transaction, while LFID provides a comprehensive list of time-series and cross-sectional variables relevant for our study. Therefore, we additionally use the Mergent Fixed Income Securities Database (FISD) to obtain key characteristics of bonds, such as issue size, issue date, maturity date, coupon, callability, putability, etc. Mergent FISD also provides bond ratings. In constructing daily bond prices, we rely on the volume-weighted average of all transaction prices during a day rather than the last transaction price of a day, to minimize the impact of small trades. The end-of-month bond price is the last available daily price in a given month. Furthermore, we also calculate the yield-to-maturity and Macaulay duration using the monthly closing price, issue date, maturity date, and coupon payment dates.

After the first stage filters (excluding financial firms, bonds with option features, observation with less than four years to maturity, and firms with less than 25 monthly observations),[23] we identify 35,428 monthly observations between July 2002 (earliest transaction date in TRACE) and December 2007. We merge this sample with I/B/E/S to generate a quarterly panel. After the second stage filters described in Section 2.1, there are 4397 quarterly observations of 441 bonds by 152 firms.

We re-estimate specifications 1–6 from Table 5 using the post-2000 sample and tabulate the results in Table 10. We note two changes in the list of independent variables. The subordination dummy is dropped in Table 10, since the final sample has no subordinated bond issues. Furthermore, the post-2000 sample includes bond issues rated lower than B, hence specification 3 has an additional dummy variable for "Lower than B Rated" issues. Our results indicate that, forecast dispersion is statistically significant at 1% or better levels in all specifications and coefficient estimates are of similar magnitude as compared to the pre-2000 results.[24] Moreover, the estimates in column 2 of Table 10 (Table 5) suggest that for two otherwise identical firms, the firm with a one standard deviation higher dispersion should be associated with a credit spread that is $0.0049 * 55.227 \approx 27.06$ ($0.0024 * 57.417 \approx 13.78$) basis points higher than the one of the other firm, with the sample average of credit spread being 190 (100) basis points. Additionally, most of the other control variables maintain their sign, and coefficients and significance levels are comparable to Table 5. Altogether, we thus obtain similar economic and statistical results for the post-2000 period.

4.3. Is forecast dispersion related to future cash flow uncertainty?

To provide further support for the second hypothesis and, that is the link between cash flow volatility and lagged dispersion, we examine whether dispersion of earnings forecasts explain the variation in future volatility of realized earnings. For this purpose, we construct a firm-level panel of 416 firms and 10,994 quarterly observations of forecast dispersion, earnings, and earnings volatility.[25] Table 11 presents the results of the empirical tests. In Panel A, we estimate current levels of earnings volatility, $VOLEARN_t$, using lagged levels of earnings volatility, $VOLEARN_{t-1}$, and lagged levels of dispersion, $DISP_{t-1}$. The first column reports the results of a OLS estimation with t-values based on Newey–West standard errors (OLS-NW), while the second column provides the pooled OLS results with firm and year fixed effects and controlling for firm-level clus-

[21] A similar regression result obtains if we use stock trading volume as a proxy of differences of opinion.

[22] We thank an anonymous referee for suggesting this point.

[23] TRACE already excludes non-depository eligible securities, sovereign debt, development bank debt, mortgage- or asset-backed securities, collateralized mortgage obligations, and money market instruments.

[24] The slope coefficients of dispersion in Tables 5 and 10 (57.417 vs. 55.227) are not statistically different from each other (t-value for the test of differences of coefficients = 0.13).

[25] We do not need to impose the filters on liquidity and rating variables here. Hence, compared to the main sample of 382 firms, we have slightly more firms in this specification.

Table 10
Structural determinants of credit spreads in the post-2000 period. Using panel data between 2002 and 2007, we regress credit spreads on corporate bonds against the variables listed below. Specifications (1)–(6) are OLS models. All variables are winsorized at the 1% level. *t*-Statistics (absolute values in parentheses) are based on robust standard errors clustered at the firm-level.

