Corporate Bond Credit Spreads and Forecast Dispersion*

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September 2007

Abstract

Recent research establishes a negative relation between stock returns and dispersion of analysts earnings forecasts, arguing that, due to short-sale constraints in equity markets, asset prices more reflect the views of optimistic investors. 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. We argue the dominating effect of dispersion is to proxy for future cash flow uncertainty due to the limited role of short-sale constraints in corporate bond markets.

Keywords: Corporate bonds; credit risk; forecast dispersion.

JEL Classification Numbers: G12; G32; G33.

*We thank Doron Avramov, Turan Bali, Gregory Duffee, Michael Faulkender, Craig Holden, Eugene Kandel, Michael Lemmon, Christian Lundblad, Spencer Martin, Roni Michaely, Vassil Mihov, Erwan Morellec, Adam Reed, Charles Trzcinka and seminar participants at Indiana University, Texas Christian University, Washington University in St. Louis, 3rd Annual Caesarea Center Conference, European Financial Management Association Meetings in Barcelona, European Finance Association Meetings in Ljubljana, Washington Area Finance Conference, and Workshop on Credit Risk and Financial Distress at the University of Rennes for helpful comments.

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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 (e.g. duration), credit quality (e.g. credit rating), and market conditions (e.g. 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.

Corporate bond prices are more volatile when firm performance is more unpredictable. If more dispersion in analysts' earnings forecasts indicates more unpredictable firm performance (i.e. more cash flow uncertainty) rather than divergence due to analyst biases, then it appears to be a promising candidate for explaining cross-sectional and time-series variation in credit spreads on corporate bonds. Given the extent to which the literature analyzes the effect of bond- and issuer-level characteristics on credit spreads, it is surprising that the implications of equity analysts' opinions for credit spreads have not yet been explored. We therefore examine the degree to which bondholders, in setting market prices, rely on firm characteristics conveyed by dispersion in analysts' earnings forecasts.

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. In particular, we study 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.

The first hypothesis is motivated by Miller (1977) 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 can not sell (unless they own the asset), while investors with optimistic views are able to purchase, which raises prices. As a result, negative views will not be completely incorporated, and bond prices will be upwardly biased, giving rise to lower credit spreads. Consistent with this hypothesis, Diether, Malloy, and Scherbina (2002) report a reliably negative relation between stock returns and forecast dispersion. More generally, they point out that any friction that prevents prices from encompassing negative opinions, but allows for full incorporation of positive opinions, produces a negative relation between forecast dispersion and future returns.[1] Thus, according to this behavioral view, forecast dispersion represents divergence of opinion among biased market participants, and higher forecast dispersion leads to higher firm values and hence lower credit spreads.

The second hypothesis contends that, in corporate bond markets, forecast dispersion

[1] See also Harrison and Kreps (1978), Chen, Hong and Stein (2002), and Scheinkman and Xiong (2003) for overvaluation as a result of heterogeneous beliefs and short-sales constraints.

predominantly proxies for future cash flow uncertainty. In the 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 volatility, including both idiosyncratic (or unpriced) volatility and systematic (or priced) volatility. A firm with more volatile operations 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.[2]

In addition to contractual differences, the second hypothesis reflects institutional differences between bond and equity markets and, in particular, the relative lack of short-sale constraints for corporate bonds. Hence Miller's argument does not apply equally to the bond market as it does to the equity market. While equity prices more reflect the views of optimistic investors in the presence of short-sale constraints, the relative lack of short-sale constraints for corporate bonds permits bond prices to reflect the views of both pessimistic and optimistic investors. We argue that if, in corporate bond markets, the dominating effect of forecast dispersion is to proxy for future cash flow uncertainty, then Merton's structural model implies that higher forecast dispersion leads to higher credit spreads.[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 explains 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%.

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, Goldstein, and Martin (2001)]. Moreover, applying the sorting procedure of dispersion quintiles in Diether, Malloy, and Scherbina (2002), to

[2]Rational investors, facing this change in risk, require more compensation in the form of higher credit spreads, which is true even if they are risk-neutral or default risk is idiosyncratic. Volatility changes influence credit spreads by changing expected payoffs, even if they do not change expected returns or risk premia.

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

corporate bonds, we document that the annually compounded return differential between the highest and the lowest dispersion portfolio equals more than 100 basis points.[4] Overall, forecast dispersion thus provides economically important information to determine credit spreads beyond what has been previously documented in the literature.

To confirm our findings, 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 our main result is not the outcome of spurious time-series or cross-sectional correlation. We also control for time-series correlation in errors by using e.g. Fama and Macbeth (1973) and 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, and excess stock returns do not subsume dispersion.

Due to accounting conventions, dispersion is based on forecasts of earnings after interest and taxes. Our goal is therefore to rule out the possibility that, like earnings per share, dispersion is also capturing 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 again find evidence supporting the view that the dominating effect of forecast dispersion in corporate bond markets is to proxy for future cash flow uncertainty.

We also implement various tests to examine the validity of our 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 future earnings volatility is predicted by forecast dispersion. Like Anderson, Ghysels, and Juergens (2005), 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. Both

[4]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)].

levels and changes of lagged dispersion are significant at the 0.1% level. Third, we document that forecast dispersion predicts squared changes in earnings and squared earnings surprises. These volatility-related tests further support the second hypothesis.

Existing literature on forecast dispersion focuses on equity markets. Harris and Raviv (1993) and Kandel and Pearson (1995) are among the earlier studies of investors with dogmatic beliefs. However, their goal is to explain trading volume rather than asset price dynamics. More recently, Anderson, Ghysels, and Juergens (2005) document that factors constructed from the disagreement among analysts about expected (short-term and long-term) earnings have explanatory power in asset pricing models. Consistent with our hypothesis, Ajinkya and Gift (1985) report that forecast dispersion is significantly positively related to equity option-implied volatility. Similarly, David and Veronesi (2004) examine predictability in asset volatilities by constructing dispersion measures based on inflation and earnings growth forecasts. Zhang (2006) applies forecast dispersion to analyze information uncertainty in equity markets, which he defines as the ambiguity regarding the implications of new information for firm value. The study by Mansi, Maxwell, and Miller (2005) looks at the link between information uncertainty, information-based trading, and governance. In related work, Barry and Jennings (1992), however, show that divergence of analyst opinion overstates information uncertainty in efficient capital markets. Other recent work on differences of opinion and asset prices includes Bessembinder, Chan, and Seguin (1996), Chen, Hong, and Stein (2002), and Scheinkman and Xiong (2003).

The paper proceeds as follows. Section 2 develops four competing hypotheses on the spread-dispersion relation. Section 3 discusses the data sources, variables, and summary statistics. The main empirical results are reported in Section 4. Section 5 presents various robustness checks, and Section 6 provides the conclusions. Appendix A contains a simple structural model with forecast dispersion as determinant of credit spreads.

2 Credit Spreads and Forecast Dispersion

The main 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. In particular, we test four competing hypotheses about the relation between credit spreads and forecast dispersion (i.e. the sign of the spread-dispersion relation). The arguments predicting different signs for the spread-dispersion relation guide the paper's empirical methodology.

Following Miller (1977), the first hypothesis views forecast dispersion as a measure of divergence of opinion. He argues that when investor biases differ and short-sale constraints bind, investors with pessimistic views can not sell (unless they own the asset), while investors with optimistic views are able to purchase, which raises prices. Thus, negative views are not completely incorporated, and asset prices are upwardly biased, giving rise to lower future returns. According to this behavioral view, higher forecast dispersion reflects higher divergence of opinion, which leads to higher firm values and to lower credit spreads.

Structural models of credit risk, pioneered by Merton (1974) and further developed in a vast literature on corporate debt pricing, have in common that debtholders can be thought of as owners of a riskfree bond who have issued a put option to the holders of the firm's equity with the par value of debt being the strike price. In Merton's framework, credit risk depends on the volatility of the firm's assets, which is, for example, affected by the uncertainty surrounding future cash flows. Thus, the second hypothesis draws on the observation that if, in the corporate bond markets, forecast dispersion proxies for future cash flow uncertainty rather than for divergence of opinion, then structural credit risk models imply that higher forecast dispersion leads to higher credit spreads.

