Debt Analysts' Views of Debt-Equity Conflicts of Interest

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Abstract

Using disclosures provided by sell-side debt analysts in their investment reports, we investigate how the tone of debt analysts’ discussions about debt-equity conflict events affects the informativeness of debt analysts’ reports in debt markets. Conflict events potentially generate asset substitution or wealth expropriation by equity holders and include events such as M&A transactions, additional borrowings, share repurchases, or excessive dividend payments. We document that debt analysts routinely discuss these conflict events in their reports. More importantly, debt analysts’ negative discussions of conflict events are associated with increases in credit spreads and bond trading volume. Consistent with the informational value of debt analysts’ discussions in secondary debt markets, we find that debt analysts’ negative conflict discussions preceding bond issuances in the primary market predict higher yields to maturity. In additional analyses, we also measure the tone of debt analysts’ discussions based on their disagreement with the tone of equity analysts’ discussions and find that the informativeness of debt analysts’ reports is higher when conflict events are viewed negatively by debt analysts but positively by equity analysts.

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1. Introduction

Recent studies such as Johnston, Markov, and Ramnath (2008), De Franco, Vasvari, and Wittenberg-Moerman (2009), and Gurun, Johnston, and Markov (2011) show that investors react to the publication of debt analysts' reports and the recommendations they provide, suggesting that debt analysts act as important information intermediaries in debt markets. Besides providing a review of firms' financial performance in their reports, debt analysts analyze and discuss the effects of debt-equity conflict events that potentially generate asset substitution and wealth expropriation by equity holders, such as M&A transactions, additional borrowings, share repurchases, and excessive dividend payments (hereafter, we refer to these as "conflict events"). This study documents the importance of debt analysts' discussions about conflict events by investigating how credit markets react to the tone of these discussions via changes in credit spreads and bond trading volume. We further test whether analysts' views about conflict events are associated with real effects on a company's cost of debt, as evidenced by analysts' ability to predict the yield to maturity of new bond issues.

While previous studies have established the existence of events that lead to debt-equity conflicts in specific settings, these studies find mixed results with respect to the extent and economic importance of such conflicts to debt holders.[1] If these conflict events have the potential to meaningfully affect debt holders' wealth, debt analysts' discussions can be informative to debt investors. However, if the effect of conflict discussions about outstanding debt securities is not material or if debt analysts' conflict event discussions do not provide valuable new information

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[1] For example, see Schipper and Smith (1983), Parrino and Weisbach (1999), Maxwell and Rao (2003), Woolridge (1983), Dhillon and Johnson (1994), and Maxwell and Stephens (2003). We discuss these papers and others in detail in Section 2.2.

or are not timely, these discussions will not expand the information set available to debt market investors.

The centerpiece of our empirical analysis is the coding of the tone of debt analysts' discussions about conflict events as published in their investment reports. We expect that reports provided by debt analysts will allow us to better assess the impact of conflict events on debt holders' wealth, given debt analysts' primary purpose of informing debt investors. We measure the extent and tone of debt analysts' discussions about different types of conflict events using a unique hand-collected dataset of 11,025 sell-side debt analysts' reports on U.S. firms. Specifically, from each debt analyst's report we extract the text around a comprehensive list of keywords associated with events such as M&A transactions, divestments, dividend payments, stock repurchases or borrowing (e.g., "M&A", "repurchases", "asset sales", "dividends", etc.). We then manually code a large randomly selected subset of these text extractions and use it to calibrate a Naïve-Bayesian model that predicts whether the analyst's discussion is negative, neutral, or positive. In the last step, we use this model to produce a predicted tone for the full sample of text extractions used in our tests.

We document that debt analysts routinely discuss events that are likely to generate debt-equity conflicts in their reports. M&A activities are frequently discussed events, with 63% of the debt analysts' reports mentioning such transactions. In 32% of the reports, analysts talk about potential wealth redistribution from debt to equity holders via stock repurchases or dividend payments. Divestment discussions characterize about 18% of the reports. Matters of financial risk and borrowing, a comprehensive category that includes discussions about "debt" and "leverage", comprise the most frequently discussed subject (91% of the reports). We also find that debt analysts' conflict discussions not only follow but also anticipate firm announcements of these conflict events, highlighting their informativeness. While debt analysts are more likely to interpret the conflict events for debt investors as positive (24% of reports) compared with negative (17% of reports), in most cases (59%) these events are interpreted as mixed or neutral news for debt investors. This finding suggests that conflict events are not always expected to destroy debt holders' wealth. Instead, these events can provide a positive signal regarding a firm's performance, represent news that is less negative than debt holders initially expected or simply not material.

We next find that the tone of debt analysts' conflict discussions is positively related to analysts' investment recommendations and recommendation revisions, the main summary outputs of their reports. These relations provide additional support for the notion that the tone of debt analysts' conflict discussions is likely informative to debt market participants. Further, the tone of the conflict discussions helps to explain disagreement between the recommendations of debt and equity analysts, consistent with the tone indicating potential wealth expropriation concerns.

Turning to our debt market tests, we first find that debt analysts' reports are more relevant to debt investors, as evidenced by stronger debt market reactions, when the reports contain negative discussions of debt-equity conflicts. After controlling for a wide range of economic factors that affect CDS spreads, we document that firms' credit default swap (CDS) spread changes are significantly increasing in debt analysts' negative discussion of conflict generating events. Relative to reports with positive or neutral discussions, reports that include negative discussions increase the CDS spread by 16 basis points over a five-day window centered on the date of debt analysts' report. In particular, we show that when equity investors' wealth improves, as evidenced by positive equity returns, analysts' negative discussions of conflict events lead to an even stronger positive effect on credit spreads. This result suggests that debt analysts' negative conflict discussions highlight potential wealth transfers from debt holders to equity holders. To corroborate these CDS reactions, we show that when debt analysts' reports include negative discussions about conflict events, relative to reports with neutral or positive discussions, the daily bond trading volume is higher by about 1.1% of the bonds' principal over the five-day window centered on the date of the report.

Consistent with our results above for the secondary debt market, we document that debt analysts' negative conflict discussions that precede the issuance of new bond securities in the primary market predict the initial pricing of these bonds. Their yield to maturity increases with the negative tone of conflict discussions in debt analysts' reports published in the six-month period before the bond issuance, after controlling for a variety of firm and bond specific characteristics, debt and equity analysts' recommendations, and the occurrence of conflict events. This result is also robust to controlling for endogeneity between bond yields and other debt contract terms such as covenants. In terms of economic significance, we find that negative conflict discussions have a meaningful effect. They increase the offering yield by 27 basis points (4.0% of the median sample yield) relative to neutral or positive discussions. This impact suggests that debt analysts' views also provide additional information to primary bond market investors and affect borrowing firms' cost of debt financing.

Next, we test whether the importance of negative conflict discussions varies cross-sectionally with firms' credit ratings across our three market variables – daily CDS spread changes, daily bond trading volume, and yields on new bond issues. We find some evidence suggesting that negative conflict discussions are more important for lower-rated debt, consistent with an increase in the informational value of debt analysts' discussions in settings where debt investors are more sensitive to news.

