Cash flow forecasts and cost of debt

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ABSTRACT

This study examines the impact of the presence and characteristics of equity analysts' cash flow forecasts on cost of debt. Evidence is presented that the presence of equity analyst cash flow forecasts is associated with a lower cost of debt relative to firm-years with only earnings estimates or neither cash flow or earnings estimates. An additional finding associates cash flow forecast characteristics with cost of debt after controlling for other known determinants of yield spreads. Further analyses decomposed earnings forecast characteristics into cash flow and accruals components and determined that the cash flow component is associated with cost of debt, but the accruals component is not. Overall, the results indicate that debt market participants find equity analyst cash flow forecasts useful in reducing information asymmetry and providing oversight monitoring.

Keywords: Cost of Debt, Equity Analysts, Cash Flow Forecasts, Earnings Forecasts

I. INTRODUCTION

Extant literature examining the determinants of cost of debt has primarily focused on the association between contemporaneous firm-level and debt-level characteristics and proxies for cost of debt. The default risk of a debt instrument, however, is largely a function of the future financial performance and financial health of a firm – information often assumed to be conveyed through credit ratings and credit rating changes. Although the default risk models used by credit rating agencies in setting ratings are not observable, it is noncontroversial to assume that forward-looking information is included in determining the default risk of a debt security. According to Reilly and Brown (2001), "Rating agencies consider expectations over the life of the issue, along with the historical and current financial position of the company" (p.704). It follows then that credit ratings explain a large portion of bond risk premiums. Still credit ratings are slow to change. Thus, additional sources of forward-looking information may be needed by bondholders to fine-tune expected returns between credit rating changes. Assuming credit ratings are adequate sources of information regarding default risk of debt securities, this research examines one forward-looking source of information: equity analyst cash flow forecasts and its effect on firms' cost of debt. [1]

This study is not the first to examine the relationship between analyst forecasts and cost of debt. Mansi, Maxwell and Miller (2011) examine the relationship between analyst earnings forecast characteristics and the cost of debt financing. They find analyst activity reduces bond yield spreads. Additionally, forecast characteristics, including average forecast error, average dispersion among analyst forecasts, and revision volatility, are statistically related to yield spreads on corporate bonds. The authors conclude that the information contained in analyst earnings forecasts is valued outside the equity market and provides an additional channel in which better information is associated with a lower cost of capital. The effect, they argue, is due to one or both of two possibilities: 1) the information contained in financial analyst earnings forecasts plays a key role in mitigating information asymmetry between firms and market participants, and 2) analysts' information production, including forecasts, serves to monitor managers by imposing market discipline.

The authors study earnings-based analyst activity and characteristics. Furthermore, debt market participants are focused on the firm's cash flows, since their return is based directly on cash payments. Given those factors, it is possible that the results in Mansi et al. (2011) are driven by the information about current and future cash flows, which are embedded in earnings forecasts along with accruals. By examining the effect of the presence of cash flow forecasts and their characteristics on the cost of debt, further insight can be realized regarding whether and how forward-looking earnings and cash flows estimates inform debt market participants.

The focus of this research - on cash flow forecasts and the characteristics of those forecasts - is due to the fundamental relationship that exists between firm cash flows and bond expected returns. Expected default risk, the major determinant of bond risk premium, is a function of future cash flow volatility or risk, levels, and timing. Therefore, it is plausible that bondholders would use the year-round cash flow forecasts and characteristics, generated by equity analysts, to update their estimates of default risk and, in turn, expected returns.

Also, an ongoing debate exists in the literature regarding whether cash flow forecasts provide useful information to securities markets. Studies by Givoly, Hayn and Lehavy (2008)

[1] This study focuses on forecasts of cash flows for the forthcoming fiscal year (one-year-ahead cash flows). Longer forecast periods are sparsely populated to examine characteristics and their association with cost of debt.

and Call, Chen and Tong (2013) provide conflicting evidence regarding both the quality and equity market effect of cash flow forecasts. By studying the effects of cash flow forecasts in a debt market setting, this study provides implicit evidence on the quality and information content of cash flow forecasts. Using yield spreads as a proxy for firms' cost of debt, this study tests whether the mere presence of a cash flow forecast for a firm in a given fiscal year is associated with a lower cost of debt. Then, tests are conducted to see if cash flow forecast characteristics are associated with cost of debt, controlling for accrual forecast characteristics and other known determinants of yield spreads.

This study finds that the mere presence of a cash flow forecast for a firm year is associated with a lower cost of debt, relative to firm years with only earnings-per-share forecasts or no forecasts at all. Cash flow forecast characteristics are positively associated with cost of debt. In additional analysis deconstructing earnings forecast characteristics into cash flow and accrual components, evidence shows that cash flow forecast characteristics are associated with cost of debt, while accrual forecast characteristics are not. Together, these results suggest cash flow forecast characteristics are useful in reducing information asymmetry or providing monitoring, or both. Cash flow forecast characteristics also convey to debtholders important information regarding expected default risk.

This paper contributes to the existing literature in three ways: First, by examining cash flow forecasts in context with earnings forecasts, this research determines which piece of information is of greater importance to bondholders. Prior research has suggested debtholders should be more focused on the firm's cash flows (DeFond and Hung 2003; Graham, Harvey and Rajgopal 2005; Edmonds, Edmonds and Maher 2011) In fact, this study reconciles previously published results regarding the relationship between earnings forecasts and bond valuation fundamentals. Second, by further documenting the association between cash flow forecasts and cost of debt, this study provides insight into the limitations of credit ratings agencies as an information intermediary. Due to the stickiness of ratings, bond market participants may look to other information sources in their development of expected return requirements. Third, this research provides evidence supporting the utility of cash flow forecasts in security pricing. Prior literature is split on whether cash flow forecasts provide useful information to financial markets. Therefore, this study presents evidence that informs this debate, showing how cash flow forecasts' presence and characteristics affect the bond market.

The remainder of this paper is structured as follows: Section 2 reviews the relevant prior literature, while Section 3 develops the hypotheses. Section 4 then describes the data and sample selection, followed by a description of the empirical specifications in Section 5. Results are presented in Section 6, accompanied by robustness checks in Section 7. The conclusion is contained in Section 8.

II. PRIOR LITERATURE

The link between earnings and the equity market has been well established in prior literature, starting with Ball and Brown (1968) and Beaver (1968). Next, a long stream of literature links equity analysts' forecasts of earnings to the equity market (Kasznik and McNichols 2002; Asquith, Mikhail and Au 2005). Still, for years, a dearth of studies instead examined the relationship between accounting earnings and forecasts of earnings and the debt market. This focus was most likely due to the lack of widely available data combined with complications related to studying the debt market, notably lack of liquidity in trading and slow-

changing credit ratings. Recent studies, however, focus on the debt market, aided by the emergence of easily accessible databases including Trade Reporting and Compliance Engine (TRACE) for individual trades, Mergent Fixed Income Securities Database (FISD) for trades undertaken by insurance companies, and SDC Global New Issues for yields and other characteristics of new bond offerings. Initial studies on the relationship between earnings variables and cost of debt have yielded surprising results: in general, earnings, earnings benchmarks, and earnings estimates all affect the debt market in one way or another.