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	1.571***	0.341	0.386*	2.933***	0.321	0.764
	(9.24)	(1.35)	(1.66)	(3.70)	(1.24)	(1.09)
DISP	85.394***	55.227***	53.866***	76.302***		58.313***
	(4.30)	(3.65)	(3.35)	(3.57)		(3.75)
(*VOLOPER*/*VOLEARN*) × *DISP*					40.510***	
					(2.67)	
VOLEARN	62.665***	37.759***	37.434***	56.575***	41.620***	38.520***
	(7.66)	(6.71)	(6.40)	(9.28)	(5.24)	(6.70)
N	−0.025*	−0.014	−0.014	−0.007	−0.017	−0.013
	(1.97)	(1.39)	(1.35)	(0.61)	(1.52)	(1.12)
RATINGSQ		0.062***			0.058***	0.058***
		(7.80)			(6.23)	(5.40)
DURATION		0.095***	0.098***	0.104***	0.096***	0.094***
		(6.70)	(7.24)	(7.43)	(6.41)	(6.67)
LIQUIDITY		−0.522***	−0.553***	−0.347**	−0.479***	−0.494***
		(3.72)	(4.13)	(2.20)	(3.41)	(3.49)
AA Rated			0.543***			
			(2.97)			
A Rated			0.450**			
			(2.52)			
BBB Rated			0.841***			
			(4.66)			
BB Rated			1.659***			
			(7.70)			
B Rated			2.401***			
			(7.41)			
Lower than B Rated			2.860***			
			(4.43)			
LEVER				0.569		−0.070
				(0.73)		(0.12)
SIZE				−0.193***		−0.032
				(2.65)		(0.54)
B/M				−0.152		−0.110
				(0.58)		(0.44)
PROFIT				−3.230***		−0.360
				(2.71)		(0.31)
Observations	4397	4397	4397	4314	4076	4314
Adjusted *R*-squared	0.502	0.606	0.612	0.568	0.604	0.603

* Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.

tering (OLS-FE). We find that the coefficient estimates for lagged dispersion are significant at the 0.1% level. While these estimation results with levels of volatility support the second hypothesis, we also perform tests using changes in volatility. The estimation results for changes in earnings volatility and changes in forecast dispersion in Panel B are similarly strong as for levels in Panel A.

Although forecast dispersion is constructed as a quarterly variable, the preceding models may be subject to an attenuation bias. Specifically, firm *i*'s earnings volatility is defined as its moving average of earnings volatilities from the past eight quarters and, therefore, it only changes slowly. To explore in more depth the dynamic behavior of earnings uncertainty, we rerun our tests with squared changes in earnings, $(\Delta EARN_t)^2$ in lieu of earnings volatility $VOLEARN_t$. Since current and future levels of $(\Delta EARN_t)^2$ are by construction based on non-overlapping data, they can be regarded as one-quarter estimates of earnings volatility. Panel C repeats the previous regressions from Panel A with this proxy for earnings uncertainty. In both OLS-NW and OLS-FE estimations, the slope coefficients of forecast dispersion are again economically and statistically significant. We thus conclude that this quarter's forecast dispersion has predictive power for the next quarter's earnings volatility and for the next quarter's squared changes in earnings.

It could be argued that changes in future earnings may be predictable due to seasonality or mean reversion. To address this concern in Panel D, we test whether dispersion can forecast the unexpected component of earnings volatility. As a proxy for the unexpected earnings volatility, we use the square of the quarterly earnings surprise, $SURPEARN_t$, which is defined as the realized earnings per quarter minus the consensus (average) earnings forecast. As tabulated in Panel D, the estimation results for this specification indicate that contemporaneous levels of forecast dispersion are reliably related to future squared earnings surprises when controlling for past earnings surprises.

4.4. Results with bond returns and stock returns on a matched sample

In this section we explore the relation between returns and forecast dispersion on a matched sample of bonds and stocks. We adopt the empirical methodology of Diether et al. (2002) as closely as possible for bonds returns (1) to compare our findings for the bond market with their findings for the stock market; (2) to confirm our results for credit spreads for bond returns; and (3) to verify that our findings are not due to a particular subsample of firms. To achieve this, we make several adjustments to our previous empirical setup. We construct a matched sample in which every firm has issued stocks and bonds and monthly prices of both securities are publicly available. Notably, we calculate monthly (instead of quarterly) dispersion measures based on 12-month

Table 11
Forecast dispersion and earnings volatility. Using panel data between 1987 and 1998, we regress levels and changes of earnings volatility on lagged earnings volatility and forecast dispersion in Panels A and B. In Panel C (D), we regress squared changes in earnings (squared earnings surprises) on lagged squared changes in earnings (squared earnings surprises) and past dispersion in earnings forecasts. The first column reports OLS estimations with t-statistics based on Newey–West standard errors. The second column contains pooled OLS results with firm and year fixed effects using robust standard errors clustered at the firm-level. Absolute values of t-statistics are in parentheses.