To provide additional evidence that debt analysts' conflict discussions capture the construct of conflict between debt and equity holders, we develop and test an alternative measure of the tone of these discussions. This measure is based on the disagreement in the tone of conflict discussions between debt and equity analyst reports, which may more directly capture the idea of conflict between debt and equity investors. We construct a firm-matched sample of equity analysts' reports that are issued prior to the debt analyst's report. As in the case of debt analysts' reports, we extract equity analysts' discussions of conflict events from these reports and measure the discussions' tone using the Naïve-Bayesian model. We then create an alternative hybrid measure of debt analysts' conflict discussions, by focusing on debt analysts' reports that contain negative conflict discussions when equity analysts' conflict discussions are positive.

Using this alternative measure, we continue to find strong CDS credit spread and bond volume reactions to debt analysts' negative conflict discussions, further supporting our conjecture that debt analysts' reports are more informative if the tone of the discussions is negative. Bond offering yields are also significantly higher when conflict events are viewed negatively by debt analysts but positively by equity analysts, confirming that debt analysts' conflict discussions are informative with respect to the initial pricing of bond securities in the primary market.

Our study contributes to the literature across several dimensions. First, we contribute to research on the role of information intermediaries such as analysts, rating agencies, and the press in shaping firms' information environments.[2] We provide unique evidence showing that the tone

[2] See, for example, studies by: Brennan, Jegadeesh, and Swaminathan (1993), Brennan and Subrahmanyam (1995), Frankel, Kothari and Weber (2006), Ederington and Goh (1998), Hand, Holthausen, and Leftwich (1992), Dichev and Piotroski (2001), Jorion, Liu and Shi (2005), Beaver et al. (2006), Fang and Peress (2009), Bushee et al. (2010), and Soltes (2010).

of debt analysts' discussions reflects new information generated by analysts that expands the information set available to debt market investors. Our conflict-event discussion variable exhibits an incremental effect after controlling for firm-initiated disclosures and the disclosures of other intermediaries such as rating agencies and equity analysts.

Second, we add to the small but growing literature on debt analysts. Although a vast number of studies investigate the activities of equity analysts or the use of their forecasts and recommendations, to date, limited evidence has been provided on the role of debt analysts. This is notable, given that the U.S. corporate debt market is the largest and most important source of capital for U.S. corporations.[3] Johnston et al. (2009), De Franco et al. (2009), and Gurun et al. (2011) find that bond and equity markets react to the publication of debt analysts' reports and their recommendations and conclude that these intermediaries enhance the price discovery process. Our analyses complement these studies by providing insights into the type of information produced by debt analysts that explains the debt market's reaction to these reports, beyond their recommendations. In addition, we provide new evidence on the relation between debt analysts' reports and firms' borrowing costs in the primary bond market.[4]

Third, we provide and examine an empirical measure that captures debt holders concerns about wealth expropriation and asset substitution without the need to directly rely on bond returns around conflict events, as much of the prior literature does. Bond returns capture these concerns with significant measurement error caused by infrequent bond trading, divergent reactions due to different bond features, or reactions to firm fundamentals. Many conflict events

[3] For example, according to Bessembinder and Maxwell (2008), for the decade ending in 2006, U.S. firms issued $4.6 trillion of corporate bonds, compared with $1.5 trillion of initial and seasoned public common equity.

[4] To our knowledge, there is no work investigating the impact of debt analysts' reports on firms' bond yields or their cost of debt. Even prior work on the relation between equity analysts' disclosures and firms' debt costs is limited. Guntay and Hackbarth (2010) and Mansi et al. (2010) find that equity analysts' forecast dispersion and forecast revision volatility increase bond yield spreads.

may also be anticipated by the market and therefore are not captured by short-window bond returns around the actual event. Further, with the exception of Parrino and Weisbach (1999), whose empirical analysis is limited to 23 firms, prior research on debt-equity conflicts has almost always focused on one particular type of conflict event in isolation, without assessing the interactions between conflict events and their simultaneous effect on debt holders' wealth. This further contributes to the inconclusive evidence prior research provides with respect to the importance of conflicts to debt holders.[5] Our approach of coding the tone of debt analysts' discussions about potential debt-equity conflicts allows us to document the importance of these conflicts as well as to determine whether and how debt holders' wealth is affected.

The next section develops our research question and reviews related literature on debt-equity conflicts. Section 3 describes our data and the measurement of debt analysts' discussions of conflict events. Section 4 discusses the results of our tests. Section 5 concludes.

2. Literature review and research questions

2.1. Background on debt analysts[6]

Most corporate bonds are traded in an opaque over-the-counter dealer market and often become absorbed in "buy-and-hold" portfolios shortly after issuance. Thus, the low ex-post and, in particular, ex-ante transparency of bond trading provides debt analysts with an opportunity to play a significant role in supporting the informational efficiency of the corporate debt market. Similar to equity analysts, debt analysts analyze firms' fundamental performance and firm-

[5] Prior studies also use very small samples, either because data on conflict events and bond prices has been difficult to collect or because of the infrequency of bond trading (Edwards, Harris, and Piwowar, 2006).

[6] Part of this background information is based on our discussions with debt analysts and other debt market participants. In particular, we thank Richard Phelan, Managing Director of the European High Yield Research Team at Deutsche Bank and Peter Morris, formerly a sell-side debt analyst at Goldman Sachs and Managing Director in the European credit research team at Morgan Stanley. Also note that our study is about sell-side debt analysts, but for parsimony we refer to them simply as debt analysts. In this paper, we do not study buy-side debt analysts or analysts employed by credit rating agencies.

specific events, except that they place a strong emphasis on how a firm's performance and events impact its credit quality. The investment recommendations they provide are driven by the perceived effect of a firm's performance and actions on its ability to pay off its debt, given market factors and the specific contractual features of debt agreements that shield debt investors from potential losses. Debt analysts' perceived market underpricing of particular bond securities, relative to other bonds of similar credit risk, contributes to the issuance of "buy" recommendations. Typically, debt analysts' investment recommendations (e.g., buy, hold, or sell) have an approximate 90-day horizon and cover all bond securities issued by a given firm that are actively trading in the secondary market. De Franco et al. (2009) find that the distribution of debt analysts' recommendations is skewed positively but less positively than the distribution of equity analysts' recommendations. This result suggests that debt analysts, relative to equity analysts, act less strategically and provide more negative information, which likely meets the asymmetric demand for negative information by bond investors.

Besides an investment recommendation, debt analysts' reports also provide discussions of firms' financial performance, including a detailed examination of EBITDA, free cash flows, capital expenditures, liquidity, and leverage ratios, and of lending market conditions or relative bond pricing. More importantly for our study, the reports extensively discuss risks associated with conflict events, such as M&A transactions, new debt issuances, asset sales, dividend payments, or share repurchases. Debt analysts' concerns about asset substitution and wealth expropriation activities that favor equity holders could lead to disagreement between debt and equity analysts. Debt analysts may anticipate these events or discuss them as they occur, although often with some lag, as reports must normally be approved by the investment bank's compliance department.[7] The value of debt analysts' reports should, inter alia, stem from the analyses they provide about conflict events. Recommendations without proper analysis and support are more likely to be ignored by institutional clients. This is detrimental to debt analysts because in the secondary over-the-counter debt market, where the overwhelming majority of debt securities trade, almost all investors are institutions (see, for example, Warga, 2004). Further, debt analysts are compensated in part based on institutional client surveys that assess the value of debt analysts' research.