Jiang (2008) finds firms that meet or beat earnings benchmarks – zero EPS, last year's EPS, and analyst forecast of EPS – have a lower cost of debt. This association is strengthened by the evidence that the relationship is mitigated in the presence of accruals manipulation. Easton, Monahan and Vasvari (2009) find that earnings announcements cause abnormal bond trading volume as well as a price reaction; they report a positive association between annual bond returns and both annual changes in earnings and annual analysts' forecast errors. Mansi et al. (2011) find the presence of equity analysts' earnings forecasts and forecast characteristics reduces firms' cost of debt. These findings may be perceived as surprising results, considering debtholders' returns are dictated entirely by cash payments. One may then conclude that cash flow metrics and estimates – not earnings metrics and estimates – should be more important to bondholders. Dechow, Kothari and Watts (1998) present findings clarifying why earnings may be important to debtholders. The authors conclude that current earnings, for up to three years in the future, are a better indicator of future cash than current cash flows. In other words, the information about future cash flows may be driving the results found in prior literature linking earnings variables and debt markets. In addition, Kim and Kross (2005) find that the ability of earnings to predict future cash flows has increased over time, although their focus is upon the ability of earnings to predict cash flows one year into the future. Lastly, Barth, Cram and Nelson (2001) build on the Dechow et al. (1998) finding by showing the predictive ability of earnings on future cash flows is enhanced significantly when accruals are disaggregated into the following major components: change in accounts receivable, change in accounts payable, change in inventory, depreciation, amortization, and other accruals. It is well accepted among academics that earnings better predict future cash flows than current cash flows.[2] The link between current earnings and future cash flows can therefore serve to reconcile the findings of Jiang (2008) and Easton et al. (2009) with bond valuation fundamentals. On the other hand, the research does not suggest that earnings forecasts better predict future cash flows than cash flow forecasts. Therefore, the association between earnings forecast characteristics and cost of debt needs further analysis to determine the causal mechanism.

This study is highly focused on testing whether analyst earnings estimates provide more information about future cash flows than analyst cash flow estimates. Prior research has identified the determinants of cash flow forecasts (DeFond and Hung 2003) and the quality of cash flow forecasts (Givoly et al. 2008; Call et al. 2013). These studies do not directly test whether information about future cash flows is contained in analyst forecasts. This study proposes that an intuitive way to gather information about a firm's future cash flows is to directly observe cash flow forecasts provided by analysts. This approach is an effective alternative to

[2] A study by Lorek and Willinger (2009) presents results contrary to those found in DeChow et al. (1998) and Kim and Kross (2005). The authors present evidence that cash flow-based models provide significantly more accurate predictions of operating cash flows than earnings-based models; they find no evidence of an increase in predictive power for either the cash-based or earnings-based prediction models in the Kim and Kross (2005) sample period. The bulk of related literature supports the view that earnings predict future cash flows better than current cash flows.

relying on historical information or forecasts of a combination of cash flows and accrued earnings.

In addition, it is plausible to consider that equity analysts use the information in current earnings about future cash flows to produce their cash flow forecasts. One primary concern here is whether cash flow estimates are of sufficient quality to update bondholders' priors regarding future cash flows and, accordingly, firm default risk. It is well known that firm cash flows are more volatile than earnings by their very nature; forecasts of a more volatile number may prove to be ineffective. Regarding this issue, Givoly et al. (2008) find that cash flow forecasts are of considerably lower quality than earnings forecasts, suggesting cash flow forecasts to be naïve extensions of earnings forecasts. The authors' result suggests that cash flow forecasts would provide no incremental information to debtholders. Call et al. (2013) debate this finding. The authors randomly selected full-text equity analyst reports that included a cash flow forecast from InvesText. Credit Union. They determine them to be more sophisticated than previously documented, finding the forecasts informative to the equity market when analyzing short-window returns around revisions. Given this finding, debtholders may find cash flow forecasts to yield important information relating to estimates of default risk and function as a monitoring service.

Other studies shed light on a possible indirect effect of cash flow estimates on cost of debt. Call, Chen and Tong (2009) examine whether analysts' earnings forecasts are more accurate when accompanied by cash flow forecasts. They find that earnings forecasts accompanied by cash flow forecasts are more accurate than those not accompanied by forecasts; analysts' earnings forecasts reflect a better understanding of the implications of current earnings for future earnings when they are accompanied by cash flow forecasts. Their results suggest analysts adopt a more structured and disciplined approach to forecasting earnings when they also issue cash flow forecasts. Thus, the presence of cash flow forecasts may be important to debtholders given that the overall information quality of analyst earnings estimates is improved.

McInnis and Collins (2011) findings also speak to the importance of not necessarily cash flow forecasts per se, but rather a combination of cash flow with earnings forecasts. The authors explain that a combination of cash flow and earnings forecasts provides an implicit forecast of accruals. They suggest that this increases the expected costs of accruals manipulation, reducing the incidence of earnings management. Furthermore, they find that accrual quality improves and firms' propensity to meet or beat earnings benchmarks declines following the additional provision of cash flow forecasts. The McInnis and Collins (2011) result suggests that cash flow forecasts may have an indirect effect on debtholders by improving transparency and reducing information asymmetry, or both.

Recent research has examined the impact of cash flow forecasts on cost of debt, but only to a limited extent. Edmonds et al. (2011) study the impact of meeting or beating analysts' operating cash flow forecasts on a firms' cost of debt; a positive relationship is documented. The authors also test whether the earnings benchmark effect from Jiang (2008) was driven by their finding, but show instead that the result holds. This paper establishes a link between cash flow forecasts and cost of debt, but the informative ability of cash flow forecasts may be much greater in scope than serving as a benchmark.

In summary, earnings have been found to predict future cash flows better than current cash flows. Earnings may understandably be perceived as more important to debt market participants than cash flows. An unanswered question is whether this extrapolates into earnings

forecasts subsuming the information in cash flow forecasts to debt market participants. This gap in the existing literature is addressed in this paper.

III. HYPOTHESES

Duffie and Lando (2001) present a model that shows when firm value is not perfectly observable and where there exists a positive probability that true firm value is near its default boundary; as investor ability to estimate the distribution of firm value increases, default probability decreases. Taking this study into account, Ashbaugh-Skaife, Collins and LaFond (2006) argue that firms with better information environments allow a more precise estimation of true firm value. Therefore, to the extent that analysts' cash flow forecast activity impacts the information environment of the firm, the forecasts should affect corporate bond yields. An improved information environment is suggested by the findings of Call et al. (2009). The authors describe the synergistic effect of the combination of earnings and cash flow estimates, whereby earnings estimates are improved when combined with cash flow estimates. By disaggregating earnings estimates into cash flow and accrual estimates, investors can determine the relevance of each estimate to firm value – that point is deemed critical in Duffie and Lando (2001).

In a different vein, McInnis and Collins (2011) suggest a mechanism for how cash flow forecasts could affect cost of debt, regarding an increase in expected costs of earnings management through the implicit estimates of accruals generated by the provision for both earnings and cash flow estimates which increases transparency and/or reduces information asymmetry.