In addition to contractual differences, the second hypothesis relies on contract-related differences between bond and equity markets and on institutional differences regarding the relative lack of short-sale constraints for corporate bonds: (1) Corporate bonds are primarily held and traded by large financial institutions rather than individual investors.[5] It has been argued that institutional investors are less prone to behavioral biases [see e.g. Brav, Michaely, Roberts, and Zarutskie (2005)]. (2) Corporate bonds are less sensitive to expected changes in firm value than equity, assuming the firm is far from financial distress. The reason for this is the concave payoff structure of debt, which provides only limited upside potential, whereas equity is often likened to a call option with an essentially unlimited upside. Hence the potential for overvaluation in corporate bond markets is more limited than in equity markets. (3) In addition, one would expect the demand for shorting bonds to be relatively lower. The higher sensitivity of stocks relative to bonds produces a higher trading effectiveness and hence an investor who, having a choice between stocks and bonds, is likely to find it optimal to place a 'convergence trade' in stocks. (4) Longstaff, Mithal, and Neis (2005) report that the cost of shorting liquid corporate bonds is only about five basis points.[6] (5) Credit default swaps are a more efficient means of shorting credit risk. These observations regarding participants and institutions in the corporate bond market imply that the likelihood of binding short-sale constraints for corporate bonds is rather limited. Hence Miller's behavioral argument does not apply equally to the corporate bond market as it does to the equity market.

To allow for alternative explanations as exhaustively as possible, we consider two further conflicting theories when analyzing the data. Like the first, the third hypothesis also regards forecast dispersion as a proxy for disagreement among bond market investors. The underlying theory for this hypothesis is developed by Diamond and Verrecchia (1987) and states that market prices are unbiased, although opinions about the correct valuation may diverge. The reversion to unbiased asset prices is achieved by a rational market maker, who can take into account that some pessimistic agents may be constrained from short-selling. More recently, Hong and Stein (2003) obtain a similar pricing result with competitive,

[5] For stocks, Nagel (2005) reports a negative effect of institutional ownership on short-sale constraints.

[6] Corporate bonds may earn "special" lending rates when their issuers are in financial distress. However, only 7.5% of all observations in our sample are bonds rated below investment-grade (i.e. BB-C).

risk-neutral, and perfectly rational arbitrageurs. Therefore, the third hypothesis predicts that there should be no relation between forecast dispersion and credit spreads.

The fourth hypothesis draws on Johnson (2004) who proposes that forecast dispersion proxies for idiosyncratic risk, that is, unpriced parameter uncertainty. When parameter uncertainty of a firm with risky debt increases, equity prices rise, since equity has the payoff structure of a call option. However, risk premia need not be affected since parameter uncertainty does not carry systematic risk, and hence the net effect of higher forecast dispersion is a decrease in expected equity returns. The reason behind this result is that a call option's elasticity is a declining function of volatility. As argued earlier, the owners of risky corporate debt can be thought of as owners of riskfree debt who have issued put options to the holders of the firm's equity. Because the volatility that is relevant for option value, and thus for corporate debt, is total volatility, higher idiosyncratic risk, as proxied by forecast dispersion, should also go hand-in-hand with higher credit spreads.

Having outlined four alternative hypotheses, we now turn to our identification strategy which is first to analyze the association between credit spreads and forecast dispersion over our entire sample of firms, with the intent of (1) signing the relation and (2) determining the relative importance of forecast dispersion vis-à-vis commonly used determinants of credit spreads. We then perform various sample splits and robustness checks aimed at capturing potentially more subtle nuances of the four theories discussed above.

3 Data and Summary Statistics

Before testing the predictions of Section 2, we discuss the data for credit spreads, forecast dispersion, and control variables. The quarterly panel data come from four sources.

1. Corporate bond prices from Fixed Income Database.

2. Equity analyst earnings forecasts from I/B/E/S database.

3. Firm-specific information from S&P's Compustat database.

4. Stock prices and returns from CRSP database.

We start with all bonds issued by US firms that can be identified in the Fixed Income Database, which reports monthly bond prices between January 1973 and March 1998.[7] Our analysis starts in January 1987 since analyst data is largely unavailable for our sample firms before 1987. We want to ensure that payout characteristics of bonds in our sample are similar; hence we include only coupon bearing, fixed-rate bonds and exclude bonds with option-like features such as callability, putability, convertibility, and sinking fund provisions. Similar to previous bond pricing studies [see e.g. Collin-Dufresne, Goldstein, and Martin (2001) or Eom, Helwege, and Huang (2004)], we exclude regulated industries

[7] Other recent studies by, for example, Elton, Gruber, Agrawal, and Mann (2001), Eom, Helwege, and Huang (2004) and Gebhardt, Hvidkjaer, and Swaminathan (2005) also rely on the Fixed Income Database.

(i.e. financial services and utilities).[8] Based on these preliminary filters, we identify 83479 monthly observations of 2421 bonds by 933 firms for our study.

From this preliminary sample, we identify issuers that have both Compustat and Institutional Brokers Estimates System (I/B/E/S) coverage. We apply several commonly used filters. We delete the bonds without ratings by either Standard & Poors (S&P) or Moody's. Following Collin-Dufresne et al. (2001), we drop bond observations with less than four years of maturity and bonds in default because they are too illiquid.[9] To ensure that each bond has significant variation in the time-series of yields, we drop bonds with less than 25 monthly observations. We also delete bonds prices with matrix quotes because traders' quotes are more likely to reflect all available information 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 obtain a quarterly panel by merging the bond and dispersion databases because forecast dispersion is produced at the quarterly frequency. After merging the two databases, we use for every quarter only the latest bond observation which precedes the earnings announcement date. Following Diether et al. (2002), we require at least two forecasts to calculate forecast dispersion, and hence we drop quarterly bond-level observations whenever the issuer is covered by less than two analysts in a quarter. To avoid biases due to outliers, all variables are winsorized at the 1% level (i.e. observations are trimmed at the 0.5% level at both tails). The final sample covers 16004 quarterly observations of 1389 bonds by 382 issuers. The average number of quarterly quotes per bond is about 12.

3.1 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

[8] To classify issuers into industries, we use the sector codes provided by the Fixed Income Database. Regulated industries face lower operating risks due to regulated entry/exit and other legal constraints. If regulation is correlated with dispersion, then this would explain our findings without offering fresh insights into the determinants of credit spreads. Removing these industries has no material effect on our results.

[9] In unreported regressions, we find that dropping bonds with less than two years of maturity does not alter our main results. Chen, Lesmond, and Wei (2005) provide a thorough study of bond-level liquidity.

that (1) quarterly forecast dispersion is calculated using non-overlapping periods and (2) forecast data always precedes bond data since the Fixed Income Database has bond prices at month-end. To make magnitudes comparable across firms, we follow e.g. 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.[10]

While I/B/E/S provides forecasted earnings after interest and taxes as a basis for calculating dispersion, our second hypotheses involves firms' operating cash flows (or earnings before interest and taxes). We therefore verify that our results are not due to variation in firms' interest expenses or their marginal corporate tax rates [see column (5) of Table 5].

3.2 Control Variables

We include a large number of standard control variables to verify that already known determinants of credit spreads do not drive our results. Most importantly, firms with a higher default probability and/or lower expected recovery rates 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 a list of all variables with brief descriptions.

[Insert Table 1 Here.]

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 to 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).[11] 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 category.

[10] 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 5.3 to analyze a matched sample of bond and stock returns.

[11] 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.

4. *Subordination.* For subordinated bonds, we include a dummy variable ($SUBDUM$). In bankruptcy, holders of subordinated bonds are paid after senior bondholders. Thus, subordinated bonds offer lower recovery rates and hence higher credit risk.

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. *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).

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). Larger firms are subject to less business risk and are more likely to meet financial obligations. Thus, we expect a negative relation between credit spreads and firm size.

9. *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).

10. *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 get $LIQUIDITY$, we then divide this count by 12, which normalizes this measure to the unit interval.

3.3 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 Figure 1, we chart the average credit spread of each bond versus average forecast dispersion. It shows a strong positive univariate relation. The correlation between the two series is 0.54. Figure 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 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.

[Insert Table 2 Here.]

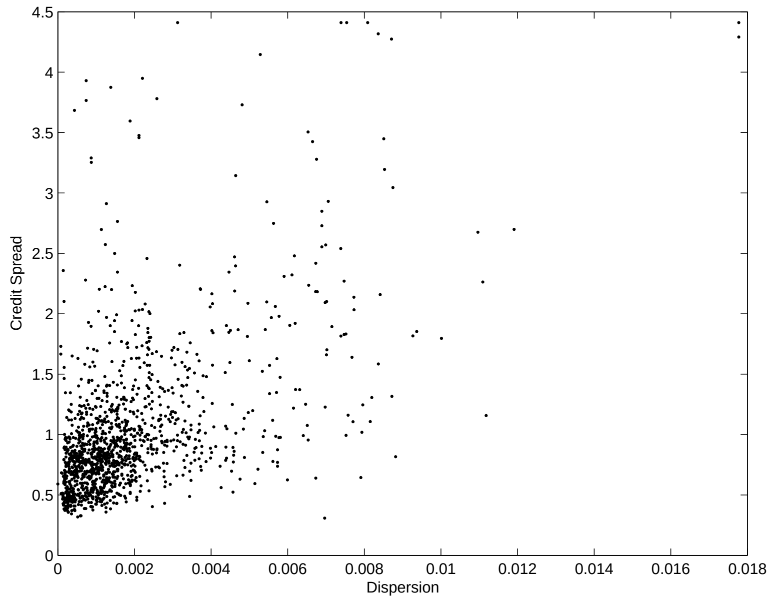

Figure 1: Cross-Sectional Relation between Credit Spreads and Forecast Dispersion
This figure plots the relation between average bond-level credit spreads and average firm-level forecast dispersion. Credit spread is the yield-to-maturity of the bond less the Treasury yield of closest maturity. Forecast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

Industries We divide our sample into ten industries: Basic Industry, Capital Goods, Consumer Cyclical, Consumer Non-cyclical, Electric, Energy, Natural Gas & Water, Technology, Transportation, and Telecommunications. For different industries, credit spreads vary between 60 and 90 basis points except for transportation, which has the highest industry-wide average spread of 136 basis points.