2.2. Importance of debt analysts' discussions of conflict events

Given the discussion in the previous section, we broadly partition the type of news that debt analysts provide their institutional investors into two groups: news concerning firms' fundamentals and news about the distribution of wealth between debt and equity investors. Our study focuses on the latter type of news (i.e., conflict events). These conflict events occur when firms take unexpected investment and financing actions that could increase the value of shareholder equity claims, but that decrease the value of the outstanding debt (e.g., Jensen and Meckling, 1976; Myers, 1977). As discussed earlier, examples of such events include asset substitution manifested through unexpected increases in risky investments (M&A transactions), asset sales or additional borrowings, and direct wealth expropriation by equity holders via excessive dividend payouts or stock repurchases. Debt analysts' views on a particular conflict event are likely to take into account the level of protection that debt holders receive from the protective features embedded in the debt contract (i.e., covenants, collateral, putability of a bond,

[7] Debt analysts in our study differ from 'desk' analysts who work closely with trading desks. Desk analysts can issue statements based on any type of information, including rumors, to select clients and do not need to obtain approval from their compliance department. Comments by desk analysts are typically not published and not widely disseminated.

sinking fund provisions, etc.). Hence if, for example, analysts were to issue a negative view of a conflict event, they may perceive these protective features as insufficient.

On one hand, because debt-equity conflicts have the potential to meaningfully affect debt holders' wealth, we expect debt holders to demand information on these events and for debt analysts to meet this demand. If the potential conflict is material, whether or not it has been anticipated, debt analysts are likely to monitor, analyze, and discuss its effect on the value of outstanding debt securities in their reports. In particular, we expect conflict discussions to distinguish debt analysts' from equity analysts' reports. If the contents of the former were limited only to an analysis of a firm's fundamentals, such as the level of EBITDA or earnings, the distinction between equity and debt analysts' reports would be blurred because we would expect both types of analysts to monitor and evaluate the firm's performance. Therefore, our prediction is that the tone of debt analysts' conflict discussions is relevant for debt investors and generates debt market reactions. Given the payoff function of debt securities, which are fixed claims against the borrowing firm and have limited upside potential, we expect debt holders to have an asymmetric demand for negative information. As a result, we predict that debt market reactions will be stronger if debt analysts have negative views about conflict events. Empirically, we measure debt market reactions by changes in secondary market CDS spreads and bond trading volume and by the level of bonds' yield to maturity on new bond issues in the primary market. Our primary market setting reinforces the economic importance of conflict discussions because yields on new issues represent real effects on a company's cost of debt financing.

On the other hand, the extent and economic importance of such conflicts to debt holders, as documented by extant studies, is far from clear. Parrino and Weisbach (1999), discussed above, is one example. In the case of spin-offs, Hite and Owers (1983) and Schipper and Smith (1983) find no evidence of a wealth transfer at the time of the announcement, while Maxwell and Rao (2003) document a wealth transfer from debt holders to equity holders. With respect to cash payouts, Woolridge (1983), Handjinicolaou and Kalay (1984), and Dann (1981) do not find that dividend payments have a detrimental effect on bondholders. In contrast, Dhillon and Johnson (1994) and Maxwell and Stephens (2003) find evidence supporting a wealth transfer from debtholders for large dividend changes and share repurchases, respectively. Finally, while, Asquith and Wizman (1990), Warga and Welch (1993) and Billett, King, and Mauer (2004) document a loss in debt holders' wealth associated with leveraged buyouts and acquisitions, Lehn and Poulsen (1991) and Marais, Schipper, and Smith (1989) find that leveraged buyouts do not result in a wealth transfer. If conflicts events are not material or have a minimal effect on debt holders' wealth, as suggested by some of these studies, the debt market should not react to the tone of debt analysts' conflict discussions. Similarly, the debt market should not react to the tone of debt analysts' conflict discussions if they do not provide valuable new information to debt investors or are not timely.

Across all three market settings – CDS spreads, bond trading volume, and new bond issues' yield to maturity – we expect the importance of conflict discussions to vary cross-sectionally with firms' debt rating. For higher quality debt, debt prices are less sensitive to new information, either because the likelihood of a loss is very small or because the upside potential is already limited. In contrast, for lower quality debt, bond prices are highly sensitive to information (De Franco et al., 2009; Easton et al., 2009), making the news provided by debt analysts' conflict discussions more valuable to debt investors. Based on this argument, we predict that the tone of debt analysts' conflict discussions leads to greater market reactions for lower rated debt.

However, there is some merit in the opposite prediction as well. If bond investors' asymmetric demand for negative information is the main driver of the demand for conflict discussion, then the market reactions could be higher when credit quality is high, as asymmetric demand is stronger for firms with higher credit quality (De Franco et al., 2009). In addition, it is likely that the discussions of conflict events conducted by debt analysts already take into account firms' credit riskiness. Hence, when the tone of these discussions is conditional on the firm's credit rating, it may not generate differential market reactions. Thus, the cross-sectional variation of the importance of conflict event discussions across rating categories is ultimately an empirical question.

3. Data and measurement of debt analysts' conflict-event discussions

3.1. Collection of debt analysts' reports

We obtain debt analysts' reports from First Call Thomson ONE Analytics. For each report we manually code the analyst name, brokerage firm, report date, investment recommendation, and the name of the company covered by the report. The majority of debt analysts' recommendations are at the firm level, i.e., they refer to all of the firm's bonds that are actively trading in the secondary market.[8] If the broker has not already done so, we standardize the debt analysts' recommendations into three categories: buy, hold, or sell.[9] We also collect current rating information (Moody's or Standard and Poor's) from the reports.

We select reports about U.S. corporate firms with bond securities for the years 2002-2007. The start of this period aligns with the availability of bond trading data from the TRACE (Trade Reporting and Compliance Engine) database. We exclude reports on Real Estate

[8] Debt analysts sometimes provide investment recommendations at the security level (for a particular bond issue), instead of at the firm level. For our research sample, in almost in all cases when recommendations at the security level are available for each of the firm's bonds, these recommendations are identical.

[9] We standardize the recommendations to Buy, Neutral, and Sell. While most brokers typically employ these three recommendation levels, some use a system of five levels (Strong Buy, Buy, Neutral, Sell, Strong Sell). The standardization to three levels allows us to pool the recommendations together in our empirical tests.

Investment Trusts; on financial institutions, such as banks or insurance companies, reports about companies domiciled in non-U.S. countries; reports about macro-economic variables; industry reports; and reports that are aggregated by time. This last type often simply repeats previously published information in reports (e.g., Stickel, 1995; De Franco and Hope, 2011). Reports missing an investment recommendation are excluded from the analysis.[10] This procedure for collecting debt analysts' reports is similar to that used in De Franco et al. (2009).

3.2. Measuring the tone of debt analysts' discussions of conflict events

We employ a computational-linguistic method to code the text in debt analysts' reports. Our objective is to obtain a detailed quantitative understanding of debt analysts' discussions of events that signal potential deterioration in the issuer's credit quality for the benefit of equity holders.[11] In particular, we take the following five steps:

Step 1. We convert the debt analysts' reports from a PDF format into text files and identify certain generic conflict-event "keywords." These words and phrases indicate the occurrence of an event that alters the credit quality of the issuer and can indicate a potential wealth transfer from debt to equity holders. Classified into five main categories, the keywords include the following words in italics (and all their linguistic derivatives): (1) Mergers & Acquisitions (M&A) – *Merger, Acquisition, Leveraged Buyout,* and *Management Buyout*; (2) Wealth distribution – *Repurchase, Dividend*, and *Cash Distribution*; (3) Divestments – *Spin-off* and *Asset Sales*; (4) Financial risk – *Debt* and *Leverage*; and (5) Other – *Capital Expenditure* (or

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[10] In some cases, multiple companies are each discussed separately in a single large report. We employ a combination of manual and automated procedures to split reports that discuss multiple companies into discussions of single companies. In our tabulated analyses, we do not distinguish between extractions obtained from these multi-company and single-company reports.