Analysts' abilities to reduce information asymmetry is supported by a long stream of prior literature (Jacobs, Lys and Neale 1999; Clement 1999). It is therefore reasonable to expect a similar effect in this setting. Taken together, it is expected that the presence of cash flow forecasts, seen through a reduced cost of debt, is important to debt market participants. Hypothesis 1 stated in an alternative form:

H1: The presence of cash flow forecasts is associated with a lower cost of debt relative to observations with 1.) only earnings forecasts, or 2.) neither cash flow nor earnings forecasts.

This study proposes that observing cash flow forecasts is the most intuitive method of revising expectations about future cash flows; prior research has shown analyst cash flow estimates to be both sophisticated and important to the equity market (Call et al. 2009). Also, a large body of capital market research has used analyst estimates as a proxy for unobservable investor expectations (Brown 1993). According to Abarbanell, Lanen and Verrecchia (1995), "The use of forecasts to proxy for investor beliefs has become a routine methodological practice in accounting and finance research" (p.34). If estimates of operating cash flows are used in revising expectations about future cash flows, it follows that levels and changes in the characteristics of the cash flow forecasts will be associated with debt market participants' expectations for cash flow volatility. For example, levels of and changes in accuracy, dispersion or revision volatility may signal the level or a change in the default risk of the firm, or both, providing valuable information regarding the value of the firm's debt. It is well known that accuracy, dispersion, and revision volatility are highly correlated (Bushman, Pitorski and Smith 2004). Thus, following prior research, the first factor from a factor analysis of the forecast

characteristics is retained and analyzed for its correlation with cost of debt, in addition to testing each characteristic separately. Hypothesis 2 stated in alternative form:

H2: The characteristics of cash flow forecasts – accuracy, dispersion, and revision volatility – are associated with cost of debt.

Earnings can be decomposed into cash flows and accruals. Likewise, earnings forecast characteristics can be decomposed into cash flow characteristics and accrual characteristics. Therefore, earnings forecast characteristics and cash flow forecast characteristics should be, and are, highly correlated. This research proposes, however, that the characteristics of cash flow forecasts are more relevant to bondholders than earnings forecast characteristics. This is a noisier proxy for cash flow information since earnings forecast characteristics are a function of both cash flow forecast characteristics and accrual forecast characteristics. This suggests that only cash flow forecast characteristics will be associated with cost of debt when accrual forecast characteristics and cash flow forecast characteristics are included in the same model, Hypothesis 3 stated in alternate form:

H3: When earnings characteristics are deconstructed into cash flow and accrual component characteristics, cash flow forecast characteristics are associated with cost of debt.

IV. EMPIRICAL SPECIFICATIONS AND DATA SOURCES

To test the first hypothesis - if the presence of cash flow forecasts is associated with a lower cost of debt, the following pooled ordinary least squares (OLS) regression is estimated and referred to as Model 1:[3]

$$\text{Spread} = \alpha_0 + \beta_1 \text{cf\_dummy} + \beta_2 \text{eps\_dummy} + \sum \beta_{3-k} \text{controls} + \varepsilon \quad (1)$$

To test the second hypothesis – if cash flow forecast characteristics are associated with cost of debt, the following pooled OLS regression is estimated and referred to as Model 2:

$$\text{Spread} = \alpha_0 + \beta_1 \text{cf\_characteristic} + \sum \beta_{3-k} \text{controls} + \varepsilon \quad (2)$$

Next, earnings forecast characteristics are broken into cash flow and accrual forecast characteristics; a factor analysis is performed on the characteristics of each, and the first factor is retained for both accrual and cash flow characteristics as an explanatory variable.

To test the third hypothesis - whether cash flow forecast characteristics, accrual characteristics or both are associated with cost of debt, the following pooled OLS regression is estimated and referred to as Model 3:

$$\text{Spread} = \alpha_0 + \beta_1 \text{cf\_factor} + \beta_2 \text{acc\_factor} + \sum \beta_{3-k} \text{controls} + \varepsilon \quad (3)$$

For all of the above regression specifications, Spread is either the log of the trade-weighted yield spread (log_wt) or the log of the most recent yield spread (log_re). In Equation 1, the cf_dummy and eps_dummy are binary variables, signaling the presence of that particular

[3] Subscripts are suppressed for ease in exposition.

forecast for a firm year. In Equation 2, the cf_characteristic represents one of the four separate measures of cash flow characteristics including revision volatility, forecast dispersion, forecast accuracy, and a factor for the three characteristics. [4] In Equation 3, the cf_factor represents an explanatory variable, calculated by retaining the first factor from a factor analysis on the three cash flow characteristics. In Equation 3, the acc_factor represents an explanatory variable, calculated by retaining the first factor from a factor analysis on the three accrual characteristics.

The vector of control variables for all the models includes both firm-specific and bond-specific characteristics known to have an effect on firms' cost of debt (Chen et al. 2012). To control for default risk, controls include the credit rating of the debt, size of the firm, the amount of leverage of the firm, and the Altman z-score for the firm-year. When the log of the trade-weighted yield spread is the dependent variable, the associated credit rating control is the trade-weighted credit rating of the bonds included in the calculation of the trade-weighted yield spread (rating_tw). When the log of the most recently traded bond yield spread is used, the associated credit rating is the credit rating from that individual bond (rating_iv). The Altman z-score (altman_z), leverage (finlev), and size (size) variables are used to control for firm-specific default risk that may be priced into the yield spread but not captured by the credit ratings; in addition, the size variable proxies for the information environment of the firm due to the fact that larger firms typically have a host of information suppliers.

To control for performance, controls include profit and productivity. Profit is earnings for the prior year scaled by total assets; productivity is the sales from the prior year scaled by total assets. To control for trading liquidity, controls include debt age. Debt age is the number of years since a bond was issued. Debt age also proxies for trading liquidity because on-the-run bond issuances have greater trading liquidity than bonds off-the-run[5]and trading gradually decreases for bond issuance with time. When the log of the trade-weighted yield spread is the dependent variable, the associated debt age control is the trade-weighted debt age of the bond used in calculating the weighted-average yield spread (debt_age_wt). the When the log of the most recently traded bond yield spread is used, the associated debt age control is the debt age for that individual bond (debt_age_re).

To control for the effects of payouts to shareholders, payout is calculated as the total amount of cash dividends and share repurchases made during the year scaled by total assets. To control for firm liquidity, controls include variables for interest coverage and net working capital. Int_cov_dummy is an indicator variable equal to unity when a firm's interest coverage ratio is negative; otherwise, if the coverage ratio is zero or positive, it is coded as zero. NWC or net working capital is equal to the difference between current assets and current liabilities scaled by total assets. To control for current cash flow volatility, controls include Tobin'sQ and earnings volatility (stdROA). Lastly, the models include year fixed effects and industry fixed effects (sic 2-digit) and errors are clustered by firm.[6]

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[4] All three forecast characteristics are not included because they are highly correlated with one another. In untabulated results, the variance inflation factors for each variable taken from regressions – including all three characteristics – are greater than 11, a number above the heuristic of 10 (Kennedy 2009) in determining if multicollinearity is problematic to coefficient estimation procedures.

[5] On-the-run refers to the most recently issued bond of a specific type and maturity. These typically have the greatest liquidity (Warga 1992). Off-the-run refers to bonds not on-the-run.