Time Periods Before 1991, there are less 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, two-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 (93.4) basis points to 83.7 (75.8) basis points (see Table 2).

Credit Ratings We split our 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 throughout the sample period. Rating has a significant, negative association with spreads. As credit ratings deteriorate from High to Medium (Low), median

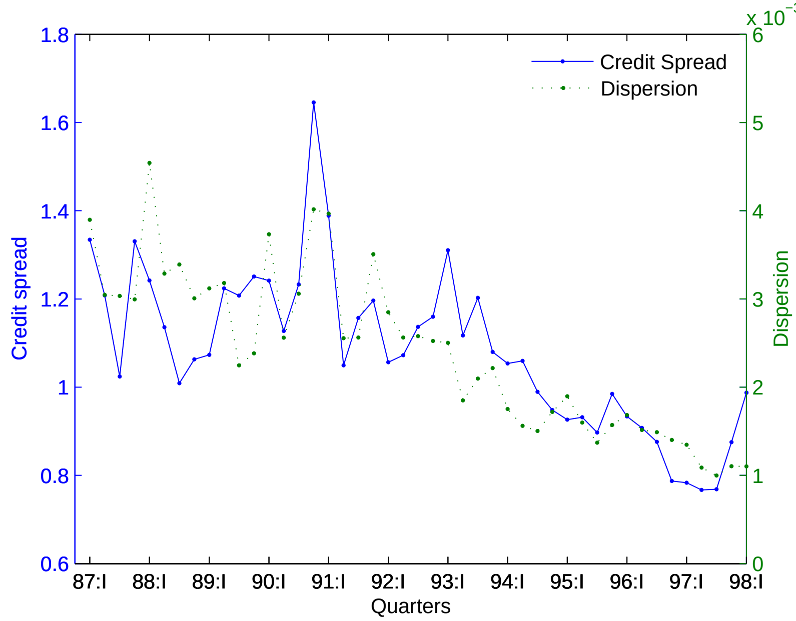

Figure 2: Time-Series Relation between Credit Spreads and Forecast Dispersion

This figure plots 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.

credit spreads gradually increase from 59.4 to 96.2 (226.4) basis points.[12]

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. Tables 2 reveals a negative relationship between firm size and credit spreads. The difference in average spreads between Small and Large firms is 26 basis points.

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.

Firm Leverage Finally, we break up the sample into firms with low, medium, and high financial leverage. The median firm leverage 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. The sample properties of credit spreads are in line with other studies, such as Duffee (1998) or Elton, Gruber, Agrawal, and Mann

[12]In unreported results of a logistic regression model, we find limited evidence for a significant relation between ratings and dispersion. In other words, forecast dispersion does not seem explain credit ratings.

(2001), the mean spread is 100 basis points with a standard deviation of 60.9 basis points.

[Insert Table 3 Here.]

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 also fall into reasonable parameter ranges. 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% 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 relatively liquid trading environment and hence dissolves concerns about substantial liquidity premia being impounded into credit spreads. The average firm has assets worth $7.97 billion, and operating income profitability is 14%. The mean book-to-market of 0.502 and 25.8% firm leverage indicate that our sample is, on average, comprised of moderately-levered firms that appear to reside far away from financial distress.

Table 4 reports the correlation matrix for the variables in our study. Based on this table, we make four observations. First and, consistent with our second hypothesis, forecast

[Insert Table 4 Here.]

dispersion is positively and significantly associated with credit spreads (i.e. a correlation of 0.53 is estimated). This strong statistical relation confirms the observations from Figures 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 a 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 have the expected signs. Although we perform more careful robustness checks later, based on Table 4, there is no univariate association between dispersion and firm size. This finding counters concerns that dispersion might latently pick up size effects in explaining credit spreads. Fourth, dispersion and volatility of forecast errors are highly correlated (0.78 not reported) supporting our modeling choice in Section 2.1. To substantiate these univariate results, we perform multivariate estimations that include control variables and impose further econometric restrictions in Section 4.

4 Empirical Results

As discussed in Section 2, the conflicting theories predict different signs for the spread-dispersion relation. Linear regressions of credit spreads on forecast dispersion and common control variables therefore suffice.[13] We therefore begin in Section 4.1 by examining the full sample over the entire period and run a series of pooled OLS regressions to illustrate the relation between credit spreads and forecast dispersion, while controlling for various fundamentals, such as bond-level liquidity, leverage, firm size, and book-to-market. In particular, we explore how forecast dispersion is distinct from other common measures of credit risk, such as credit rating and bond duration. In Section 4.2, we stratify the panel into subsets of firms and reestimate the baseline regression from Section 4.1 on these subsamples. This enables us to demonstrate that our main findings from Section 4.1 are largely confirmed within various subsamples of the panel. In the alternative econometric tests of Section 4.3, we look again at the full sample over the entire period and estimate the baseline model under different specifications with different fixed effects in OLS regressions, OLS with Newey-West standard errors, Fama-MacBeth regressions, and pure cross-sectional regressions. In addition to these results on levels, changes of credit spreads as a function of changes in forecast dispersion are estimated in Section 4.4.

4.1 Findings for Levels of Credit Spreads in the Full Sample

In this subsection, we examine several structural determinants of credit spreads. For each bond i trading in month t, we denote credit spread by $CS_{i,t}$, which is the difference between the yield of corporate bond i and the associated yield on Treasury bonds with the closest matching maturity. Looking at the full sample of 16004 $CS_{i,t}$ observations of 1389 bonds and 382 issuers, we estimate the following linear model:

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

which explains credit spreads using forecast dispersion, earnings volatility, and various other control variables. The results for pooled OLS regressions are gathered in Table 5.

[Insert Table 5 Here.]

Consistent with our 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). In this paper, all regressions use robust (i.e. heteroscedasticity adjusted) standard errors corrected for correlation across multiple observations of a given firm (i.e. firm-level clustering). The estimates 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

[13] We also examine the possibility of a 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 reasonably 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.

$0.0024 * 78.820 \approx 18.92$ basis points higher than the one of the other firm. This finding supports our prediction that credit spreads are an increasing function of dispersion.

The regression results are also consistent with the implication of the modeling framework in Section 2.1 that credit spreads are an increasing function of earnings volatility. That is, 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. Economically, earnings volatility is about as important as forecast dispersion, i.e. a firm with a one standard deviation higher earnings volatility is expected to have a $0.0088 * 18.318 \approx 16.12$ basis points higher credit spread. In the first specification of equation (1), we only control for earnings volatility and analyst coverage. Column 1 reveals a negative and better than 0.1% significant relation between credit spreads and analyst coverage. It is interesting that these three variables alone can explain nearly 30% of the variation in credit spreads. Notably, earnings volatility does not subsume forecast dispersion.

In column 2, we investigate whether the strong 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 $RATINGSQ$, subordination $SUBORD$, duration $DURATION$, and liquidity $LIQUIDITY$. This specification will be referred to as our *baseline regression model*, which we will continue to analyze from different angles throughout the remainder of Section 4. The results of the baseline specification remain consistent with our conjectures. Forecast dispersion and earnings volatility continue to be both economically and statistically significant after including these controls. However, the number of analysts loses significance, probably due to the correlation with rating squared. The coefficient estimates of all control variables are statistically significant and have the expected signs. Compared to column 1, the adjusted R-squared of 58% is almost twice as high. This increase is due to credit rating, which is obviously the most important default risk proxy.[14]

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 therefore uses 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. Relative to the baseline rating of AAA, a bond issue rated AA, A, BBB, BB, or

[14]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 Investor Services (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.

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.[15]

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 $LEVER$, firm size $SIZE$, book-to-market ratio B/M, and operating profitability $PROFIT$. Within the sample, 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 (see correlation of 0.46 in Table 4).