[11] Our Naïve Bayesian updating algorithm approach, as we describe below, builds on the burgeoning accounting and finance research that uses the tools of computational linguistics (i.e., Tetlock, 2007; Tetlock, Saar-Tsechansky, and Macskassy, 2008; Kothari, Li, and Short, 2009; Fieldman, Govindaraj, Livnat, and Segal, 2009; Li, 2010, Rogers, Van Buskirk, and Zechman, 2011). Review articles such as Core (2001) and, more recently, Beyer, Cohen, Lys, and Walther (2010) call for more work in this area.

Capex), *Event Risk, Shareholder Pressure, Shareholder Friendly, Shareholder Focus, Wealth Transfer*, and *Covenants*. The financial risk category is meant to capture a variety of management actions that could lead to changes in financial risk, and hence to a wealth transfer from equity to debt holders. The last category captures miscellaneous discussions about capital expenditures, changes in covenants or the likelihood of covenant violations, and general notions such as "event risk" and management's "equity focus."

Step 2. For each keyword appearing in a debt analyst's report, we extract the text discussion surrounding the keyword. For example, if the word "repurchase" appears in the report, we extract the words contained in the five sentences around each keyword occurrence (i.e., the sentence that contains the key word and the two sentences before and after it).[12] For each report, we then accumulate the text extractions by keyword. For example, if the word "repurchase" appears again in the report, we extract the surrounding text and group it with the text surrounding the first occurrence of the keyword. Thus, for each keyword, we are able to extract from the report all of the analyst's discussion about that keyword. Each keyword text extraction corresponds to a different conflict event.

Step 3. We use a "Naive Bayes" approach (implemented via the "Rainbow" program) to classify the keyword text extractions identified in the previous step as positive, negative, or neutral.[13] This approach has been used by researchers such as Antweiler and Frank (2004) and Li (2010). To estimate the Naive Bayes model, we need a set of data to "train" the algorithm. We create this training data set by manually classifying 5,933 randomly selected text extractions as positive, negative, or neutral. Appendix 2 provides some examples of text extractions and the

[12] The computerized identification of sentences in text is an approximation because in some instances there are errors in distinguishing periods from decimal points and text from words contained in figures and tables. We have no reason to believe that this error is systematically related to any of our tested relations, and hence it should not affect our inferences.
[13] "Rainbow" software is publicly available from Andrew McCallum at http://www.cs.cmu.edu/~mccallum/bow.

manual coding (positive, neutral, or negative) for each extraction.[14] We then use the text and the manually coded tone from the training dataset to generate a Naive Bayes model that predicts the analyst's tone conditional on the words in the text extraction.

Step 4. We use the model to generate predictions of the tone for all the text extractions in our sample. This prediction equals negative one if the Naïve Bayes algorithm classifies the text extraction as negative, zero if it is classified as neutral, and one if it is classified as positive. To determine the accuracy of the Naïve Bayes algorithm, we use a procedure similar to that of Li (2010) and Antweiler and Frank (2004) to calculate both the "within-sample" and "out-of-sample" accuracies of the classifications by comparing the algorithmic classifications with the manual classifications (from step 3). To calculate the out-of-sample accuracy, we randomly partition the manually coded training dataset into two parts. One part is used to train and estimate the model, while the other is used to test the classification accuracy. For expositional purposes, in Table 1, Panel A we present the results of partitioning the sample into two equal halves (50% each). For an example, refer to the first row of Panel A. Out of a total of 262 manually classified negative text extractions, 124 were correctly classified as negative by the model — an accuracy rate of 47%. The out-of-sample accuracy is 77% for neutral tone extractions, 31% for positive tone extractions, and 67% across all extractions. To evaluate the within-sample accuracy, we use the entire manually coded training dataset to estimate the Naive Bayes model, and then compare the algorithmic classifications with the manual classifications. Panel B of Table 1 presents these within-sample accuracies, which, as expected, are generally higher than the out-of-sample

[14] We use the services of a team of ten senior-year business school undergraduate and MBA research assistants to complete this step. The task is carried out in a standardized manner with the help of a process document we developed. Given the subjective nature of the task, we engage two different research assistants to independently code each text extraction. We then engage a third research assistant to reconcile the differences when they arise. Untabulated analyses indicate that the accuracy of our model using this "three RA" coding approach is similar to an alternative approach in which we limit the sample to those text extractions in which the first two RAs coding the extraction agreed on the classification.

accuracies in Panel A. These in- and out-of-sample accuracies are similar to those reported by Antweiler and Frank (2004) and Li (2010).

Step 5. Since our tests are at the report level, we aggregate the extraction-level scores and create a measure per report. The score for each extraction is weighted by the logarithm of the number of words in that extraction scaled by the total number of words across all extractions in the report. We then generate report-level scores by summing up the weighted scores of all extractions in a report (*Conflict Discuss*); by construction, the measure for the tone of a report lies between -1 and 1. Last, we define *Neg Conflict Discuss* as an indicator variable that takes a value of one if the continuous report-level score (*Conflict Discuss*) is negative, and zero otherwise. [15] As an (untabulated) robustness test, we find that inferences for our main tests are robust to the use of the General Inquirer (GI) classification algorithm as an alternative way to measure debt analysts' conflict discussions.[16]

3.3. Bond and CDS data

We analyze secondary market corporate bond trades retrieved from the National Association of Securities Dealers' (NASD) TRACE system and the Mergent Fixed Income Securities Database (FISD).[17] TRACE provides the date, price, and size of bond trades.[18] We

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[15] In untabulated analyses, we find that our main inferences are similar if we employ the continuous measure of conflict discussions (*Conflict Discuss*). However, given our interest in the potential effect of conflict events on bondholders' wealth expropriation, which is a negative outcome, we believe that the indicator variable *Neg Conflict Discuss* better captures our intended construct.

[16] The GI algorithm is operationalized as follows. A word is classified as positive (negative) if it is included in the GI list of words associated with a positive (negative) tone (see http://www.wjh.harvard.edu/~inquirer/ for the GI word lists). The word is ignored if it is not on the GI lists. To create a measure for each text extraction, similar to Li (2010), we take the positive GI words less the negative GI words and scale this amount by the total number of positive and negative GI words in the text. We then create a report-level measure by summing up the weighted scores of all extractions in a report and converting it into a categorical variable in a manner analogous to how *Neg Conflict Discuss* is computed. While the GI measure has the advantage of being easily replicated, the GI set of words was developed mainly for non-business documents. In contrast, the Naive Bayes model has the advantage of being estimated using the exact type of text we want to code (i.e., the Naive Bayes model incorporates the context of how analysts talk about conflict events).

[17] TRACE data are relatively new. On July 2002, the NASD began to report some bond transactions through TRACE, and by February 2005, essentially all corporate bond trades were reported through TRACE. Because

match the debt analysts' report data with the combined TRACE-FISD data at the firm level by manually merging the debt analysts' reports using the issuer's firm name. We successfully match about 82% of our debt analysts' report data. We then match the borrowers with debt analysts' reports and bond trading information in the merged TRACE-FISD dataset with Compustat. We limit the sample to firms with publicly traded equity because our analysis requires equity analyst coverage. The final step involves merging this extensive data set with the textual analysis data.