[6] Analysts' decisions to provide cash flow forecasts is endogenous. Nevertheless, each of the determinants found to influence the decision to provide a cash flow forecast in DeFond and Hung (2003) are positively associated with cost of debt, for example, large accruals, heterogeneous accounting choices relative to industry peers, high earnings

Information gathered to calculate yield spreads is from the Trade Reporting and Compliance Engine (TRACE) from its inception in 2002 through 2011.[7][8] Daily Treasury yields are gathered from the Federal Reserve Bank Treasury Constant Maturities file on Wharton Research Data Services (WRDS). Debt-specific variables such as debt age, coupon, and credit rating are gathered from Mergent FISD; firm-specific control variables are gathered through Standard & Poor's Compustat database. Data, in a given year, for both the presence of earnings and cash flow forecasts and forecast characteristics are gathered through the Institutional Brokers' Estimate System (I/B/E/S) annual consensus files.

V. RESULTS

Table 2 presents sample statistics of key variables. The skewness of the yield spread variables measured in basis points is apparent with a mean far in excess of the median (bp_sprd_wt mean = 325, median = 227; bp_sprd_re mean = 322, median = 219). This suggests the need to log transform the variable to serve as the dependent variable. Firms in the sample are profitable and have a wide range of financial leverage. The mean of the cash flow forecast dummy (cf_dummy) and earnings forecast dummy (eps_dummy) is transformed to show how many firm years in the sample have the relevant forecast: 906 firm years have a cash flow forecast, 1,438 have an earnings forecast, and 826 firm-year observations have no forecasts.[9] On a firm basis, 203 firms in the sample always had a cash flow forecast, 92 firms went from not having a cash flow forecast to having a cash flow forecast during the sample period, and 393 firms never had a cash flow forecast during the sample period. The median credit rating is 10, which corresponds to a Standard & Poor's 500 (S&P) rating of BBB-. The average age of the bonds in the sample is about 2.7 years. This average age is not surprising since more recently issued, or "on-the-run" bonds, trade more frequently than older bonds. Thus, these are more likely to be captured from the TRACE database in the required sample periods.

Table 2 also presents descriptive statistics for the earnings and cash flow characteristics. As expected, each cash flow characteristic is greater than its earnings counterpart (cf_rev_vol mean =.331, rev_vol mean =.206; cf_avg_disp = .554, avg_disp = .147; cf_avg_error = .855, avg_error = .287). This suggests: 1) cash flows are more difficult to forecast, which is reasonable considering, on average, cash flows are more volatile than earnings, 2) analysts are worse at forecasting cash flows than earnings, or 3) both.

Table 3 presents both Pearson and Spearman correlations with the variables of interest and controls. The cf_dummy variable is negatively and significantly associated with the proxy for cost of debt, but multivariate analysis is needed to infer the association. Table 3 also shows a

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volatility, high capital intensity, and poor financial health,. This research design choice biases against finding a result that cash flow forecasts are negatively associated with cost of debt.

[7] TRACE coverage started on July 1, 2002, with 498 bond issues, issuance size of $1 billion or greater; self-reporting was required within seventy-five minutes of trade execution. Additional coverage of trades occurred in steps, with full coverage of publicly traded bonds starting in February 2005; self reporting was required within fifteen minutes of trade execution.

[8] Although bond transactions are also reported on Mergent FISD in a longer time series, the data is limited to include only insurance companies' transactions. Insurance companies hold approximately thirty percent of outstanding bonds (Campbell and Taksler 2003) and are responsible for about a quarter of bond transactions (Hong and Warga 2000). Due to capital requirements necessary to hold non-investment grade bonds, transaction data is sparse for a large portion of the debt market.

[9] In this sample, all of the firm years with cash flow forecasts also have earnings forecasts.

significant correlation between control variables and cost of debt as well as the cf_dummy, validating the inclusion of the variables as controls. Also, these significant correlations suggest tests for multicollinearity to be necessary following the regression procedures.

Table 4 presents both Pearson and Spearman correlations with the variables of interest for the second and third hypotheses. Two important observations are taken from this table. First, the cash flow forecast characteristics are highly correlated with one another, suggesting the individual characteristics are unable to be included in the same regression. Second, the cash flow forecast characteristics and earnings forecast characteristics are highly correlated with one another, suggesting the individual characteristics are unable to be included in the same regression. This validates the decision to decompose earnings forecast characteristics into cash flow forecast characteristics and implicit accrual forecast characteristics in order to test the third hypothesis.

Table 5 presents the results for the tests of H1. Column 1 tests whether the mere presence of an earnings forecast is associated with a lower cost of debt, where the cost of debt proxy is the log of the trade-weighted yield spread of all bonds traded within thirty days following the earnings announcement (log_re). The coefficient of eps_dummy is negative but insignificant, suggesting the presence of earnings forecasts alone is not associated with a lower cost of debt. [10] Column 2 adds in the dummy variable for whether the firm year had a cash flow estimate, cf_dummy. The coefficient on cf_dummy is negative and significant at the 5 percent level, suggesting that the mere presence of a cash flow forecast in combination with an earnings forecast is associated with a lower cost of debt. The significance of this coefficient signals that firm years with cash flow and earnings forecasts have a lower cost of debt relative to firm years with neither forecast. To test whether firm years with cash flow forecasts have a lower cost of debt relative to firm years with only earnings forecasts, this study tests whether the difference is less than zero between the coefficients on eps_dummy and cf_dummy. The null is rejected that the difference is equal to zero ($F= 4.86$, $p > F = .0597$) at the 10 percent level, suggesting firm years with cash flow forecasts have a lower cost of debt relative to firm years with only earnings forecasts.

Column 3 repeats the same test as Column 1, but with the alternative proxy for cost of debt, the most recently traded bond yield spread (log_re). In Column 3, the coefficient on eps_dummy is again negative, but insignificant similar to the result in Column 1. In Column 4, the cash flow dummy is added and is negative and significant at the 5 percent level. A test regarding whether the difference is less than zero between the coefficients on eps_dummy and cf_dummy rejects the null that the difference is equal to zero ($F= 3.11$, $p > F = .0911$) at the 10 percent level. Together, these results support the first hypothesis, that the mere presence of a cash flow forecast is associated with a lower cost of debt. This suggests that cash flow forecasts provide useful information to debt market participants. As far as economic significance is concerned, the coefficient of -.07 on cf_dummy corresponds to a 7 percent decrease in the non-log-transformed basis point spread.[11] Evaluated at the mean (median), this relates to an on-average effect of 22.75 (15.82) basis points. In other words, cost of debt in firm years with cash flow forecasts is on average 22.75 (15.82) basis points lower than cost of debt in firm years with no cash flow forecasts.

[10] This result does not contradict findings from Mansi et al. (2011), who do not test whether the presence of an earnings forecast is associated with cost of debt. They find an association between the number of analyst following and cost of debt.

[11] *Introductory Econometrics: A Modern Approach* by Wooldridge (2011) presents this derivation and interpretation.