As mentioned earlier, forecast dispersion is based on forecasts of earnings after interest and taxes. In column 5, we analyze the possibility that dispersion is merely capturing the variation in firms' interest expenses and their marginal tax rates. For this purpose, we multiply dispersion ($DISP$) with the absolute value of the ratio of operating cash flow ($EBITDA$) over net income (NI). When we rerun our baseline regressions with the adjusted dispersion measure, the coefficient estimate on dispersion adjusted in this way is significant at the 0.1% level. Thus, we find similarly strong support for our hypothesis using a dispersion measure that is based on operating cash flows instead of earnings.

A 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). We therefore examine in column 6 of Table 5 if and how this regression model 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. Specification 6 explains 65% of the variation in the levels of credit spreads.

Altogether, the evidence in this table is consistent with our framework's implications. More importantly, the explanatory power of forecast dispersion and earnings volatility remains unexpectedly strong when we include common determinants of credit spreads,

[15] 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).

with adjusted R^2s between 50% and 70%. Consequently, forecast dispersion and earnings volatility significantly explain variation of credit spreads on corporate bonds.

4.2 Findings for Levels of Credit Spreads in Various Subsamples

To examine the strength of our cross-sectional results, we reestimate our baseline regression on various subsamples. We divide the full sample into different 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.

[Insert Table 6 Here.]

First, we check whether the empirical predictions continue to hold within subsamples and ensure that they are not driven by any specific subset of firms or type of firm characteristics. Second, we examine whether the variations of slope coefficients for forecast dispersion and earnings volatility across subsamples are in line with our hypotheses.

Time Periods Panel A reports the estimates for two-year periods from 1987 to 1998.[16] 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. The weakness of forecast dispersion during the first subperiod is probably due to the low number of observations. The general reliance on equity analysts' reports may have been weaker during the time period following the stock market crash of October 1987. 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 result appear not to be driven by a particular subperiod.

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 3, 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. While we continue to control for e.g. duration and liquidity in these rating subsamples, the magnitude of coefficients increases as credit rating deteriorates. 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

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

dispersion tends to be economically more important for firms closer to financial distress. However, the high 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, Mithal, and Neis (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. If our first hypothesis involving short-sale constraints captured the dominating effect of the spread-dispersion relation, it should be negative (or at least insignificant) for the bonds of lowest credit quality in our sample.

Firm Size The results for size subgroups are reported in Panel C. The dispersion's coefficient estimates 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). Hence, the non-monotone behavior does not contradict the intuition that forecast dispersion should be economically more important for smaller firms. The dispersion coefficients' invariably high statistical significance across subsamples dissolves concerns that the spread-dispersion relation is largely driven by small firms with higher cash flow volatility.

Bond Maturity As shown in Panel D, the coefficient estimates of forecast dispersion and earnings volatility remain significant within the three 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).

Firm Leverage In the fifth stratification, we construct different groups of firms based on financial leverage. To detect any possible leverage bias in our baseline regressions, we split the sample into three groups based on low (below 33-percentile), medium (between 33- and 67-percentile) and high (above 67-percentile) book 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 our hypothesis, forecast dispersion's coefficient estimates are still reliable determinants of credit spreads, with increasing economic importance from Low to Medium to High leverage.

In sum, our main results of Section 4.1 are surprisingly robust within the five different types of subsamples that we consider. We next study different econometric specifications.

4.3 Findings for Levels of Credit Spreads under Different Specifications

In this section, we consider more restrictive econometric specifications to examine the significance of the baseline results. We estimate four different types of models [i.e. pooled OLS with fixed effects, OLS with Newey-West standard errors, Fama-MacBeth regression, and pure cross-sectional regression] to ensure that our results are not driven by spurious correlations in the cross-section and the time-series of credit spreads. The results of these robustness checks

[Insert Table 7 Here.]

are located in Table 7. To prevent estimation biases in the time-series, we include time-series fixed effects in our regressions. Columns 1 and 2 augment the baseline regression (see column 2 in Table 5) with yearly and quarterly dummies, respectively.[17] 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. Finally, 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 three different ways. In Panel B, we run OLS regressions with Newey-West standard errors.[18] Column 6 contains these results. Notably, all regressors are still significant at better than 0.1%. The coefficient estimates for forecast dispersion and earnings volatility are very similar to the ones in the baseline model. In line with the regression results on the full and on the stratified sample, this alternative econometric specification therefore presents further support for the view that the relation between credit spreads and forecast dispersion is reliably positive.

In Panel C, we first implement the Fama-Macbeth approach by running cross-sectional regressions for each quarter and report average coefficient estimates in column 7. We find that dispersion is significant at the 0.1% level with a slightly reduced economic significance. To further verify our cross-sectional results, we run a pure cross-sectional regression

[17] 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.

[18] 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.

based on time-series averages of bond-level observations in our third time-series correlation test. These estimation results are summarized as specification 8. Under this alternative econometric specification for the cross-section, both economic and statistical importance of forecast dispersion increase relative to the Fama-MacBeth regressions in column 7.

In sum, our baseline results of Section 4.1 are similarly strong under various econometric specifications. Moreover, earnings volatility does not subsume the economic and statistical significance of forecast dispersion. Coefficient estimates for both forecast dispersion and earnings volatility are highly significant throughout the various tests, with their values being roughly in the range of the baseline results. We therefore conclude from these alternative estimation methodologies that forecast dispersion and earnings volatility are economically meaningful and statistically important determinants of credit spreads beyond what has been previously documented in the literature.

4.4 Findings for Changes of Credit Spreads

To further evaluate the importance of forecast dispersion for credit spread, we now turn to the analysis of changes of credit spreads. With quarterly observations and a large panel of corporate bonds, most of our identification so far comes from the cross-section. However, the cross-sectional relation between credit spreads 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 subsection addresses this concern, the relation between changes in credit spreads and changes in forecast dispersion provides another opportunity to test the competing hypotheses. Additional identification will therefore come from relating changes in credit spreads to changes in dispersion. Moreover, this relation represents an important subject of independent interest.[19]

We define changes in credit spreads, $\Delta CS_{i,t}$, as the difference in credit spreads between two consecutive quarters, $\Delta CS_{i,t}$. We arrive at a total of 13193 $\Delta CS_{i,t}$ observations in the full sample from January 1987 to March 1998, out of which 98.7 percent are from differences in quotes from consecutive quarters. To test our empirical predictions, we estimate the following regression equation for bond i at time t:

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

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 our first specification, we follow Duffee (1998) and Collin-Dufresne, Goldstein and Martin (2001) and include as control variables the quarterly change in the level of the 10-year

[19] 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. These portfolios are highly sensitive to changes rather than to levels in credit spreads.

Treasury yield, $\Delta R_t(10yr)$;[20] the quarterly change in rating squared, $\Delta RATINGSQ_{i,t}$; and the quarterly change in the slope of the yield curve, $\Delta SLOPE_t$, where the slope of yield curve is defined as the differential between the 10-year and 2-year Treasury bond yields, $SLOPE_t = R_t(10yr) - R_t(2yr)$. This proxy captures expectations of future short rates and expectations of future macroeconomic conditions. The estimation results of pooled OLS regression given by equation (2) are located in Table 8.

[Insert Table 8 Here.]

The positive sign of the coefficient estimate of $\Delta DISP$ is consistent with our second hypothesis. Column 1 also reveals that changes in credit spreads depend significantly on changes in forecast dispersion. However, they do not seem to be affected by changes in earnings volatility. As expected, the coefficient estimates for the level and the slope of the term structure 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).

In column 2 of Table 8, we include additional control variables to the first specification.

1. To incorporate changes in the overall business climate, we use quarterly S&P 500 index returns, $RETSP_t$, as a proxy for the state of the economy.

2. As argued earlier, we seek to verify whether or not the importance of forecast dispersion for credit spreads is due to the hypothesis that forecast dispersion is a proxy for idiosyncratic (i.e. unpriced parameter) risk. To this end, we construct the variable $\Delta VOLRET_t$ to measure quarterly changes in idiosyncratic stock return volatility.

3. A firm's future stock return volatility can be extracted from option-implied volatility if it has issued publicly traded options [see e.g. Chiras and Manaster (1978)]. This would provide an opportunity to test whether such a risk proxy weakens the explanatory power of dispersion. However, the firms we investigate, to a large extent, lack data on publicly traded options. We therefore resort to the best available substitute: changes in the VIX index, VIX_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 can not be obtained at the firm level. We therefore 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, $\sigma(K) = a+bK+cK^2$,

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

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 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 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, $\Delta DISP$ 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 switch to 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 hardly changes. 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.