We obtain Credit Default Swap (CDS) data from the database provided by Markit Partners. This data includes daily composite quotes of CDS spreads collected from major banks, as well as information about restructuring clauses, credit ratings, and CDS contract maturities. To maintain contract homogeneity, we focus on the most liquid CDS contract, the five-year CDS contract with the modified restructuring clause. Finally, we obtain bond yield to maturity at issuance and bond characteristics such as size, maturity, and other features from Mergent FISD.

3.4. Test sample

Our potential sample of to-be-coded reports consists of 22,247 reports. We successfully "parse" 13,525 reports from pdf format into text format. Of these, 11,052 have at least one conflict-event extraction classified by Rainbow. This final set of reports generates 39,121 conflict-event extractions. Each report has a mean (median) of 3.5 (3) text extractions, which corresponds to a report mentioning a mean 3.5 (median 3) unique conflict-event keywords. Table 2 provides a summary of this selection process. Our regression tests have smaller samples due to additional restrictions of data availability to calculate variables in each specification.

TRACE coverage of firms is not complete until February 2005, we augment our TRACE bond data with that of FISD. If, on a certain day, a bond issue does not have any trades reported in TRACE but FISD indicates that a trade occurred, we include the FISD trade information in our tests. A missing trade in TRACE is almost always because TRACE does not cover that specific issue at the time.

[18] For investment grade bonds, if the par value of the transaction is greater than $5 million, the quantity field in TRACE contains the value of "5MM+." We set these transaction values to $5 million. For high yield and unrated bonds, TRACE codes trades of above $1 million as "1MM+." We set these transaction values to $1 million.

4. Results

4.1. Content analysis of debt analysts' conflict-events discussions

The frequency of conflict events is presented in Panel A of Table 3. Debt analysts extensively discuss merger and acquisition activities, with 63% of the reports including such discussion. In 32% of the reports, analysts discuss wealth distribution, including stock repurchases and dividend payments. Divestment discussions characterize 18% of the reports. The broadest category, financial risk, is the most frequently discussed event; these discussions cover 91% of the reports.

Panel B of Table 3 reports the classification of conflict events by the tone of analysts' discussions according to the Naïve Bayes model. The majority of conflict event extractions are classified as neutral; this result holds for all conflict event categories. A neutral tone is consistent with analysts monitoring conflict events and reporting to debt investors that conflict events are proceeding as expected by debt market participants. For example, in some cases, analysts discuss that a firm, as expected, announced a share repurchase program or a similar program at an expected amount/number of shares. As an additional example of neutral conflict discussions, analysts point out that given a firms' liquidity position and cash flow generating ability, they are comfortable with share repurchasing or additional capital investment activity. Alternatively, analysts alert investors about the conflict event, but indicate that it is either not material or otherwise unlikely that management will be able to pursue an activity that favors equity holders. Debt analysts use a positive tone in approximately 27%, 20%, and 29% of the discussion extractions related to M&A, wealth distribution, and divestments, respectively, even though these events are typically perceived as negative news for bond holders. This positive tone can be driven by the conflict event having a less-than-expected negative effect or by acting as a signal of the operating fundamentals' strength. For example, in some cases, analysts discuss management's decision to continue its share repurchase program, but at a reduced repurchase rate. As another example, repurchases are often associated with better-than-expected operating results, providing a net positive wealth effect for debt holders.

4.2. Timing of other events relative to debt analysts' conflict discussion

Debt analysts exercise discretion in their decision to issue reports that contain discussions of conflict events. Table 4 presents the frequency of actual conflict events around the publication date of debt analysts' reports with conflict discussions. We retrieve the announcement dates of these events from Thompson One (this dataset was formerly known as SDC Platinum). For example, the first row shows that, for 18.2% of these reports with conflict discussions, firms announced M&A-related activity in the period ranging from 30 to 3 trading days before the report. Approximately 1.5% of conflict-discussion reports are contemporaneous (i.e., day -2 to +2) with a firm's M&A announcement. For 17.3% of these debt analyst reports with conflict discussions, firms announced M&A-related activity in the period from 3 to 30 days after the report. The pattern is similar to other events, suggesting that debt analysts discuss both past and future potential events. The evidence that debt analysts anticipate, to some extent, conflict events supports the notion that the tone of their discussion may provide relevant and timely information to debt investors.

In addition, in untabulated analysis we examine the timing of the negative conflict event discussion in debt analysts' reports relative to credit rating downgrades. Because credit rating agencies care about rating stability, they often deliver more timely information to investors by adding firms to credit watchlists. Therefore, we also examine the timing of negative conflict discussions relative to when a firm is added to a negative watchlist. We test for the relative timing of these events by performing Granger causality analyses. We estimate multivariate logistic models that predict rating downgrades and negative watchlist additions using lagged values of debt analysts' negative discussions, negative rating agency actions and CDS spread changes as independent variables (see Beaver, Shakespeare, and Soliman (2006) and De Franco et al. (2009) for similar Granger causality analyses). We find that debt analysts' negative conflict discussions significantly lead rating downgrades and negative watchlist additions up to two months prior to the month of the respective credit event. These untabulated tests also show that negative conflict discussions lead increases in CDS spreads. These results are consistent with the idea that debt analysts' discussions anticipate the deterioration in credit quality that is associated with conflicts, which suggests that these discussions should be informative to debt market investors.

4.3. Effect of debt analysts' conflict discussions on their recommendations

Before proceeding to our main tests, we investigate the effect of debt analysts' conflict discussions on their recommendations. We expect that investment recommendations and their revisions should be affected, in part, by how debt analysts perceive the significance of the conflict events. These relations should provide some early evidence on the informativeness and importance of the tone of these discussions. More importantly, if debt analysts' conflict discussions relate to concerns about debt holder wealth expropriation or asset substitution, then these discussions should also help to explain those occasions when debt analysts' recommendations disagree with those of equity analysts. We start by first estimating the following ordered probit model at the debt-analyst report level:

$$\begin{aligned} \textit{Debt Recommendation}_{it} = \; & \beta_0 + \beta_1\,\textit{Conflict Discuss Neg}_{it} + \beta_2\,\textit{Text Count}_{it} \\ & + \beta_3\,\textit{Bond Characteristic Controls}_{it} + \beta_4\,\textit{Other Information Controls}_{it} \\ & + \text{Rating Effects} + \text{Year Effects} + \eta_{it}. \end{aligned} \tag{1}$$

Debt Recommendation is an ordered variable that equals one, two, or three if the debt analyst's recommendation level is a sell, hold, or buy, respectively. These recommendations are taken from the same report as the coded tone of the debt analyst's conflict discussion. We expect the *Conflict Discuss Neg* coefficient to be negative, consistent with debt analysts' negative discussions of conflict events leading them to issue more negative investment recommendations or to downgrade the investment recommendation. *Text Count* is the logarithm of the sum of the number of words in the report's text extractions and captures the extent of debt analysts' conflict discussions. We have no prediction about the relation between this variable and investment recommendations, given that the specification already includes the *Conflict Discuss Neg* variable, which measures the sign of the discussion.