	(1) OLS-NW	(2) OLS-FE		(1) OLS-NW	(2) OLS-FE
Panel A. Dependent variable: $VOLEARN_t$			*Panel B. Dependent variable: $\Delta VOLEARN_t$*		
Constant	0.001***	0.001***	Constant	−0.001***	−0.001
	(5.51)	(3.39)		(−3.88)	(1.62)
$VOLEARN_{t-1}$	0.823***	0.786***	$\Delta VOLEARN_{t-1}$	0.127***	0.076***
	(49.00)	(58.90)		(6.24)	(3.17)
$DISP_{t-1}$	0.446***	0.417***	$\Delta DISP_{t-1}$	0.090***	0.083***
	(8.11)	(6.33)		(3.63)	(3.65)
Observations	9801	9801	Observations	9575	9575
Adj. R-squared	0.9013	0.9034	Adj. R-squared	0.0225	0.0325
Panel C. Dependent variable: $(\Delta EARN_t)^2$			*Panel D. Dependent variable: $(SURPEARN_t)^2$*		
Constant	0.001	0.002	Constant	0.001	0.001***
	(0.59)	(1.46)		(0.14)	(2.88)
$(\Delta EARN_{t-1})^2$	0.463***	0.310***	$(SURPEARN_{t-1})^2$	0.169***	0.091 **
	(14.04)	(11.81)		(3.31)	(2.01)
$DISP_{t-1}$	1.131***	0.869***	$DISP_{t-1}$	0.321***	0.177***
	(6.91)	(3.55)		(8.55)	(3.04)
Observations	10,616	10,616	Observations	10,783	10,783
Adj. R-squared	0.2805	0.3422	Adj. R-squared	0.1162	0.1751

* Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.

(instead of 3-month) earnings forecasts deflated by absolute earnings (instead of stock price).

Instead of quarterly credit spreads, we now turn to monthly bond returns from period t to $t+1$, which we compute as in Gebhardt et al. (2005): $r_{t+1} = [(P_{t+1} + AI_{t+1}) + C_{t+1} - (P_t + AI_t)]/(P_t + AI_t)$, where P_t denotes the quoted bond price at time t, AI_t is accrued interest which equals the coupon payment scaled by the ratio of days since the last payment date to the days between last payment and next payment, and C_{t+1} is the semi-annual coupon payment (if any) at time $t+1$. Every firm, identified by a CRSP permanent number, has one stock issue but typically has several bond issues outstanding. As a consequence, we end up with 27,984 stock return observations for 391 firms and 71,559 bond return observations for 1621 corporate bonds during the 1987–1998 period.

In constructing mean returns for dispersion portfolios, we follow Diether et al. (2002) and sort stocks and bonds separately into five portfolios based on the forecast dispersion of the firm from the previous month. Monthly portfolio returns are calculated as the equal-weighted average of the returns of all securities in the portfolio.[26] We then average these returns over the sample period of 135 months to obtain mean portfolio returns. Table 12 Panel A reports the mean stock returns for five dispersion quintiles. As documented by Diether et al., the average future stock returns decrease as forecast dispersion increases. However, the relation in our sample is weaker. The difference in mean stock return between the highest and lowest dispersion quintile is −0.26%, and the difference is not statistically significant.[27] Similarly, Wilcoxon's signed rank test implies an insignificant stock return differential. This result is not unexpected, since the mean firm size, as measured by the natural logarithm of market capitalization, in our sample is $7.97 million, whereas it is $1.8 million for the sample of firms studied by Diether et al. (2002); our sample corresponds to the fourth and fifth size quintiles of their sample. Indeed, mean return and mean dispersion in Panel A of Table 12 display very similar patterns as their largest size quintiles (i.e., S4 and S5).