5 Robustness

So far we have found empirical support for the prediction 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 investigate what exactly makes forecast dispersion such an important determinant of credit spreads. We 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 5.1, we attempt to further disentangle the role of forecast dispersion from other risk measures by performing a series of quarterly cross-sectional regressions. Each time, we extend the baseline model by one alternative explanatory variable. In particular, we show that the significance of forecast dispersion is hardly affected by including various proxies for corporate bond market characteristics, idiosyncratic risk, differences of opinion, and contemporaneous risk factors of bond issuers. We find evidence in favor of our structural (contingent claims) model from Section 2 and therefore conjecture that, in the corporate bond market, forecast dispersion is a proxy for future cash flow uncertainty. To verify our conjecture, Section 5.2 examines the explanatory power of forecast dispersion with respect to proxies for future cash flow uncertainty in lagged time-series regressions. In Section 5.3, we revisit the relation between forecast dispersion and stock returns, studied by Diether et al. (2002), for the intersection of our firms with publicly traded stocks. This allows us (1) to compare our findings for the bond market with their findings for the stock market; (2) to confirm our findings for credit (i.e. bond yield) spreads for bond returns; and (3) to verify that our main findings are not due to a particular subsample of firms (i.e. selection bias). We conclude from these robustness tests that the dominating effect of forecast dispersion on stock returns differs from the one on bond returns due to contract-related and institutional differences between bond and stock markets.

5.1 Is Forecast Dispersion subsumed in other Risk Factors?

In a series of robustness checks, we seek to verify further the significance of our main findings, with particular attention to the interaction between forecast dispersion and other risk proxies. More specifically, we now perform tests to identify the relative merits of the competing hypotheses discussed in the introduction. We therefore extend our baseline regression model from Section 4 each time by including one additional variable; that is, we reestimate several specifications to tackle the following competing explanations:

1. Aggregate risk premiums of the corporate bond market ($CORP_t$ and DEF_t);
2. Interaction between dispersion and leverage ($DISP_t$ vs. $DISP_t * LEVER_t$);
3. Idiosyncratic stock return volatility ($VOLRET_t$);
4. Differences of opinion ($TURNOVER_t$);
5. Firm-level reporting noise ($VOLERR_t$); and
6. Historical cash flow uncertainty ($VOLOPER_t$).

We first test 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)]. By introducing $CORP$ and DEF as independent variables, we address concerns regarding risk factors that are unique to the corporate bond market. 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 measures the default risk spread DEF. It is a proxy for the default risk premium in the corporate bond market. The results, reported in column 1 of Table 9, indicate that the slope coefficient of

[Insert Table 9 Here.]

$CORP$ is insignificant, and coefficient estimate of DEF is positive and significant at better than 1%. However, both variables have a minimal impact on dispersion. We thus see that dispersion is not subsumed in aggregate risk factors in the corporate bond market.

Turning from the market-wide level to the firm-level, we revisit the role of firm leverage for the importance of forecast dispersion. More specifically, our goal to investigate whether forecast dispersion is priced as a type of cash flow risk employing a leverage test in the spirit of Johnson (2004). The simple structural model in the Appendix implies that variation in forecast dispersion across firms will, all else equal, be associated with variation in credit spreads because of the differing debt levels in firms' capital structures. The reason is that corporate bonds are so-called contingent claims on the firm's cash flows. If forecast dispersion proxies for (contemporaneous or future) earnings volatility and higher debt levels lever up earnings uncertainty, then the sensitivity of credit spreads to forecast dispersion should increase with firm leverage. In other words, the slope coefficient for dispersion should be an increasing function of leverage. To test this hypothesis, we add two variables to the baseline regression: (1) firm leverage $LEVER$ and (2) the dispersion-leverage interaction term $DISP * LEVER$. In the estimation results for specification 2, the interaction term is significant, whereas forecast dispersion alone loses significance. Hence, the sensitivity of credit spreads to forecast dispersion is a monotonically increasing function of firm leverage. This finding confirms that firm leverage is a "gearing factor" between credit spreads and future cash flow uncertainty.[21] More importantly, this robustness test together with several earlier regression results casts doubt on the validity of the third hypothesis that there is no meaningful relation between credit spreads and forecast dispersion.

Having established dispersion proxies for future cash flow uncertainty, we explore now in more detail the nature of risk it conveys to the corporate bond markets. In an intriguing paper, 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 see 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 specification 3, the coefficient estimate of idiosyncratic risk is significant and, as expected, has a positive sign. This is consistent with Campbell and Tak-

[21] 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.

sler (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 have an impact on either the economic or statistical significance of forecast dispersion. Therefore, this robustness test provides little support for the fourth hypothesis that the dominating effect of dispersion in the corporate bond market is to capture idiosyncratic risk.

As mentioned earlier, dispersion may be a measure for disagreement among investors [e.g. Diether et al. (2002)]. Harris and Raviv (1993) and Lee and Swaminathan (2000) argue that turnover is a measure for differences of opinion. To test this hypothesis for the corporate bond markets, we need to include a turnover measure in our regression. However, the Fixed Income Database reports neither turnover nor trading volume for corporate bonds. As the closest substitute, we introduce 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 the differences of opinion among investors, then turnover measures in stock and bond markets should be positively correlated. In column 4, we include this variable in our baseline regression to verify 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.[22] Therefore, this robustness reveals that dispersion is unlikely to capture differences of opinion, as stipulated by hypotheses one and three. As a result, we regard these findings as evidence of contract-related and institutional differences between bond and equity markets.

We finally include two further uncertainty measures based on past observations to see whether forecast dispersion is subsumed by these risk factors. The first one is the volatility of past analyst forecast errors, $VOLERR$. It is a proxy for the forecast precision of equity analysts. The second one is the volatility of operating profits, $VOLOPER$. In contrast to earnings volatility, the second risk measure is not affected by interest expenses and taxes. Hence it is an alternative test of column 5 in Table 5 and presumably a better proxy for cash flow volatility. Both risk measures enter significantly at better than 1% into specifications 6 and 7, respectively. However, their impact on the significance of forecast dispersion is negligible. These findings lead us to believe that forecast dispersion is unlikely to be a proxy for historical cash flow uncertainty. Consequently, the question emerges whether forecast dispersion proxies for future cash flow uncertainty. We address this question in the next section by a series of lagged time-series regressions, in which we estimate the predictive power forecast dispersion for future earnings volatility.

[22]The same regression result obtains if we use stock trading volume as a proxy of differences of opinion.

5.2 Is Forecast Dispersion related to Future Cash Flow Uncertainty?

By successively excluding possible explanations, the preceding section has argued that forecast dispersion is a proxy for future cash flow uncertainty. As a consequence, an important question is whether forecast dispersion has any predictive power for future cash flow volatility. To provide further empirical support for our hypothesis and, in particular, for the link between cash flow volatility and lagged dispersion in this section, we examine whether variation in contemporaneous dispersion of earnings per share estimates is significantly correlated with future realizations of earnings per share volatility.[23] For this purpose, we construct a firm-level panel data set based on quarterly observations of forecast dispersion, earnings, and earnings volatility for the same firms included in the bond sample. Table 10 presents the results of the empirical tests in this section, based on a sample of 10994 observations of 416 firms with forecast estimates and quarterly earnings. In Panel A, we estimate current levels of earnings volatility $VOLEARN_t$ as a function of lagged levels

[Insert Table 10 Here.]

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 clustering (OLS-FE). We find that the coefficient estimates for lagged dispersion are significant at the 0.1% level in these specifications. While these estimation results support our conjectures, we want to be cautious about possible misspecifications. After performing further tests on changes in Panel B, we find that the results are similarly strong if we use changes in earnings volatility and changes in forecast dispersion instead of the levels of these variables.

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

[23]For consistency, we use estimates or realizations of earnings per share instead of operating cash flow.

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 summarized in Panel D, the estimation results for this specification indicate that contemporaneous levels of forecast dispersion are significantly associated with future squared earnings surprises when controlling for past earnings surprises.

In sum, four different volatility tests offer further support for our hypothesis. We find that regressions with lagged uncertainty variables are consistent with our hypothesis that forecast dispersion is largely a measure for future cash flow uncertainty in the corporate bond market. Against the backdrop of the first two tests of robustness, our objective in the next subsection is to shed light on the similarities and differences in the relation between bond rather than stock returns and forecast dispersion.

5.3 Is there Difference between Bond Markets and Stock Markets?

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, Malloy, and Scherbina (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 findings for credit spreads for bond returns; and (3) to verify that our findings are not due to a particular subsample of firms (e.g. selection bias). To achieve this, we make several adjustments to our previous empirical setup. We construct a matched sample in which every firm has publicly traded stocks and bonds outstanding and prices of both securities are available monthly. Previously, forecast dispersion equals the quarterly standard deviation of three-month forecasts, adjusted for stock splits and scaled by the stock price. We now construct monthly (instead of quarterly) forecast dispersion measures based on twelve-month (instead of three-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, Hvidkjaer, and Swaminathan (2005):

$$r_{t+1} \;=\; \left[(P_{t+1} + AI_{t+1}) \,+\, C_{t+1} \,-\, (P_t + AI_t)\right] / (P_t + AI_t) \ , \tag{3}$$

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 27984 stock return observations for 391 firms and 71559 bond return observations for 1621 corporate bonds bonds between January 1987 and March 1998.[24]

[24]The data on stock returns are obtained from the monthly CRSP tapes.