We control for two bond characteristics that indicate whether bonds are highly traded (*Highly Traded*) or have more complex features *(Complexity High*). Highly traded bonds are likely to be associated with a higher demand for information since more debt investors trade them. Similarly, the demand for information is higher for bonds with complex features whose pricing is more challenging. It is unclear, however, how this higher demand for information affects recommendations, and hence we make no predictions on the coefficients of these two variables. To control for other information, we include equity analysts' forecast revisions. *Fcst Revision* is the average of one-year-ahead earnings per share forecast revisions by equity analysts for the period ranging from 45 days prior to the debt analyst's report date to 2 days after it. This variable controls for changes in firm fundamentals, which are typically discussed in the report. We expect this variable to have a positive coefficient. We also control for when recommendations are issued for bonds of firms that are on rating agencies' positive and negative watch lists. Expected changes in a firm's credit quality, as reflected by rating agencies' decision to place a firm on a watch list, are likely to affect debt analysts' recommendations. Rating fixed effects are included to control for general credit risk effects associated with debt analysts' recommendations (De Franco et al. (2009) demonstrate that these recommendations are systematically related to rating levels). Appendix 1 provides detailed variable definitions.

Table 5, Panel A provides descriptive statistics on the variables used in these tests. The mean and median debt analyst recommendation is a hold. Δ*Debt Recommendation* equals -1 if debt analysts downgrade their recommendation (i.e., from buy to hold or sell, or from hold to sell), 0 if the recommendation does not change, and 1 if debt analysts upgrade their recommendation (i.e., from sell to hold or buy, or from hold to buy). The results are robust when we define *ΔDebt Recommendation* as the difference between the current and the previous recommendation level (untabulated). As evidenced from the zero mean and median value of the Δ*Debt Recommendation* variable, debt analysts typically reiterate their previous recommendations. Consistent with the idea that both debt and equity analysts analyze firm fundamental performance, they tend to agree in their investment recommendation. The mean value of *Conflict Discuss Neg* is 0.24, indicating that 24% of the sample's reports contain negative discussions of conflict events. A mean *Text Count* of 7.02 (the logarithm of the number of words) indicates that a typical report has around 1,096 words devoted to the discussion of conflict events. Approximately 11% (2%) of reports are issued for firms that are on the negative (positive) watchlist.

The first column of Table 5, Panel B presents the results from estimating Equation 1. The negative and statistically significant coefficient on the *Conflict Discuss Neg* variable suggests that when debt analysts view conflict events as negative, they are less likely to issue buy recommendations. These results are consistent with the idea that debt analysts pay special attention to conflict events and that these events are important enough to impact their recommendations. In terms of economic significance, when the *Conflict Discuss Neg* variable changes from being positive or neutral to being negative, the probability of a sell recommendation increases by about 6.1%. For our control variables, we find that longer reports are associated with more positive recommendations. For the bonds of firms on a rating agency's positive watch list, analysts are more likely to issue positive recommendations, consistent with an expected improvement in a firm's credit quality. An untabulated χ^2-statistic indicates that the rating fixed effects are jointly statistically significant.

In the second column, we estimate Equation 1 but use recommendation revisions (*ΔDebt Recommendation*) as the dependent variable instead of recommendation levels. This sample is limited to observations in which a recommendation change or the previous recommendation level is provided in the report. In this specification, the coefficient on *Conflict Discuss Neg* is negative and statistically significant, as expected. Hence, when debt analysts view conflict events as negative, they are less likely to revise their recommendations upwards. In terms of control variables, the positive coefficient on the variable *On Watch Pos* indicates that debt analysts are more likely to upgrade when bonds are placed on a rating agency's positive watch list.

In the third column, using the same set of explanatory variables, we predict the disagreement between debt and equity analysts' recommendations. The dependent variable is the debt analyst's recommendation less the most recent equity analyst's recommendation issued for the same firm in the 21-trading-day window before the debt analyst report. Of the 7,035 observations used in this test, 4,107 represent a recommendation disagreement between debt and equity analysts. We find that the coefficient on *Conflict Discuss Neg* is negative and statistically significant, indicating that when debts analysts have negative discussions about conflict events, they are more likely to issue more negative recommendations than are equity analysts. This result is consistent with our prediction that debt analysts' discussions of debt-equity conflicts provide important information to debt holders that is different from the information provided by equity analysts. In terms of the control variables, debt analysts are likely to issue more positive recommendations than those of equity analysts when firms have bonds that are less complex and are on a rating agency's negative watch list. This latter result could potentially be explained by debt analysts believing (more than equity analysts) that the debt markets are over-reacting to the rating agency's negative views.

In sum, the results in this section support the idea that debt analysts' views on conflict events affect their decisions to recommend debt securities. In particular, debt analysts' discussions of debt-equity conflicts are positively related to their recommendations and revisions to their recommendations − the main summary outputs of analyst reports. These relations provide initial support to and empirical validation for the notion that the tone of debt analysts' conflict discussions is likely to be informative to debt market participants. Further, the tone of the conflict discussions helps to explain the disagreement between the recommendations of debt and equity analysts, consistent with tone communicating debt analysts' concerns about potential debt-equity conflicts of interest.

4.4. Effect of debt analysts' conflict discussions on debt market reactions

Because we expect debt analysts to provide an analysis and interpretation of conflict events from the perspective of debt holders, we expect debt holders to react to these discussions, as demonstrated by CDS and bond market reactions. Note that the majority of event studies in the extant literature examining bond-related announcements use equity returns to measure investors' reaction.[19] These studies implicitly assume that what is positive (negative) news to

[19] An important reason why previous studies use the equity-market reaction is that the low frequency of bond trade data makes it difficult to conduct short-window tests in bond markets (see, e.g., Goodhart and O'Hara, 1997 and

equity holders, as evidenced by positive (negative) stock returns, indicates good (bad) news for debt holders. This is unlikely to be true in our context of potential debt-equity conflicts, where we expect good news for equity holders to imply bad news for debt holders.[20]

First, we test whether daily CDS spreads changes react to the tone of debt analysts' conflict discussions after controlling for other features of the report, such as the recommendation, and a wide variety of other information events. CDS contracts capture the credit quality level (probability of default) and have the advantage of trading far more frequently than the underlying bond securities.[21] Not only are CDS quotes available on a daily basis, but they are much less affected by liquidity problems, changes in interest rates, and contract design features that are specific to bond securities (see, e.g., Bushman, Le, and Vasvari, 2010). These features can be difficult to control for in empirical tests (e.g., option-like features, collateral requirements). The informational role of the CDS market is well-documented by numerous studies.[22]

Second, as an alternative debt market reaction test, we investigate whether the daily bond trading volume is associated with the tone of debt analysts' conflict discussions. Volume reactions are associated with new information (e.g., Karpoff, 1987; Kim and Verrecchia, 1991),

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Hotchkiss and Ronen, 2002). Our sample is not immune to this concern, despite having the benefit of the combined TRACE-FISD data. We use this data for volume tests, but for price tests we use Markit CDS spread changes, which are available on a daily basis.

[20] For example, Alexander, Edwards, and Ferri (2000) find that events associated with conflicts between bondholders and stockholders (e.g., adoption of a risky project, stock repurchases, or changes in dividend payments) lead to bond and equity returns that move in opposite directions. Goh and Ederington (1993) show that rating downgrades due to changes in firms' leverage do not convey negative information for stock holders because these announcements likely lead to a wealth transfer from bondholders to stockholders. Further, while bond and stock returns are correlated at the aggregate level, measured, for example, using portfolios of firms or monthly or annual observations, the individual firm level correlation is weak (Alexander et al., 2000; Collin-Dufresne et al., 2001; Hotchkiss and Ronen, 2002).