Table 6 presents the initial tests of the second hypothesis. Each individual forecast characteristic for both earnings and cash flows is regressed on the proxy for cost of debt with controls suppressed for ease of exhibition. [12] This approach is employed for two reasons: 1) to corroborate the results of Mansi et al. (2011), who find earnings forecast characteristics to be positively associated with cost of debt, validating the sample and empirical design, and 2) the regressions are unable to include all of the forecast characteristics for either earnings or cash flows.

Columns 1, 3, and 5 test individual cash flow characteristics and Columns 2, 4, and 6 test individual earnings forecast characteristics. In Columns 1, 3, and 5, the coefficients on cf_rev_vol, cf_avg_disp, and cf_avg_error are positive and significant, indicating firm years with higher cash flow forecast revision volatility, higher dispersion among analyst estimates, and larger average cash flow forecast errors are associated with higher yield spreads. In Columns 2, 4 and 6, the coefficients on rev_vol, avg_disp, and avg_error are positive and significant, indicating firm years with higher earnings forecast revision volatility, higher dispersion among analyst estimates of earnings, and larger average earnings forecast errors are associated with higher yield spreads. In Columns 7 and 8, the factors obtained from a factor analysis are regressed on cash flow forecast characteristics (cf_factor) and earnings forecasts characteristics (e_factor) on the proxy for cost of debt. Both the cf_factor and e_factor coefficients are positive and significant, providing further evidence of the positive relationship between both cash flow and earnings characteristics and cost of debt and supporting H2. This result speaks to the debate regarding whether cash flow forecasts contain useful information to investors and adds to the result from Chen et al. (2013), which finds the equity market behaves as if cash flow forecasts are informative. By documenting an association between cash flow forecast characteristics and cost of debt, this study provides evidence of the usefulness of cash flow forecasts in the debt market setting. Cash flows are correlated with earnings. Furthermore, earnings forecast characteristics have already been shown to be associated with cost of debt. Thus, additional tests are needed to determine which piece of information is more important to debt market participants.

Table 7 presents the test results of the third hypothesis, whether cash flow or accrual forecast characteristics or both are associated with cost of debt. Due to space constraints, the only results presented are those using the retained factors cf_factor and acc_factor as explanatory variables. As noted previously, each individual forecast characteristic is highly correlated and has been shown to be associated with cost of debt; the factor analysis condenses the characteristics into one clean explanatory variable used to test the hypothesis.[13] In Column 1, the dependent variable is log_wt; in Column 2, the dependent variable is log_re. In support of the third hypothesis, the coefficients on cf_factor are positive and significant at the 5 percent level; the coefficients on acc_factor are insignificant in both models. Together, these results suggest that the characteristics of cash flows are driving previously published results in Mansi et al. (2011) in which an association between earnings forecast characteristics and cost of debt is identified. If earnings forecast characteristics, not simply cash flow forecasts embedded in earnings forecast characteristics, is associated with cost of debt then both accrual and cash flow

[12] The results presented are for the log of the trade-weighted yield spread proxy of cost of debt (log_re). Untabulated results are qualitatively similar when the most recent trade yield spread (log_re) is used.

[13] Analyses were also performed with the individual characteristics of cash flows and accruals, similar to the second hypothesis; the results are qualitatively similar.

forecast characteristics should be associated with cost of debt. However, in this study, only cash flow forecast characteristics were found to be associated with cost of debt.

This study provides evidence in support of all three hypotheses, that the presence of cash flow forecasts and characteristics of cash flow forecasts are associated with a lower cost of debt, cash flow forecasts convey useful information to debt investors by reducing information asymmetry and/or providing monitoring, and also provide information regarding expected default risk. Together, these results provide evidence in support of the argument from Call et al. (2013) that cash flow forecasts provide useful information to investors. It should be noted that this research provides evidence of associations between cash flow forecasts and cost of debt; thus, inferring causality is not possible.

VI. CONCLUSIONS

This study finds that the presence of cash flow forecasts is associated with a lower cost of debt relative to firm-years with only earnings estimates or neither cash flow or earnings estimates. Also, cash flow forecast characteristics are associated with cost of debt after controlling for other known determinants of yield spreads. Additional analyses decomposing earnings forecast characteristics into cash flow and accruals components find the cash flow component is associated with cost of debt, but the accruals component is not. Overall, the results indicate that debt market participants find cash flow forecasts useful in reducing information asymmetry or providing monitoring or both as well as being useful in providing information regarding expected default risk in determining expected returns. These results speak to the debate regarding whether cash flow forecasts contain useful information to security market participants. Subsequent research should attempt to isolate scenarios when earnings forecasts become more informative than cash flow forecasts to debt market participants. Also, additional research should be done regarding how other sources of forward-looking information interact with the debt market.

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Appendix A: Variable definitions

Variable	Definition
log_wt	The natural log of the trade-weighted yield spread.
log_re	The natural log of the yield spread for the debt issue traded most recently to the earnings announcement date.
eps_dummy	An indicator variable equal to 1 if analysts provided a forecast for EPS during the fiscal year.
cf_dummy	An indicator variable equal to 1 if analysts provided a forecast for CF during the fiscal year.
rating_iv	A variable representing the credit rating associated with the relevant yield spread. AAA=1 to D=17.
payout	Dividends plus stock repurchases scaled by total assets.
HHI	The Herfindahl index of sales concentration in firm industry.
stdROA	The standard deviation of quarterly return on assets for previous four years.
Tobinsq	The market value of assets scaled by the book value of assets.
finlev	The book value of debt scaled by total assets.
size	The natural log of book value of debt plus market value of equity.
neg_equity	An indicator variable equal to 1 if book equity is negative and zero otherwise.
productivity	The total sales scaled by total assets.
nasdaq	An indicator variable equal to 1 if a firm is listed on the NASDAQ exchange.
profit	The operating income scaled by total assets.
intang	Intangible assets scaled by total assets.
NWC	Current assets less current liabilities scaled by total assets.
int_cov_dummy	An indicator variable equal to 1 if interest coverage is less than 1.
debt_age	The time between trade and offering date in years for the relevant yield spread.

Appendix A (cont'd): Variable definitions

Variable	Definition
cf_rev_vol	The revision volatility for cash flow forecasts in a given fiscal year. Calculated as the standard deviation in the change of median cash flow forecast over the fiscal year.
rev_vol	The revision volatility for earnings forecasts in a given fiscal year. Calculated as the standard deviation in the change of median earnings forecast over the fiscal year.
cf_avg_disp	The average dispersion of analyst forecasts of cash flows for a given fiscal year. Calculated as the average of standard deviations in each month of analyst cash flow forecasts.
avg_disp	The average dispersion of analyst forecasts of earnings for a given fiscal year. Calculated as the average of standard deviations in each month of analyst earnings forecasts.
cf_avg_error	The average forecast error for cash flow forecasts in a given year. Calculated as the average of the absolute value of the difference between the median forecast of cash flows in a given month and the IBES actual value.
avg_error	The average forecast error for earnings forecasts in a given year. Calculated as the average of the absolute value of the difference between the median forecast of earnings in a given month and the IBES actual value.
acc_rev_vol	The implied revision volatility of accruals for a given year. Implied accrual estimate are calculated for each month by subtracting the median cash flow forecast from the median earnings forecast, compute the month-to-month changes, and the standard deviation of those changes for each fiscal year.
acc_avg_disp	The implied average dispersion of accruals for a given year. Calculated as the average standard deviations in each month of analyst accrual forecasts.
acc_avg_error	The implied average error of accruals for a given year. Calculated as the average of the absolute value of the difference between the median forecast of accruals in a given month and the IBES implied actual value.