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.[25] We then average these returns over the sample period of 135 months to obtain mean portfolio returns. Table 11 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

[Insert Table 11 Here.]

the highest and lowest dispersion quintile is -0.26%, and the difference is not statistically significant.[26] 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 market capitalization, in our sample is \$7.97 billion, whereas it is \$1.8 billion for the sample of firms studied by Diether, et al. (see Table I Panel B of their paper). Therefore, our sample corresponds to the fourth and fifth size quintiles of their sample. Consistent with this observation, mean return and mean dispersion in Panel A of Table 11 display very similar patterns as the two largest size quintiles (i.e. S4 and S5) of Diether et al.

Turning to bond returns in Panel B of Table 11, we observe a positive relation between mean bond returns and dispersion. This 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 sizeable, 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 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 previous findings concerning the levels and changes in 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). Two further observations follow: (1) Our results should not stem from differences in sample properties nor selection biases. (2) 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).

Based on the three sets of robustness tests of this section, we conclude that the dominating effect of forecast dispersion on stock returns differs from the one on bond returns. As argued earlier, corporate debt tends to be less sensitive to expected changes in firm value and hence to future cash flow uncertainty than equity. The reason for this is the con-

[25]This methodology was developed by Jegadeesh and Titman (1993) to reduce return variability.

[26]In this subsection, t-statistics are based on Newey-West standard errors.

cave payoff structure of debt, which provides only limited upside potential, whereas equity is often likened to a call option with essentially unlimited upside. Corporate bonds are primarily held and traded by institutional investors who are less prone to behavioral biases and less likely to face short-sale constraints. Hence the lack of evidence favoring the first hypothesis seems plausible. In addition, idiosyncratic stock return volatility can explain a portion of credit spreads, but it does not subsume forecast dispersion. Consequently, the way in which forecast dispersion is incorporated into the cross-section of security prices is, as suggested by our findings, driven by (1) different contractual characteristics of bonds and stocks and (2) institutional differences between debt and equity markets.

6 Summary and Conclusions

In this paper, we explore the relation between dispersion of analysts' earnings forecasts and credit spreads on corporate bonds. We provide evidence that otherwise similar corporate bonds demand significantly higher credit spreads and also earn significantly higher future returns when forecast dispersion is higher. This finding is robust to the inclusion of common control variables, stratification of the sample, and alternative econometric specifications. Moreover, we document that changes in forecast dispersion reliably predict changes in credit spreads, supporting our cross-sectional results. We also verify, in a matched sample of firms with publicly traded 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, we interpret forecast dispersion as a proxy for future cash flow uncertainty (hypothesis two) and show that our evidence is consistent with the notion that debt values incorporate pessimistic and optimistic investors' views. More specifically, our results reject the hypothesis that forecast dispersion can be viewed as a proxy for disagreement among bond market investors. That is, the significantly positive relation between levels (changes) of forecast dispersion and levels (changes) of credit spreads is inconsistent with an adaptation of Miller (1977) to corporate bonds. Moreover, we present evidence that standard risk-based explanations of credit spreads, in spite of being also significant, can not weaken the significantly positive association between forecast dispersion and credit spreads. For example, it has recently been argued that if firm fundamentals are unobservable, forecast dispersion may proxy for idiosyncratic (i.e. unpriced parameter) risk about the firm's future cash flows. We find support for idiosyncratic risk as a determinant of credit spreads, but our results suggest that forecast dispersion does not proxy for idiosyncratic (parameter) uncertainty in our sample of firms.

This study 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 driven to some extent by independent demand/supply shocks in both markets. It would therefore be fruitful, in future research, to examine to which extent these markets are segmented.

Appendix: A Simple Structural Model

In this Appendix, we apply a structural model [see e.g. Merton (1974)] to link behavioral and rational components of forecast dispersion to the pricing of risky corporate debt. The quantitative guidance of the simple model succinctly clarifies the intuition for our main hypotheses about the sign of the relation between credit spreads and forecast dispersion.

Suppose time t_i is discrete with $t_i \in \{..., t_{-1}, t_0, t_1, ...\}$ 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 $i = 1, ..., N$ 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 $\text{Cov}(Y, Z^i) = 0$. We assume that the firm's cash flow and analyst-specific forecast are normally distributed:

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

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

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

where $\xi_i \geq 0$ is the part of analyst i's forecast variance that is attributable to different degrees of analyst biases in form of optimism or pessimism (i.e., divergence of opinion due to different β_{Z_i}s) and $\zeta_i \geq 0$ represents analyst i's ability (i.e., precision of earnings estimates) to forecast cash flow uncertainty, σ_Y^2.[27]

Importantly, rational investors disregard the behavioral forecast components; that is, $\mu_{Z_i} = 0$ 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 $\sigma_{X_i}^2 = \sigma_Y^2 + \sigma_{Z_i}^2$:

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

Although analysts tend to disagree on forecasts, their forecasts tend to be correlated. We therefore assume that $\text{Cov}(Z_i, Z_j) = \rho_{ij} \, \sigma_{Z_i} \sigma_{Z_j}$ for all $i = 1, ..., N$ and $i \neq j$. If rational investors disregard all behavioral forecast components, the unbiased analyst (consensus) forecast $\overline{X} \;=\; \frac{1}{N} \sum_{i=1}^{N} (X_i \,-\, \beta_{Z_i})$ has an unbiased mean of $\mu_{\overline{X}} \;=\; \mu_Y$ and an unbiased

[27] The latter is in line with the available evidence. The association between standard deviation of average forecast errors and operating cash flow volatility yields a correlation coefficient of 0.76 in our sample.

variance of $\sigma^2_{\overline{X}} = \sigma^2_Y + \sigma^2_{\overline{Z}}$, where $\sigma^2_{\overline{Z}} = \frac{1}{N}\ \overline{\sigma}^2 + \frac{N-1}{N}\ \overline{\rho}$ with $\overline{\sigma}^2 = \frac{1}{N}\sum_{i=1}^N \sigma^2_{Z_i}$ and $\overline{\rho} = \frac{1}{N(N-1)}\sum_{i=1}^N \sum_{j=1,j\neq i}^N \rho_{ij}\,\sigma_{Z_i}\,\sigma_{Z_j}$. Thus, the posterior distribution of Y given $\overline{X}$ is:

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

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 ($\sigma^2_Y \gg \sigma^2_{\overline{Z}}$). The opposite holds when forecasts are much less informative ($\sigma^2_Y \ll \sigma^2_{\overline{Z}}$). 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

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

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

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

where $\Phi(\cdot)$ is the normal distribution function and $d(X_1, .., X_N, Y) = \big(F - \mu_{Y|\overline{X}}\big)\sigma^{-1}_{Y|\overline{X}}$ 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 $CS(F, X_1, .., X_N, Y) = F/D - R$ and simplifies to:

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

Equation (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 equation (A.5), and hence higher credit spreads according to equation (A.8).

In sum, the simple structural model predicts a positive relation between credit spreads and forecast dispersion in a rational corporate bond market (hypothesis 2). Moreover, consistent with Miller (1977), analyst biases, $\sum_i^N \beta_{Z_i}$, and the portion of forecast dispersion resulting from differences of opinion, $\sum_i^N \xi_i$, will only have an impact on bond prices if we assume, in addition, that short-sale constraints bind and hence negative views will not be completely incorporated into bond prices. This behavioral argument then generate a negative relation between credit spreads and forecast dispersion (hypothesis 1).

References

Ajinkya, B., and M. Gift, 1985, "Dispersion of analysts' earnings forecasts and the (option model) implied standard deviations of stock returns," *Journal of Finance* 40, 1353-1365.

Anderson, E., E. Ghysels, and J. Juergens, 2005, "Do heterogenous beliefs matter for asset pricing?," *Review of Financial Studies* 18, 875-924.

Brav, A., R. Michaely, M. Roberts, and R. Zarutskie, 2005, "Evidence on the tradeoff between risk and return for IPO and SEO firms," Working Paper, Duke University.

Barry, C., and R. Jennings, 1992, "Information and diversity of analyst opinion," *Journal of Financial and Quantitative Analysis* 27, 169-183.

Bessembinder, H., K. Chan, and P. Seguin, 1996, "An empirical examination of information, differences of opinion, and trading activity," *Journal of Financial Economics* 40, 105-134.