Turning to Panel B, we observe a positive relation between mean bond returns and dispersion. This observation is also consistent with the second hypothesis in Section 2. The difference between the fifth and the first quintile is statistically significant (t-value = 1.95). Its economic magnitude is notable too, with 8 basis points per month or, equivalently, more than 100 basis points annually compounded. Wilcoxon's signed rank test suggests the same significance level. The return differential between dispersion portfolios is larger for stocks

Table 12
Monthly bond and stock returns on dispersion portfolios. From January 1987 to March 1998, each month's bonds and stocks are sorted into five groups (or quintiles) based on the forecast dispersion of the previous month. As in Diether et al. (2002), dispersion equals the standard deviation of analysts' current-fiscal-year annual earnings per share forecasts divided by the absolute value of the average forecast. Dispersion quintiles are constructed based on equally weighing at the bond and stock levels, respectively. One-month holding period returns are computed for bonds and for stocks based on equal-weighted portfolios. In addition, the table reports differences in average monthly returns between high and low dispersion portfolios and Newey–West-adjusted t-statistics (absolute values) for bonds and stocks.

Dispersion quintiles	Mean return	Mean dispersion
Panel A: Stock returns and forecast dispersion		
$D1$ (low)	1.49%	0.017
$D2$	1.39%	0.031
$D3$	1.31%	0.048
$D4$	1.22%	0.083
$D5$ (high)	1.23%	0.547
$D5 - D1$	−0.26%	
t-Statistic	0.97	
Panel B: Bond returns and forecast dispersion		
$D1$ (low)	0.76%	0.017
$D2$	0.79%	0.032
$D3$	0.76%	0.049
$D4$	0.80%	0.087
$D5$ (high)	0.84%	0.571
$D5 - D1$	0.08%	
t-Statistic	1.95	

[26] This methodology was developed by Jegadeesh and Titman (1993) to reduce return variability.
[27] In this subsection, t-statistics are based on Newey–West standard errors.

than for bonds, perhaps because our sample consists of profitable and large firms. For firms far from default, the concavity of debt limits the sensitivity of its value to cash flow uncertainty, while equity of such firms has a much higher sensitivity.

Overall, the results for bond returns support our findings concerning the levels and changes of credit spreads. At the same time, we confirm the negative relation between stock returns and forecast dispersion on a sample of matched stock returns (for our sample of bond issuers). By replicating the methodology of Diether et al., we establish that our results are robust to different specifications of forecast dispersion (e.g., in terms of observation periods, forecast horizons, and scaling factors).

5. Summary and conclusions

This paper explores the relation between dispersion of analysts' earnings forecasts and credit spreads on corporate bonds. We provide evidence that corporate bonds with higher forecast dispersion have significantly higher credit spreads and earn higher future returns than otherwise similar bonds. This finding is robust to the inclusion of common control variables, stratification of the sample, and alternative econometric specifications. Moreover, changes in forecast dispersion reliably predict changes in credit spreads, supporting our cross-sectional results. We verify, in a matched sample of firms with publicly traded corporate bonds and stocks, that bond returns exhibit the same behavior as credit spreads, while future stock returns are negatively related to forecast dispersion.

Within the context of the corporate bond markets, our results suggest that forecast dispersion largely proxies for future cash flow uncertainty, which is consistent with a rational explanation for the link between credit spreads and forecast dispersion. Put differently, our results lend little support to alternative hypotheses, such as forecast dispersion reflecting disagreement among bond market investors. That is, the significantly positive relation between levels (changes) of forecast dispersion and levels (changes) of credit spreads is in line with a structural model of credit spreads à la Merton (1974), but inconsistent with an adaptation of Miller (1977) argument to corporate bonds. Moreover, robustness checks indicate that alternative risk-based determinants of credit spreads, in spite of being also significant, cannot weaken the significantly positive spread–dispersion relation.

This study therefore highlights that contract-related and institutional differences between bond and equity markets are important. If, however, different investors trade in bonds and stocks, then security prices and expected returns in those markets could be influenced by independent demand/supply shocks in both markets. Similarly, the relative speed with which both markets incorporate new information may differ (see, e.g., Forte and Peña, 2009). It would therefore be fruitful, in future research, to examine to which extent these markets are segmented.

Appendix A. A model of credit spreads and forecast dispersion

In this appendix, we develop a stylized model to link behavioral and rational components of forecast dispersion to the pricing of risky corporate debt; for an overview of credit risk modeling (see, e.g., Duffie, 2005).