Table 1: Sample Selection Procedures

This table presents a summary of sample selection procedures with detailed descriptions of each step and the effect on the sample for this study.

Step	Description	Effect on Sample	Observations
Firms with TRACE data.	Number of firm-years that have at least one trade during a calendar year.		11,936
Compustat variables and trade window.	Number of firm years that have a trade within the designated window following a fiscal year-end and COMPUSTAT data for control variables.	-9,638	2,298
Unusual Yield	Deleted observations of yields greater than 100% to prevent using data entry errors.	-16	2,282
Truncation (Sample for H1)	Deleted firm-year observations with continuous variables in the 1st and 99th percentile of the sample.	-18	2,264
Forecast Characteristics (Sample for H2)	Deleted firm-year observations with missing data for forecast characteristics of both earnings and cash flows	-1,762	502

Table 2: Descriptive Statistics

Variable	Mean	Median	Std Dev	5th Pctl	25th Pctl	75th Pctl	95th Pctl
bp_sprd_wt	325.004	226.976	291.429	59.357	119.698	434.646	945.648
bp_sprd_re	322.164	218.784	297.325	58.094	117.526	432.524	945.556
log_wt	5.429	5.425	0.856	4.084	4.785	6.075	6.852
log_re	5.412	5.388	0.860	4.062	4.767	6.070	6.852
profit	0.041	0.043	0.060	-0.058	0.020	0.073	0.130
payout	0.036	0.019	0.045	0.000	0.004	0.053	0.130
tobinsq	1.571	1.394	0.598	0.957	1.163	1.795	2.787
size	8.932	8.980	1.401	6.620	7.882	9.934	11.264
finlev	0.329	0.310	0.156	0.115	0.218	0.412	0.620
intang	0.204	0.155	0.190	0.000	0.036	0.328	0.579
nwc	0.099	0.075	0.126	-0.065	0.001	0.183	0.332
productivity	0.928	0.790	0.630	0.275	0.457	1.177	2.248
hhi	0.064	0.043	0.061	0.013	0.027	0.072	0.209
stdROA	0.015	0.008	0.018	0.003	0.005	0.017	0.050
cf_dummy	0.400	0.000	0.490	0.000	0.000	1.000	1.000
eps_dummy	0.635	1.000	0.482	0.000	0.000	1.000	1.000
nasdaq	0.129	0.000	0.336	0.000	0.000	0.000	1.000
rating_iv	10.328	10.000	3.725	5.000	7.000	14.000	16.000
trade_weighted_rating	10.325	10.000	3.688	5.000	7.400	14.000	16.000
debt_age	2.721	2.000	1.711	1.000	1.000	4.000	6.000
trade_weighted_age	2.686	2.448	1.491	1.000	1.615	3.698	5.458
int_cov_dummy	0.304	0.000	0.460	0.000	0.000	1.000	1.000
neg_equity	0.026	0.000	0.158	0.000	0.000	0.000	0.000
cf_rev_vol	0.331	0.216	0.342	0.041	0.104	0.422	1.135
rev_vol	0.206	0.088	0.310	0.014	0.037	0.228	0.854
cf_avg_disp	0.554	0.429	0.473	0.083	0.210	0.748	1.498
avg_disp	0.147	0.065	0.200	0.019	0.036	0.153	0.613
cf_avg_error	0.855	0.518	1.045	0.074	0.252	1.066	2.493
avg_error	0.287	0.134	0.415	0.019	0.058	0.323	1.114
acc_rev_vol	0.233	0.162	0.224	0.028	0.082	0.301	0.671
acc_avg_error	0.766	0.422	1.060	0.057	0.210	0.853	2.702