Campbell, J., and G. Taksler, 2003, "Equity volatility and corporate bond yields," *Journal of Finance* 58, 2321-2349.

Chen, J., H. Hong, and J. Stein, 2002, "Breadth of ownership and stock returns," *Journal of Financial Economics* 66, 171-205.

Chen, L., D. Lesmond, and J. Wei, 2005, "Corporate yield spreads and bond liquidity," Forthcoming *Journal of Finance*.

Chiras, D., and S. Manaster, 1978, "The information content of option prices and a test of market efficiency," *Journal of Financial Economics* 6, 213-234.

Collin-Dufresne, P., R. Goldstein, and J. Martin, 2001, "The determinants of credit spread changes," *Journal of Finance* 56, 2177-2207.

David, A., and P. Veronesi, 2004, "Inflation and earnings uncertainty and volatility Forecasts," Working Paper, University of Chicago.

Diamond, D., and R. Verrecchia, 1987, "Constraints on short-selling and asset price adjustment to private information," *Journal of Financial Economics* 18, 277-311.

Diether, K., C. Malloy, and A. Scherbina, 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.

Elton, E., M. Gruber, D. Agrawal, and C. Mann, 2001, "Explaining the rate spread on corporate bonds," *Journal of Finance* 56, 247-277.

Eom, Y., J. Helwege, and J. Huang, 2004, "Structural models of corporate bond pricing: An empirical analysis," *Review of Financial Studies* 17, 499-544.

Fama, E., and K. French, 1993, "Common risk factors in the returns on stocks and bonds," *Journal of Financial Economics* 33, 3-56.

Fama, E., and J. MacBeth, 1973, "Risk, return, and equilibrium: Empirical tests," *Journal of Political Economy* 81, 67-105.

Gebhardt, W., S. Hvidkjaer, and B. Swaminathan, 2005, "The cross-section of expected corporate bond returns," *Journal of Financial Economics* 75, 85-114.

Harris, M., and A. Raviv, 1993, "Differences of opinion make a horse race," *Review of Financial Studies* 6, 475-506.

Hong, H., and J. Stein, 2003, "Differences of opinion, short-sales constraints and market crashes," *Review of Financial Studies* 16, 487-525.

Hoven Stohs, M., and D. Mauer, 1996, "The determinants of corporate debt maturity structure," *Journal of Business* 69, 279-312.

Jegadeesh, N., and S. Titman, 1993, "Returns to buying winners and selling losers: Implications for stock market efficiency," *Journal of Finance* 48, 6591.

Johnson, T., 2004, "Forecast dispersion and the cross-section of expected returns," *Journal of Finance* 59, 1957-1978.

Kandel, E., and N. Pearson, 1995, "Differential interpretation of public signals and trade in speculative markets," *Journal of Political Economy* 103, 831-872.

Lee, C., and B. Swaminathan, 2000, "Price momentum and trading volume," *Journal of Finance* 55, 2017-2069.

Longstaff, F., S. Mithai, and E. Neis , 2005, "Corporate yield spreads: Default risk or liquidity? New evidence from the credit-default swap market," *Journal of Finance* 60, 2213-2253.

Mansi, S., W. Maxwell, and D. Miller, 2005, "Information risk and the cost of capital," Working Paper, University of Arizona.

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.

Scheinkman, J., and W. Xiong, 2003, "Overconfidence and speculative bubbles," *Journal of Political Economy* 111, 1183-1219.

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.

Table 1: Variable Descriptions

This table defines and summarizes the variables we use in the 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 firm-specific 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 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).
$\|EBITDA/NI\|$	Adjustment Ratio	Absolute value of the ratio of operating income before depreciation and amortization (CS item # 21) over net income (CS item # 69) for the corresponding quarterly forecast period.
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 operating profitability over the last eight quarters preceding the observation (i.e., current) date.
$EARN$	Earnings per share	Realized quarterly earnings per share.
$SURPEARN$	Surprise in earnings per share	Realized quarterly earnings per share minus the average of most recent analyst forecasts.

Table 2: Mean and Median Credit Spreads on Corporate Bonds

Using the entire panel data from 1987 to 1998, the table reports mean and median credit spreads (in percentage points) on corporate bonds. The table also provides breakdowns by industries, two-year time periods, credit ratings, firm size, bond maturities, and firm leverage groups.

	Observations	**Mean Spread**	**Median Spread**
All	16004	1.000	0.845
Industries			
Basic	2405	1.040	0.874
Capital	2211	0.968	0.853
Consumer Cyclical	3208	1.064	0.903
Consumer Noncyclical	2591	0.818	0.729
Electric	1624	0.903	0.726
Energy	1243	0.990	0.870
Natural Gas & Water	830	1.167	0.950
Technology	469	0.935	0.682
Telecommunications	315	0.708	0.670
Transportation	1108	1.355	1.135
Time Periods			
87–88	666	1.160	0.934
89–90	711	1.253	1.080
91–92	2126	1.139	0.955
93–94	4398	1.092	0.898
95–96	4883	0.905	0.750
97–98	3220	0.837	0.758
Credit Ratings			
High (AAA–AA)	2599	0.594	0.553
Medium (A–BBB)	12203	0.962	0.869
Low (BB–C)	1202	2.264	2.093
Firm Size			
Small (bottom 33%)	3650	1.106	0.896
Medium (33%–67%)	3720	0.972	0.818
Large (top 33%)	3749	0.845	0.771
Bond Maturity			
Short (< 7 years)	4953	0.902	0.697
Medium (7–12 years)	5494	0.965	0.805
Long (> 12 years)	5557	1.122	0.968
Firm Leverage			
Low (bottom 33%)	3678	0.797	0.700
Medium (33%–67%)	3748	0.883	0.798
Large (top 33%)	3693	1.241	1.003

Table 3: Summary Statistics

This table summarizes the sample properties of credit spreads on corporate bonds and forecast dispersion. In addition, it reports summary statistics of the main control variables for, e.g., credit risk and bond liquidity at the firm-level.

	Observations	**Mean**	**Median**	**St. Dev.**	**Min.**	**Max.**
Credit Spread (CS)	16004	1.000	0.845	0.609	0.308	4.410
Forecast Dispersion ($DISP$)	16004	0.002	0.001	0.002	0.000	0.018
St. Dev. of Earnings ($VOLEARN$)	16004	0.009	0.005	0.009	0.001	0.056
Number of Analysts (N)	16004	10.032	9.000	5.041	2.000	33.000
Rating Squared ($RATINGSQ$)	16004	11.822	9.000	6.224	1.000	36.000
Subordination ($SUBORD$)	16004	0.014	0.000	0.116	0.000	1.000
Duration ($DURATION$)	16004	7.089	6.383	2.621	3.364	13.874
Book-to-Market Ratio (B/M)	11090	0.502	0.453	0.278	-0.237	1.646
Firm Leverage ($LEVER$)	11119	0.258	0.252	0.117	0.011	0.896
Firm Size ($SIZE$)	11119	8.423	8.460	1.041	5.944	11.496
Profitability ($PROFIT$)	10991	0.142	0.140	0.057	-0.004	0.337
Liquidity ($LIQUIDITY$)	16004	0.987	1.000	0.081	0.000	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. * denotes significance at the 0.1% 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

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)–(5) are OLS models. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, and t-statistics (absolute values in parentheses) are based on robust standard errors and firm-level clustering. Subsequently, specification (2) becomes our baseline regression model.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Constant	0.826***	0.272***	0.504***	1.472***	0.447***	0.575***
	(16.65)	(2.70)	(5.27)	(6.55)	(3.75)	(3.18)
DISP	78.820***	57.417***	56.512***	67.373***		54.679***
	(7.68)	(8.50)	(8.11)	(7.36)		(8.01)
$\lvert\frac{EBITDA}{NI}\rvert * DISP$					1.372***	
					(3.78)	
VOLEARN	18.318***	9.141***	8.250***	18.465***	18.862***	10.192***
	(5.79)	(4.23)	(4.18)	(4.67)	(6.45)	(3.70)
N	-0.013***	-0.003	-0.005**	-0.002	-0.007***	-0.001
	(3.84)	(1.54)	(2.33)	(0.70)	(2.97)	(0.50)
RATINGSQ		0.055***			0.055***	0.047***
		(17.14)			(14.73)	(13.70)
SUBORD		0.264**	0.262**	0.462***	0.089	0.121
		(2.02)	(2.16)	(3.29)	(0.75)	(1.18)
DURATION		0.039***	0.040***	0.036***	0.040***	0.041***
		(12.64)	(13.00)	(8.96)	(12.31)	(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	18364	16004	16004	10966	10012	10966
Adjusted R-squared	0.287	0.578	0.605	0.524	0.616	0.654

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. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, and OLS t-statistics (absolute values in parentheses) are based on robust standard errors and firm-level clustering.