Suppose time t_i is discrete with $t_i \in \{\ldots, t_{-1}, t_0, t_1, \ldots\}$ and there is a one-period, riskfree bond yielding a gross return of $R > 1$. Consider a firm with a one-period project at time 0 (t_0), which produces an uncertain level of operating cash flow Y at time 1 (t_1). To finance its ongoing operations, the firm needs to issue a one-period, risky bond with face value F. At t_1, the firm can either make the promised debt payment or it can default, in which case the firm's bondholders recover only a fraction $\theta \in (0, 1)$ of the debt's face value. At t_0, analysts $i = 1, \ldots, N$ make cash flow forecasts X_i. In setting risky debt values, rational investors readily translate earnings forecasts into cash flow forecasts that are given by:

$$X_i = Y + Z_i, \tag{A.1}$$

where X_i is i's forecast, Z_i denotes i's analyst-specific forecast, and $\mathrm{Cov}(Y, Z^i) = 0$. We assume that the firm's cash flow and analyst-specific forecast are normally distributed:

$$Y \sim \mathcal{N}(\mu_Y, \sigma_Y^2) \quad \text{and} \quad Z_i \sim \mathcal{N}\left(\beta_{Z_i}, \sigma_{Z_i}^2\right), \tag{A.2}$$

where β_{Z_i} reflects an analyst i's bias and the analyst-specific forecast variance is given by:

$$\sigma_{Z_i}^2 = \xi_i + \zeta_i \sigma_Y^2, \tag{A.3}$$

where $\xi_i \geqslant 0$ represents the idiosyncratic part of analyst i's forecast variance which is attributable to analyst skill and experience and $\zeta_i \geqslant 0$ determines the systematic component of analyst i's forecast variance related to the firm's cash flow risk, σ_Y^2.

Importantly, rational investors disregard the behavioral and idiosyncratic forecast components; that is, $\beta_{Z_i} = 0$ and $\sigma_{Z_i}^2 = \zeta_i \sigma_Y^2$. Bondholders' Bayesian updated beliefs (posterior) of Y given X_i is then based on $\mu_{X_i} = \mu_Y$ and $\sigma_{X_i}^2 = \sigma_Y^2 + \sigma_{Z_i}^2$:

$$Y|X_i \sim \mathcal{N}\left(\frac{\sigma_Y^2 X_i + \sigma_{Z_i}^2 \mu_Y}{\sigma_Y^2 + \sigma_{Z_i}^2}, \frac{\sigma_Y^2 \sigma_{Z_i}^2}{\sigma_Y^2 + \sigma_{Z_i}^2}\right). \tag{A.4}$$

Although analysts tend to disagree on forecasts, their forecasts tend to be correlated. We therefore assume that $\mathrm{Cov}(Z_i, Z_j) = \rho_{ij}\sigma_{Z_i}\sigma_{Z_j}$ for all $i = 1, \ldots, N$ and $i \neq j$. If rational investors disregard all behavioral forecast components, the unbiased analyst (consensus) forecast $\overline{X} = \frac{1}{N}\sum_{i=1}^{N}\left(X_i - \beta_{Z_i}\right)$ has an unbiased mean of $\mu_{\overline{X}} = \mu_Y$ and an unbiased variance of $\sigma_{\overline{X}}^2 = \sigma_Y^2 + \sigma_{\overline{Z}}^2$, where $\sigma_{\overline{Z}}^2 = \frac{1}{N}\bar{\sigma}^2 + \frac{N-1}{N}\bar{\rho}$ with $\bar{\sigma}^2 = \frac{1}{N}\sum_{i=1}^{N}\sigma_{Z_i}^2$ and $\bar{\rho} = \frac{1}{N(N-1)}\sum_{i=1}^{N}\sum_{j=1, j\neq i}^{N}\rho_{ij}\sigma_{Z_i}\sigma_{Z_j}$. Thus, the posterior distribution of Y given $\overline{X}$ is:

$$Y|\overline{X} \sim \mathcal{N}\left(\frac{\sigma_Y^2 \overline{X} + \sigma_{\overline{Z}}^2 \mu_Y}{\sigma_Y^2 + \sigma_{\overline{Z}}^2}, \frac{\sigma_Y^2 \sigma_{\overline{Z}}^2}{\sigma_Y^2 + \sigma_{\overline{Z}}^2}\right), \tag{A.5}$$

which shows that investors place more weight on unbiased consensus forecasts than on future mean cash flows when cash flow volatility (σ_Y) is higher $\left(\sigma_Y^2 \gg \sigma_{\overline{Z}}^2\right)$. The opposite holds when forecasts are much less informative $\left(\sigma_Y^2 \ll \sigma_{\overline{Z}}^2\right)$. Finally, forecast variance due to forecast biases (i.e., divergence of opinion) does not affect rational investors' posteriors.