Table 3: Correlations of Variables, H1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) payout	1.000	-0.013	**-0.194**	**0.423**	**-0.244**	**0.441**	**-0.081**	**-0.131**	**0.512**	**0.105**	**-0.090**	**-0.411**	**-0.565**	**-0.070**	**-0.332**	**0.214**	**0.151**
		0.531	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.001	<.0001	<.0001	<.0001
(2) hhi	**0.059**	1.000	**0.100**	**0.070**	**-0.108**	**-0.176**	-0.013	0.028	**0.054**	**0.124**	**0.235**	0.024	**0.166**	0.022	**0.183**	-0.021	-0.018
	0.004		<.0001	0.001	<.0001	<.0001	0.519	0.174	0.009	<.0001	<.0001	0.253	<.0001	0.282	<.0001	0.312	0.394
(3) stdROA	**-0.122**	**0.042**	1.000	0.012	0.012	**-0.218**	**0.148**	**0.121**	**-0.124**	**-0.146**	**0.220**	**0.228**	**0.265**	**0.049**	**0.273**	**-0.081**	**-0.065**
	<.0001	0.046		0.578	0.577	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.019	<.0001	<.0001	0.002
(4) tobinsq	**0.522**	0.016	-0.013	1.000	**-0.238**	**0.329**	**0.055**	**-0.047**	**0.608**	**0.095**	**0.077**	**-0.399**	**-0.340**	**-0.135**	**-0.359**	**0.153**	**0.106**
	<.0001	0.431	0.527		<.0001	<.0001	0.008	0.024	<.0001	<.0001	0.000	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
(5) finlev	**-0.148**	**-0.060**	**0.117**	**-0.165**	1.000	**-0.262**	**0.212**	**0.144**	**-0.389**	0.006	**-0.249**	**0.406**	**0.417**	**0.049**	**0.267**	**-0.165**	**-0.068**
	<.0001	0.004	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001	0.774	<.0001	<.0001	<.0001	0.018	<.0001	<.0001	0.001
(6) size	**0.343**	**-0.096**	**-0.200**	**0.330**	**-0.264**	1.000	**-0.077**	**-0.232**	**0.319**	**0.053**	**-0.292**	**-0.306**	**-0.696**	**-0.113**	**-0.473**	**0.360**	**0.179**
	<.0001	<.0001	<.0001	<.0001	<.0001		0.000	<.0001	<.0001	0.011	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
(7) neg_equity	-0.008	-0.021	**0.213**	**0.044**	**0.339**	**-0.089**	1.000	**0.052**	**-0.114**	**-0.045**	**-0.071**	**0.167**	**0.147**	**0.035**	**0.136**	**-0.065**	-0.031
	0.703	0.312	<.0001	0.035	<.0001	<.0001		0.012	<.0001	0.030	0.001	<.0001	<.0001	0.089	<.0001	0.002	0.134
(8) nasdaq	**-0.055**	-0.002	**0.110**	-0.025	**0.189**	**-0.236**	**0.052**	1.000	**-0.132**	**0.116**	**0.092**	**0.165**	**0.272**	0.001	**0.185**	-0.020	**0.094**
	0.009	0.933	<.0001	0.234	<.0001	<.0001	0.012		<.0001	<.0001	<.0001	<.0001	<.0001	0.959	<.0001	0.345	<.0001
(9) profit	**0.430**	-0.007	**-0.354**	**0.487**	**-0.325**	**0.300**	**-0.146**	**-0.119**	1.000	**0.065**	**0.104**	**-0.756**	**-0.433**	**-0.073**	**-0.312**	**0.156**	**0.066**
	<.0001	0.734	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		0.002	<.0001	<.0001	<.0001	0.000	<.0001	<.0001	0.002
(10) intang	**0.076**	-0.010	**-0.088**	**0.042**	**0.039**	**0.055**	**-0.049**	**0.130**	0.023	1.000	**0.095**	-0.026	**-0.060**	**-0.045**	-0.022	0.019	**0.092**
	0.000	0.622	<.0001	0.043	0.061	0.008	0.019	<.0001	0.272		<.0001	0.206	0.004	0.029	0.289	0.354	<.0001
(11) nwc	-0.033	**0.122**	**0.177**	**0.076**	**-0.225**	**-0.299**	**-0.061**	**0.099**	**0.038**	-0.012	1.000	-0.026	**0.145**	-0.003	**0.120**	**-0.084**	-0.001
	0.116	<.0001	<.0001	0.000	<.0001	<.0001	0.004	<.0001	0.070	0.561		0.212	<.0001	0.870	<.0001	<.0001	0.964
(12) int_cov_dummy	**-0.316**	0.024	**0.265**	**-0.327**	**0.433**	**-0.310**	**0.167**	**0.165**	**-0.656**	-0.023	-0.028	1.000	**0.455**	**0.094**	**0.344**	**-0.144**	**-0.061**
	<.0001	0.254	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.260	0.180		<.0001	<.0001	<.0001	<.0001	0.003
(13) trade_weighted_rating	**-0.422**	**0.091**	**0.278**	**-0.340**	**0.446**	**-0.699**	**0.153**	**0.281**	**-0.396**	-0.026	**0.149**	**0.456**	1.000	**0.149**	**0.601**	**-0.307**	**-0.164**
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.220	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001
(14) trade_weighted_age	**-0.075**	0.013	**0.079**	**-0.129**	**0.041**	**-0.130**	**0.038**	0.006	**-0.057**	-0.024	0.005	**0.098**	**0.131**	1.000	**0.225**	0.021	0.005
	0.000	0.532	0.000	<.0001	0.050	<.0001	0.068	0.790	0.006	0.255	0.814	<.0001	<.0001		<.0001	0.315	0.803
(15) log_wt	**-0.231**	**0.131**	**0.276**	**-0.320**	**0.285**	**-0.471**	**0.134**	**0.186**	**-0.324**	-0.013	**0.128**	**0.338**	**0.589**	**0.237**	1.000	**-0.185**	**-0.119**
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.526	<.0001	<.0001	<.0001	<.0001		<.0001	<.0001
(16) cf_dummy	**0.180**	**-0.047**	**-0.069**	**0.151**	**-0.159**	**0.351**	**-0.065**	-0.020	**0.119**	0.020	**-0.091**	**-0.144**	**-0.305**	0.003	**-0.188**	1.000	**0.618**
	<.0001	0.024	0.001	<.0001	<.0001	<.0001	0.002	0.345	<.0001	0.337	<.0001	<.0001	<.0001	0.879	<.0001		<.0001
(17) eps_dummy	**0.115**	-0.033	**-0.060**	**0.100**	**-0.060**	**0.188**	-0.031	**0.094**	**0.045**	**0.087**	-0.010	**-0.061**	**-0.163**	-0.009	**-0.120**	**0.618**	1.000
	<.0001	0.112	0.004	<.0001	0.004	<.0001	0.134	<.0001	0.031	<.0001	0.625	0.003	<.0001	0.660	<.0001	<.0001	

The above table lists the correlations between the variable of interest and control variables for the first hypothesis. Pearson correlations are beneath the diagonal; Spearman correlations are above the diagonal. P-values are listed below the correlations. Significant correlations are in bold.

Table 4: Correlations of Variables, H2

	log_wt	cf_rev_vol	rev_vol	cf_avg_disp	avg_disp	cf_avg_error	avg_error
log_wt	1.000	**0.162**	**0.258**	**0.103**	**0.286**	**0.106**	**0.238**
		0.000	0.000	0.020	0.000	0.017	0.000
cf_rev_vol	**0.150**	1.000	**0.678**	**0.704**	**0.640**	**0.578**	**0.650**
	0.001		0.000	0.000	0.000	0.000	0.000
rev_vol	**0.177**	**0.944**	1.000	**0.435**	**0.790**	**0.467**	**0.908**
	0.000	0.000		0.000	0.000	0.000	0.000
cf_avg_disp	**0.094**	**0.891**	**0.808**	1.000	**0.535**	**0.521**	**0.443**
	0.035	0.000	0.000		0.000	0.000	0.000
avg_disp	**0.168**	**0.915**	**0.927**	**0.860**	1.000	**0.465**	**0.757**
	0.000	0.000	0.000	0.000		0.000	0.000
cf_avg_error	0.046	**0.812**	**0.757**	**0.918**	**0.820**	1.000	**0.486**
	0.304	0.000	0.000	0.000	0.000		0.000
avg_error	**0.114**	**0.914**	**0.900**	**0.927**	**0.909**	**0.943**	1.000
	0.010	0.000	0.000	0.000	0.000	0.000	

The above table lists the correlations between the earnings and cash flow forecast characteristics in the sample for the second hypothesis. Pearson correlations are beneath the diagonal; Spearman correlations are above the diagonal. P-values are listed below the correlations. Significant correlations are in bold.

Table 5: Tests of H1

Variable	1	2	3	4
intercept	4.557***	4.520***	4.851***	4.815***
	0.000	0.000	0.000	0.000
cf_dummy		-0.073**		-0.067**
		0.026		0.033
eps_dummy	-0.019	0.023	-0.031	0.007
	0.476	0.470	0.199	0.799
tw_rating	0.113***	0.112***		
	0.000	0.000		
payout	0.391	0.409	0.301	0.319
	0.217	0.198	0.341	0.316
hhi	0.642***	0.628***	0.444**	0.431**
	0.003	0.004	0.041	0.050
stdroa	2.221***	2.214***	1.743**	1.735**
	0.004	0.004	0.018	0.018
tobinsq	-0.036	-0.037	-0.020	-0.021
	0.201	0.192	0.450	0.438
finlev	0.120	0.116	0.211*	0.206*
	0.303	0.314	0.052	0.057
size	-0.041***	-0.036***	-0.070***	-0.065***
	0.002	0.007	0.000	0.000
neg_equity	0.142*	0.139*	0.022	0.019
	0.087	0.089	0.775	0.799
altman_z	0.045*	0.048*	0.039	0.042
	0.096	0.076	0.142	0.117
nasdaq	-0.006	-0.005	0.010	0.010
	0.900	0.905	0.832	0.830
profit	-0.750**	-0.758**	-0.826***	-0.833***
	0.016	0.014	0.005	0.005
intang	0.006	-0.002	0.000	-0.009
	0.931	0.969	0.993	0.898
nwc	0.226*	0.207*	0.276**	0.258**
	0.060	0.085	0.019	0.028
int_cov_dummy	0.030	0.029	0.021	0.021
	0.339	0.352	0.485	0.502
tw_age	0.019**	0.020**		
	0.021	0.018		
rating_iv			0.109***	0.108***
			0.000	0.000
debt_age			0.017***	0.017***
			0.005	0.005
N	2,264	2,264	2,264	2,264
R^2	0.667	0.668	0.714	0.715