[21] When bond price changes are used in previous studies, either the sample is often small (e.g., Alexander et al. (2000) study 139 events across 39 bonds; Hotchkiss and Ronen (2002) study 99 events for 36 bonds) or the event window is coarse (e.g., Hite and Warga (1997) examine monthly returns). Hand et al. (1992) is an exception, studying bond price reactions using short-event windows and a larger sample (approximately 250 watchlist additions and 1,100 rating changes).

[22] Hull, Predescu, and White (2004) find that the CDS market anticipates credit rating events. Longstaff, Mithal, and Neis (2004) and Blanco et al. (2005) find that the CDS market plays an important role in the bond price discovery process. In addition, Acharya and Johnson (2005) document the presence of an information flow from the CDS market to the equity market for firms with a large number of bank relationships or that are under financial distress.

as well as information that leads to a divergence of opinions among investors (e.g., Harris and Raviv, 1993; Kim and Verrecchia, 1994).[23] If debt analysts' reports matter to debt investors, then they should generate additional trading.

4.4.1. Daily CDS spread changes. The empirical analysis presented in Table 6 includes observations for *all* trading days during the six-year period we study for which we have CDS spread data available for each of the sample firms. Within this framework, we have the flexibility to control for all firm, analyst, rating agency and macro-economic disclosures in the same test. Therefore, this approach should allow us to better estimate the true relationships between debt market reactions and information events. Using the full sample of days also allows for the comparison of the magnitude of the CDS spread change reactions across different information events. For each event, we assign the news to the announcement day, and to each of the two trading days immediately before and after it (i.e., we use a five-day event window).[24] To test whether the CDS market reacts to debt analysts' conflict discussions, we estimate:

$$\begin{aligned} \Delta CDS\ Spread_{it} = {} & \beta_0 + \beta_1\ Conflict\ Discuss\ Neg_{it} + \beta_2\ Debt\ Report\ Controls_{it} \\ & + \beta_3\ Other\ Information\ Controls_{it} + \text{Rating Effects} + \eta_{it}. \end{aligned} \tag{2}$$

ΔCDS Spread is the daily change in the CDS spread. Increases in CDS spreads indicate deterioration in an issuer's credit quality. We expect the *Conflict Discuss Neg* coefficient to be positive, indicating that negative conflict discussions will increase CDS spreads. As we are interested in examining the effect of debt analysts' conflict discussions on CDS spreads

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[23] Note also that Cready and Hurtt (2002) study the differential ability of equity volume and equity price return metrics to assess the equity investor response to information events. They find that volume-based metrics provide more powerful tests of investor response than do return-based metrics.

[24] We use a 5-day window because it is difficult to precisely identify when the information in the debt analysts' reports is released to debt investors. For example, it is possible that a summary of the news contained in the report is issued to clients a day or two before the formal publication date. As another example, if the report is issued at the end of the business day, it could be released to clients the following day. It is also possible that reports issued at the end of a trading day generate trading responses in the days that follow. The bond market is an over-the-counter market and the low liquidity of some bonds could lead to the passage of a day or two before a counterparty to trade can be found. In addition, De Franco et al. (2009) show that the market reaction to a debt analyst's report is spread over the five days centered on the day of the report. (Other examples of debt market and analyst-related papers that use five-day windows in their analysis include Hand et al. (1992), Asquith et al. (2005), and Bonner et al. (2007)).

incremental to the effect of their recommendations, we include both the levels and changes in debt analysts' recommendations.

To control for other information, we include systematic market movements in CDS prices, estimated by the variable *ΔCDS Market Spread*. This variable equals the change in the average daily CDS spread change of all entities with the same credit rating category. We also incorporate into our analysis controls for the disclosures of other major information sources, which should assist with the objective of controlling for changes in operating fundamentals. We include dummy variables that indicate whether equity analysts have issued a buy or sell recommendation. The specification also includes a dummy variable that indicates a negative rating agency action, such as a negative rating change, negative watch list addition, or a negative outlook change (*Rating Agency Action Neg*).[25] Rating agencies are established as important information providers in the bond market. Following Reg FD, certified rating agencies continue to have access to private information from management, as these agencies are exempt from the regulation, and therefore may have access to information that is not available to debt analysts. However, because ratings are used for contracting, rating agencies prefer ratings stability, which may lead to less timely information production (Beaver et al., 2006). Last, we control for whether a firm announces negative earnings.

The results of estimating equation 2 are presented in column (1) of Table 6. The coefficient on *Conflict Discuss Neg* is positive as expected, consistent with debt analysts' negative conflict discussions predicting a deterioration in an issuer's creditworthiness beyond the standard

[25] Throughout our empirical analyses we often combine multiple events into a single variable for parsimony. Untabulated analysis indicates that our results do not change when we instead incorporate multiple indicator variables, one for each event. For example, in the case of negative rating agency actions, our inferences are robust to the inclusion of not one but three indicator variables, each reflecting the different types of rating actions: negative rating change, negative watch list addition, or a negative outlook change. Besides *Rating Agency Action*, another variable that appears in our analyses below and represents multiple events is *Conflict Event Firm Announcement*.

investment recommendation. Relative to reports with positive or neutral discussions, reports that include negative discussions increase the CDS spread by 16 basis points [3.1 basis points × 5 days] over the five-day window centered on the date of debt analysts' reports. In terms of control variables, not surprisingly, market changes in CDS spreads explain firm-specific changes in CDS spreads, as evidenced by the positive and statistically significant coefficient on *ΔCDS Market Spread*. Equity analysts' buy recommendations are negatively associated with CDS spread changes. The coefficients on the other control variables are not significant. An untabulated *F*-statistic indicates that the rating fixed effects are jointly statistically significant.

In the following specifications, to better capture the idea of wealth transfers from debt to equity holders, we focus on situations in which the news is negative for debt holders and positive for equity holders.[26] We incorporate daily stock returns (*Equity Return*) into our specification and restrict the sample to those observations in which news for equity holders is positive, as proxied by daily stock returns greater than zero. We also interact the *Conflict Discuss Neg* and *Equity Return* variables. The coefficient on the *Equity Return* variable captures days when debt analysts' conflict discussions are positive or neutral, or when there are no debt analysts' reports. We expect this coefficient to obtain a negative sign, capturing news about firms' operating fundamentals of the business that is common to debt and equity investors, such as earnings announcements, other firm disclosures, and non-firm announcements. The predicted coefficient is negative because CDS spreads move in the opposite direction to changes in debt holder wealth. We expect that on days when debt analysts have negative views of conflict events, greater gains to equity holders are associated with greater losses to debt holders. Hence we predict a positive coefficient on the *Conflict Discuss Neg* × *Equity Return* interaction variable. This specification is consistent with Alexander et al. (2000), who show that on days with no

[26] We thank an anonymous reviewer for suggesting the incorporation of equity returns into the analyses.

conflict events (with conflict events), positive equity returns are associated with an increase (decrease) in bond prices.