The volatility that is relevant for option value, and thus for corporate debt, is total volatility, including both idiosyncratic (or unpriced) volatility and systematic (or priced) volatility. We can therefore use the posterior distribution of Y to obtain corporate debt values and credit spreads. At t_0, debt value D is the sum of the expected present value of debt service payments in non-default states and recoveries in default-states, that is:

$$D(\theta, F, R, X_1, \ldots, X_N, Y) = \mathbb{E}[R^{-1}F|Y|\overline{X} \geqslant F] + \mathbb{E}[R^{-1}\theta F|Y|\overline{X} < F], \tag{A.6}$$

where $\mathbb{E}[\cdot|\cdot]$ denotes the conditional expectation operator. Evaluating these terms yields:

$$D(\theta, F, R, X_1, \ldots, X_N, Y) = R^{-1}F - (1-\theta)R^{-1}F(1 - \Phi(d(X_1, \ldots, X_N, Y))), \tag{A.7}$$

where $\Phi(\cdot)$ is the normal distribution function and $d(X_1, \ldots, X_N, Y) = (\mu_{Y|\overline{X}} - F)\sigma_{Y|\overline{X}}^{-1}$ denotes the distance-to-default for Y conditional on $\overline{X}$. The expression in (A.7) indicates that risky corporate debt equals a portfolio consisting of a riskfree bond (first term) and a written put option (second term) that bondholders have conferred upon shareholders.

The credit spread is then given by $CS(F, X_1, \ldots, X_N, Y) = F/D - R$ and simplifies to:

$$CS(\theta, F, R, X_1, \ldots, X_N, Y) = R\left\{\left[1-(1-\theta)\left(1-\Phi\left((F-\mu_{Y|\overline{X}})\sigma^{-1}_{Y|\overline{X}}\right)\right)\right]^{-1}-1\right\}. \tag{A.8}$$

Eq. (A.8) demonstrates that the credit spread on risky corporate debt is determined by (1) the conditional mean and variance of future cash flows, that is, $\mu_{Y|\overline{X}}$ and $\sigma^2_{Y|\overline{X}}$; (2) the recovery rate in case of default θ; and (3) the gross risk-free interest rate R. The simple structural model predicts that if future cash flows are more uncertain, analyst-specific variances are higher, analysts' forecasts diverge more from each other, and hence forecast dispersion is higher. This, in turn, implies a higher conditional cash flow variance, according to Eq. (A.5), and hence higher credit spreads according to Eq. (A.8).

Forecast dispersion is the standard deviation of all available analysts forecasts, X_i:

$$DISP^2 = \frac{1}{N-1}\sum_{i=1}^{N}(X_i-\overline{X})^2 = \frac{1}{N-1}\sum_{i=1}^{N}(Z_i-\overline{Z})^2. \tag{A.9}$$

Recall $Z_i = \beta_{Z_i} + \epsilon_i$, where $\epsilon_i \sim \mathcal{N}\left(0, \sigma^2_{Z_i}\right)$ is the unbiased forecast error, and hence we obtain:

$$DISP^2 = \frac{1}{N-1}\sum_{i=1}^{N}\left[\left(\beta_{Z_i}-\bar{\beta}_Z\right)^2 + 2\left(\beta_{Z_i}-\bar{\beta}_Z\right)\epsilon_i + \epsilon_i^2\right]. \tag{A.10}$$

Taking expectations on both sides of (A.10), we decompose dispersion squared into two components:

$$\mathbb{E}[DISP^2] = \underbrace{\frac{1}{N-1}\sum\nolimits_{i=1}^{N}\left(\beta_{Z_i}-\bar{\beta}_Z\right)^2}_{\text{Divergence of Opinion}} + \underbrace{\left(\bar{\xi}+\bar{\zeta}\sigma^2_Y\right)}_{\text{Cash Flow Risk}}. \tag{A.11}$$

Therefore, as already argued by Miller (1977), the portion of forecast dispersion resulting from differences of opinion, $\frac{1}{N-1}\sum_{i=1}^{N}\left(\beta_{Z_i}-\bar{\beta}_Z\right)^2$, has a positive effect on bond prices if we assume, in addition, that short-sale constraints bind and hence negative views are not completely incorporated into bond prices. This behavioral story then generates a negative relation between credit spreads and forecast dispersion (hypothesis 1). Notably, consistent with the Merton (1974) model, a positive relation between credit spreads and dispersion obtains in a rational corporate bond market because of the second term in (A.11) when there is no disagreement (hypothesis 2).