	Panel A: Consecutive, Two-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	0.000	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	12203	1202
R-Squared	0.629	0.423	0.603	0.673	0.593	0.628	0.406	0.341	0.393

Table 6: Regressions for Stratified Data *(Continued)*

	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
R-Squared	0.608	0.675	0.675	0.558	0.591	0.610	0.616	0.614	0.623

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 and firm-level clustering. Specification (6) reports results of OLS estimations with t-statistics based on Newey-West standard errors. Specification (7) 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 1298 bonds, reported in (8). *, **, and *** denote significance at the 10%, 5%, and 1% level.

	Panel A: Pooled OLS					*Panel B: OLS-NW*	*Panel C: Cross-Section*	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Constant	0.120	0.158	0.277**	0.076	0.366***	0.272***	-0.025	-0.153*
	(1.25)	(1.55)	(2.35)	(0.60)	(2.75)	(3.61)	(0.18)	(1.67)
DISP	43.435***	55.683***	46.680***	42.407***	38.598***	57.417***	33.856***	78.167***
	(6.26)	(7.97)	(5.97)	(5.50)	(4.85)	(15.48)	(6.32)	(9.93)
VOLEARN	7.720***	7.845***	8.300***	11.367***	11.400***	9.141***	6.823***	4.183**
	(3.68)	(3.72)	(3.53)	(4.99)	(4.61)	(8.08)	(6.59)	(2.47)
N	-0.003	-0.004*	-0.009***	-0.008***	-0.006***	-0.003***	-0.005***	0.000
	(1.55)	(1.88)	(3.76)	(3.91)	(2.91)	(3.47)	(3.57)	(0.09)
RATINGSQ	0.059***	0.056***	0.062***	0.053***	0.048***	0.055***	0.063***	0.063***
	(18.41)	(17.53)	(20.24)	(9.08)	(6.64)	(37.07)	(25.14)	(34.10)
SUBORD	0.241*	0.220*	0.170	0.218**	-	0.264***	0.241***	0.342**
	(1.93)	(1.71)	(1.39)	(2.57)	-	(3.48)	(4.34)	(4.39)
DURATION	0.045***	0.041***	0.045***	0.049***	-0.006	0.039***	0.044***	0.023***
	(14.81)	(13.32)	(15.67)	(23.96)	(0.27)	(21.24)	(12.22)	(6.64)
LIQUIDITY	-0.086	-0.273***	-0.100	-0.080	-0.034	-0.360***	0.006	0.052
	(0.96)	(3.08)	(1.15)	(0.99)	(0.47)	(4.90)	(0.04)	(0.58)
Observations	16004	16004	16004	16004	16004	16004	16004	16004
Adjusted R-squared	0.625	0.596	0.646	0.774	0.813	0.578	0.592	0.658
Year Dummies	Yes	-	Yes	Yes	Yes	-	-	-
Quarterly Dummies	-	Yes	-	-	-	-	-	-
Industry Dummies	-	-	Yes	-	-	-	-	-
Firm Dummies	-	-	-	Yes	-	-	-	-
Bond Dummies	-	-	-	-	Yes	-	-	-

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 and firm-level clustering. Specification (5) documents the results of an OLS estimation with t-statistics (absolute values in parentheses) based on Newey-West standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(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)
$\Delta R(10yr)$	-0.072***	-0.083***	-0.083***	-0.093***	-0.083***
	(10.34)	(11.03)	(10.59)	(10.06)	(16.46)
$\Delta SLOPE$	-0.033***	-0.037***	-0.039***	-0.045***	-0.037***
	(3.36)	(3.57)	(3.66)	(2.63)	(4.75)
$\Delta DISP$	5.577**	7.904**	8.040**	7.535**	7.668***
	(2.11)	(2.49)	(2.44)	(2.34)	(3.81)
$\Delta VOLEARN$	-2.477	-1.895	-1.443	-1.451	-1.846
	(0.86)	(0.58)	(0.41)	(0.45)	(0.93)
$\Delta RATINGSQ$	0.013**	0.012*	0.011	0.011*	0.012***
	(2.05)	(1.90)	(1.57)	(1.67)	(3.26)
$\Delta VOLRET$		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)
ΔVIX		0.004***	0.004***	0.005***	0.004***
		(3.46)	(3.56)	(4.37)	(5.15)
$\Delta JUMP$		0.020***	0.020***	0.018***	0.020***
		(3.92)	(3.52)	(3.12)	(4.95)
Observations	13197	11981	11981	11981	11981
Adjusted R-squared	0.035	0.052	0.096	0.124	0.054
Year Dummies	-	-	-	Yes	-
Firm Dummies	-	-	Yes	Yes	-

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)–(6) contain pooled OLS estimates. Each specification contains one additional uncertainty proxy relative 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 ($VOLERR$), and (6) volatility of operating cash flows ($VOLOPER$). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, and OLS t-statistics (absolute values in parentheses) are based on robust standard errors and firm-level clustering.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Constant	-0.586***	0.342***	-0.039	0.269***	0.212**	0.316***
	(4.37)	(3.08)	(0.34)	(2.63)	(1.99)	(3.04)
$DISP$	45.732***	15.494	51.241***	58.013***	53.402***	52.405***
	(6.78)	(1.09)	(8.15)	(8.08)	(7.52)	(7.14)
$CORP$	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)
$VOLEARN$	7.821***	10.191***	8.848***	8.505***	2.576	9.913***
	(3.76)	(4.14)	(4.20)	(3.89)	(0.82)	(3.81)
N	-0.003	-0.006***	-0.007***	-0.004*	-0.002	-0.007***
	(1.56)	(2.86)	(3.24)	(1.76)	(1.06)	(3.13)
$RATINGSQ$	0.058***	0.050***	0.048***	0.054***	0.055***	0.053***
	(18.07)	(14.16)	(17.12)	(15.52)	(16.87)	(15.62)
$SUBORD$	0.234*	0.123	0.231**	0.263**	0.266**	0.117
	(1.90)	(1.10)	(2.04)	(2.05)	(2.07)	(1.02)
$DURATION$	0.045***	0.039***	0.040***	0.039***	0.040***	0.038***
	(14.90)	(14.36)	(13.65)	(12.63)	(12.79)	(13.42)
$LIQUIDITY$	-0.132	-0.399***	-0.319***	-0.357***	-0.307***	-0.402***
	(1.42)	(4.33)	(3.62)	(4.02)	(3.33)	(4.30)
Observations	16004	11123	15791	15791	16004	10796
Adjusted R-squared	0.615	0.649	0.599	0.566	0.585	0.646

Table 10: 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 and firm-level clustering. Absolute values of t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A. Dependent Variable : $VOLEARN_t$

	(1) OLS-NW	**(2)** OLS-FE
Constant	0.001***	0.001***
	(5.51)	(3.39)
$VOLEARN_{t-1}$	0.823***	0.786***
	(49.00)	(58.90)
$DISP_{t-1}$	0.446***	0.417***
	(8.11)	(6.33)
Observations	9801	9801
Adjusted R-squared	0.9013	0.9034

Panel B. Dependent Variable : $\Delta VOLEARN_t$

	(1) OLS-NW	**(2)** OLS-FE
Constant	-0.001***	-0.001
	(-3.88)	(1.62)
$\Delta VOLEARN_{t-1}$	0.127***	0.076***
	(6.24)	(3.17)
$\Delta DISP_{t-1}$	0.090***	0.083***
	(3.63)	(3.65)
Observations	9575	9575
Adjusted R-squared	0.0225	0.0325

Panel C. Dependent Variable : $(\Delta EARN_t)^2$

	(1) OLS-NW	**(2)** OLS-FE
Constant	0.001	0.002
	(0.59)	(1.46)
$(\Delta EARN_{t-1})^2$	0.463***	0.310***
	(14.04)	(11.81)
$DISP_{t-1}$	1.131***	0.869***
	(6.91)	(3.55)
Observations	10616	10616
Adjusted R-squared	0.2805	0.3422

Panel D. Dependent Variable : $(SURPEARN_t)^2$

	(1) OLS-NW	**(2)** OLS-FE
Constant	0.001	0.001***
	(0.14)	(2.88)
$(SURPEARN_{t-1})^2$	0.169***	0.091**
	(3.31)	(2.01)
$DISP_{t-1}$	0.321***	0.177***
	(8.55)	(3.04)
Observations	10783	10783
Adjusted R-squared	0.1162	0.1751

Table 11: 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.

Panel A: Stock Returns and Forecast Dispersion

Dispersion Quintiles	Mean Return	Mean 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

Dispersion Quintiles	Mean Return	Mean 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	