Significance of coefficients is marked by asterisks, with ***, **, and * representing significance at the 1%, 5%, and 10% levels, respectively, from an OLS regression. In Columns 1 and 2, the dependent variable is the log of trade-weighted yield spread (log_wt). In Columns 3 and 4, the dependent variable is the log of the most recently traded bond yield spread (log_re). Both industry and year fixed effects are included; errors are clustered by firm in all four models. Independent variables include: cf_dummy, an indicator variable equal to 1 if a firm has a cash flow during the fiscal year; eps_dummy, an indicator variable equal to 1 if a firm has an earnings forecast during the fiscal year; trade_weighted_rating, the trade-weighted credit rating of the bond issues used to calculate the dependent variable ; payout, the sum of dividends plus stock repurchases scaled by total assets; hhi, the Herfindahl index of sales concentration in firm industry; stdroa, the standard deviation of quarterly return on assets

for the previous four years; tobinsq, the market value of assets scaled by the book value of assets; finlev. The book value of debt scaled by total assets; size, the natural log of book value of debt plus market value of equity; neg_equity, an indicator variable equal to 1 if book equity is negative and zero otherwise; altman_z, altman's default risk measure; nasdaq, an indicator variable equal to 1 if a firm is listed on the NASDAQ exchange; profit, operating income scaled by total assets; intang. Intangible assets scaled by total assets; nwc, current assets minus current liabilities scaled by total assets; int_cov_dummy, an indicator variable equal to 1 if interest coverage is less than 1; tw_age, the trade-weighted time between trade and offering date in years for the relevant yield spread.

Table 6: Tests of H2

Variable	1	2	3	4	5	6	7	8
intercept	3.478***	3.481***	3.493***	3.493***	3.501***	3.491***	3.508***	3.506***
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
cf_rev_vol	0.068***							
	0.003							
rev_vol		0.115***						
		0.002						
cf_avg_disp			0.022***					
			0.002					
avg_disp				0.103***				
				0.008				
cf_avg_error					0.001***			
					0.000			
avg_error						0.0296***		
						0.004		
cf_factor							0.034***	
							0.001	
e_factor								0.048***
								0.007
tw_rating	0.101***	0.100***	0.102***	0.101***	0.103***	0.102***	0.101***	0.102***
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	502	502	502	502	502	502	502	502
R^2	0.644	0.646	0.643	0.644	0.642	0.644	0.644	0.643

Significance of coefficients is marked by asterisks, with ***, **, and * representing significance at the 1%, 5%, and 10% levels, respectively, from an OLS regression. In all eight columns the dependent variable is the log of trade-weighted yield spread (*log_wt*). All controls and fixed effects from tests of H1 are included in the estimation of these coefficients, but excluded from this table for the sake of exposition. The independent variables tested include rev_vol and cf_rev_vol, defined as the standard deviation of the changes in consensus earnings and cash flow forecast during the fiscal year, avg_disp and cf_avg_disp, defined as the average standard deviation of earnings and cash flow forecasts throughout the fiscal year, avg_error and cf_avg_error, defined as the average of the absolute value of the difference between consensus earnings and cash flow forecast and actual earnings and cash flows during the fiscal year, and tw_rating, defined as the trade weighted credit rating of the bond issues used to compute the dependent variable yield spread. The variables suppressed include: payout, the sum of dividends plus stock repurchases scaled by total assets; hhi, the Herfindahl index of sales concentration in firm industry; stdroa, the standard deviation of quarterly return on assets for the previous four years; tobinsq, the market value of assets scaled by the book value of assets; finlev. The book value of debt scaled by total assets; size, the natural log of book value of debt plus market value of equity; neg_equity, an indicator variable equal to 1 if book equity is negative and zero otherwise; altman_z, altman's default risk measure; nasdaq, an indicator variable equal to 1 if a firm is listed on the NASDAQ exchange; profit, operating income scaled by total assets; intang. Intangible assets scaled by total assets; nwc, current assets minus current liabilities scaled by total assets; int_cov_dummy, an indicator variable equal to 1 if interest coverage is less than 1; trade_weighted_age, the trade-weighted time between trade and offering date in years for the relevant yield spread. Both industry and year fixed effects are included, and errors are clustered by firm.

Table 7: Tests of H3

	(1)		(2)	
Variable	coefficient	p-value	coefficient	p-value
intercept	3.578	0.000**	4.259	0.000***
cf_factor	0.074	0.014**	0.236	0.022**
acc_factor	-0.012	0.924	-0.062	0.724
trade_weighted_rating	0.102	0.000***	0.108	0.000***
payout	0.379	0.578	-0.209	0.740
hhi	1.522	0.023**	1.221	0.075*
stdroa	1.369	0.491	0.004	0.998
tobinsq	0.005	0.951	0.075	0.269
finlev	0.415	0.138	0.449	0.108
size	-0.049	0.187	-0.079	0.025**
neg_equity	-0.108	0.601	-0.381	0.145
altman_z	-0.001	0.943	0.003	0.859
nasdaq	-0.036	0.657	0.009	0.933
profit	-0.373	0.523	-0.651	0.292
intang	-0.024	0.882	0.053	0.727
nwc	0.485	0.110	0.322	0.281
int_cov_dummy	0.095	0.263	0.124	0.143
trade_weighted_age	-0.003	0.907	0.008	0.569
N	502		502	
R^2	0.641		0.713	

Significance of coefficients is marked by asterisks, with ***, **, and * representing significance at the 1%, 5%, and 10% levels, respectively, from an OLS regression. The dependent variable is the log of trade-weighted yield spread (log_wt) in Column (1) and the log of the most recently traded bond yield spread (log_re) in Column (2). Independent variables include cf_factor, a variable created by running a factor analysis on the three cash flow forecast characteristics and retaining the first factor; acc_factor, a variable created by running a factor analysis on the three accrual forecast characteristics and retaining the first factor; trade_weighted_rating, the trade-weighted credit rating of the bond issues used to calculate the dependent variable variable; payout, the sum of dividends plus stock repurchases scaled by total assets; hhi, the Herfindahl index of sales concentration in firm industry; stdroa, the standard deviation of quarterly return on assets for the previous four years; tobinsq, the market value of assets scaled by the book value of assets; finlev. The book value of debt scaled by total assets; size, the natural log of book value of debt plus market value of equity; neg_equity, an indicator variable equal to 1 if book equity is negative and zero otherwise; altman_z, altman's default risk measure; nasdaq, an indicator variable equal to 1 if a firm is listed on the NASDAQ exchange; profit, operating income scaled by total assets; intang. Intangible assets scaled by total assets; nwc, current assets minus current liabilities scaled by total assets; int_cov_dummy, an indicator variable equal to 1 if interest coverage is less than 1; trade_weighted_age, the trade-weighted time between trade and offering date in years for the relevant yield spread.