References

Campbell, J., Taksler, G., 2003. Equity volatility and corporate bond yields. Journal of Finance 58, 2321–2349.
Chen, L., Lesmond, D., Wei, J., 2007. Corporate yield spreads and bond liquidity. Journal of Finance 62, 119–149.
Chiras, D., Manaster, S., 1978. The information content of option prices and a test of market efficiency. Journal of Financial Economics 6, 213–234.
Collin-Dufresne, P., Goldstein, R., Martin, J., 2001. The determinants of credit spread changes. Journal of Finance 56, 2177–2207.
Cremers, M., Driessen, J., Maenhout, P., Weinbaum, D., 2008. Individual stock-option prices and credit spreads. Journal of Banking and Finance 32, 2706–2715.
Diether, K., Malloy, C., Scherbina, A., 2002. Differences of opinion and the cross-section of stock returns. Journal of Finance 57, 2113–2141.
Duffee, G., 1998. The relation between treasury yields and corporate bond yield spreads. Journal of Finance 53, 2225–2241.
Duffie, D., 2005. Credit risk modeling with affine processes. Journal of Banking and Finance 29, 2751–2802.
Elton, E., Gruber, M., Agrawal, D., Mann, C., 2001. Explaining the rate spread on corporate bonds. Journal of Finance 56, 247–277.
Eom, Y., Helwege, J., Huang, J., 2004. Structural models of corporate bond pricing: An empirical analysis. Review of Financial Studies 17, 499–544.
Fama, E., French, K., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.
Fama, E., MacBeth, J., 1973. Risk, return, and equilibrium: Empirical tests. Journal of Political Economy 81, 607–636.
Forte, S., Peña, J., 2009. Credit spreads: An empirical analysis on the informational content of stocks, bonds, and CDS. Journal of Banking and Finance 33, 2013–2025.
Gebhardt, W., Hvidkjaer, S., Swaminathan, B., 2005. The cross-section of expected corporate bond returns. Journal of Financial Economics 75, 85–114.
Harris, M., Raviv, A., 1993. Differences of opinion make a horse race. Review of Financial Studies 6, 475–506.
Hoven Stohs, M., Mauer, D., 1996. The determinants of corporate debt maturity structure. Journal of Business 69, 279–312.
Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. Journal of Finance 48, 65–91.
Johnson, T., 2004. Forecast dispersion and the cross-section of expected returns. Journal of Finance 59, 1957–1978.
Jones, C., 2003. Shorting restrictions, liquidity, and returns. Working Paper, Columbia University.
Kandel, E., Pearson, N., 1995. Differential interpretation of public signals and trade in speculative markets. Journal of Political Economy 103, 831–872.
Lee, C., Swaminathan, B., 2000. Price momentum and trading volume. Journal of Finance 55, 2017–2069.
Livingston, M., Naranjo, A., Zhou, L., 2007. Asset opaqueness and split bond ratings. Financial Management 36, 49–62.
Livingston, M., Naranjo, A., Zhou, L., 2008. Split bond ratings and rating migration. Journal of Banking and Finance 32, 1613–1624.
Longstaff, F., Mithal, S., Neis, E., 2005. Corporate yield spreads: Default risk or liquidity? New evidence from the credit-default swap market. Journal of Finance 60, 2213–2253.
Merton, R., 1974. On the pricing of corporate debt: The risk structure of interest rates. Journal of Finance 29, 449–470.
Miller, E., 1977. Risk, uncertainty, and divergence of opinion. Journal of Finance 32, 1151–1168.
Moody's Investors Service, 2004. Default report: Annual default study. Special Report.
Nagel, S., 2005. Short sales, institutional investors and the cross-section of stock returns. Journal of Financial Economics 78, 277–309.
Newey, W., West, K., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.
Petersen, M., 2009. Estimating standard errors in finance panel data sets: Comparing approaches. Review of Financial Studies 22, 435–480.
Tang, D., Yan, H., 2010. Market conditions, default risk and credit spreads. Journal of Banking and Finance 34, 724–734.
Thomas, S., 2002. Firm diversification and asymmetric information: Evidence from analysts' forecasts and earnings announcements. Journal of Financial Economics 64, 373–396.
Zhang, F., 2006. Information uncertainty and stock returns. Journal of Finance 61, 105–137.