Column (2) of Table 6 shows the results of this specification. As predicted, the coefficient on *Equity Return* is negative and statistically significant, consistent with both equity returns and CDS spread changes capturing news about operating fundamentals. It is also consistent with the evidence in Collin-Dufresne et al. (2001) and Hotchkiss and Ronen (2002), who document modest comovement between bond and equity market returns. As expected, the coefficient on the *Conflict Discuss Neg* × *Equity Return* interaction variable is positive and statistically significant, which is consistent with a wealth transfer from debt to equity holders when analysts provide negative discussions of conflict events. The results for the control variables are generally similar to the results in Column 1. The exception is that both there and in the last column, the coefficient on *Debt Report Upgrade* (*Downgrade*) is negative (positive) and statistically significant, which indicates that a positive (negative) recommendation change is associated with an improvement (deterioration) in credit quality. Also, equity buy recommendations are no longer significant.[27]

We next examine how this result changes as a function of the creditworthiness of the firm. We define three new conflict discussion indicator variables based on the credit rating category of the firm: Above A rating, BBB-A rating, and below BBB rating. The first variable,

[27] In untabulated analyses, we conduct the following alternative CDS-reaction test. We examine whether the analysts' view of conflict events explains changes in CDS spreads around debt analysts' reports that contain a discussion of conflict events. In these tests, each observation corresponds to a debt analyst's report that contains a discussion of conflict events. We regress the change in the CDS spread over the event window around debt analysts' reports on *Conflict Discuss* and controls for the change in the market CDS spread and characteristics of bond and equity analysts' recommendations. In addition, in this regression we control for whether a firm is on a negative watchlist, as debt investors are likely to be more sensitive to negative conflict discussions when a decrease in a firm's credit quality is expected. We find a significant increase in the CDS spread when debt analysts' reports include negative discussions of conflict events, particularly when equity returns over the same event window are positive. These results provide further support for the notion that investors' reaction to debt analysts' reports is more pronounced when debt analysts view conflict events negatively.

Conflict Discuss Neg: Above A Rating, equals one if debts analysts' conflict discussion is negative and the firm's senior debt rating is above A. Similarly, *Conflict Discuss Neg: BBB-A Rating* and *Conflict Discuss Neg: Below BBB Rating* equal one if debts analysts' conflict discussion is negative and the firm's senior debt rating ranges from BBB to A and is below BBB, respectively, and zero otherwise. We then interact these three variables with *Equity Return*.[28] The results are presented in column (3) of Table 6. As expected, we find that the coefficients are increasing as creditworthiness declines. An untabulated test indicates that the difference in coefficients between the highest and lowest credit risk categories is statistically significant (p-value = 0.07), but the difference between the medium and low risk categories is not significant (p-value = 0.15). These findings provide some support to our cross-sectional prediction that the news provided by debt analysts' conflict discussions is more valuable for lower rated debt.

4.4.2. Daily bond trading volume. Similar to the empirical analyses of CDS spread changes, we use a panel data of observations for all trading days during our six-year period for each of the sample firms and test whether bond trading reacts to debt analysts' discussions of conflict events. For each event we assign the news to a five-trading-day event window and estimate the following model:

$$\begin{aligned} \textit{Bond Volume}_{it} = \beta_0 + \beta_1\, &\textit{Conflict Discuss Neg}_{it} + \beta_2\, \textit{Debt Report Controls}_{it} \\ &+ \beta_3\, \textit{Other Information Controls}_{it} + \text{Rating Effects} + \text{Year Effects} + \eta_{it}. \end{aligned} \qquad (3)$$

Bond Volume is the dollar volume of principal traded on a given day, scaled by the size of the bond on the issue date, averaged over all the firm's bonds. We control for the existence of a debt analysts' report, and whether the report contains a conflict discussion, so that we can focus our interpretation on the effect of negative versus positive or neutral discussions. We also control for

[28] As we are interested in examining the effect of conflict discussions as a function of the creditworthiness of the firm, we omit rating fixed effects from this specification. (The same holds for the volume and offering yield analyses, when we conduct similarly motivated cross-sectional tests.)

conflict discussions that are longer, as evidenced by a larger text count. More extensive discussions should generate stronger volume reactions since they are likely to provide more information or discuss in more detail the effects of a conflict event.

While the motivation for the remaining control variables in this test remains the same as in the CDS spread analyses, the set of control variables for this test is larger and differs somewhat. As CDS spread changes are "signed," either improving or deteriorating, the control variables for that test consist of signed control variables (for instance, recommendation upgrades and downgrades, or negative rating actions). In addition to these signed control variables, because trading volume is an unsigned measure, the set of bond trading volume controls includes indicator variables for the existence of events. These other controls include variables that indicate the existence of the following: actual firm conflict event announcements (such as an M&A, dividend, or stock repurchase announcement), an equity analysts' report, a rating agency action, an earnings announcement, and a federal funds rate change announcement.[29] In general, we expect the coefficient on each of the event indicator variables to be positive, consistent with incremental bond volume occurring around the news associated with each event. Note that our tests allow for the differential effect of negative versus positive news by including separate indicator variables for negative news, when appropriate. Consistent with the demand for negative news, as shown by studies such as Easton et al. (2009) and the results of De Franco et al. (2009), we expect indicator variables that designate negative news to have an incremental effect on trading volume. Last, we add equity volume to control for broad firm-level information.

The results of this test are reported in Table 7. In column (1), the coefficient on *Conflict Discuss Neg* is 0.220 (*t*-statistic = 5.93). Over the five-day event window, an incremental 1.10%

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[29] The inclusion of these additional control variables in the CDS spread regression does not affect our findings and inferences regarding the informativeness of debt analysts' discussions.

(5 days × 0.220% per trading day) of the bonds' principal is traded around debt analysts' reports with negative conflict discussions relative to debt analysts' reports with positive or neutral conflict discussions. This volume "reaction" is similar to the incremental response to negative announcements by rating agencies (as captured by the coefficient on *Rating Agency Action Neg*), an important source of information in debt markets.

To better assess the role of negative versus positive conflict discussions, in Column (2), we include a separate indicator for positive conflict discussions (*Conflict Discuss Pos*), which is defined in a way that is analogous to our main negative conflict variable. The coefficient on *Conflict Discuss Pos* is not significant, suggesting that the discussions of conflict events that are positive do not produce a greater volume reaction than those that are neutral. Overall, these results are consistent with our prediction that debt investors find the reports of debt analysts more informative if they contain negative discussions of conflict events.

In terms of control variables, positive coefficients on *Debt Report* and *Debt Report with Conflict Discussion* reflect the incremental bond volume around the publication of debt analysts' reports in general and reports with a non-negative conflict discussion. Longer reports are negatively correlated with trading volume, possibly because shorter reports allow debt analysts to provide more timely information. Debt analysts' reports with sell recommendations generate higher trading volume than reports with hold recommendations, while those with buy recommendations generate about the same volume as those with hold recommendations. Debt recommendation upgrades lead to greater volume reactions than do downgrades. Equity trading volume is positively related to debt trading volume, consistent with some news affecting both equity and debt holders. Bond market reactions are also greater for debt analysts' recommendations than they are for equity analysts' recommendations, consistent with De Franco et al. (2009). As expected, credit rating actions, particularly negative actions, generate additional volume. Earnings news that is positive or neutral does not lead to any trading volume reaction, but trading volume does respond to negative earnings news. With respect to macroeconomic news, higher volume is associated with a Federal Funds rate change.[30]

In column (3), we test for whether the effect of conflict discussions on volume differs by a firm's creditworthiness. We find some support for our prediction that the market reaction is increasing in credit risk. The coefficients on *Conflict Discuss Neg: BBB-A Rating* and *Conflict Discuss Neg: Below BBB Rating* are positive and statistically significant, at the 1% and 10% one-sided levels, respectively. Although there is no difference between the *Conflict Discuss Neg* coefficients for the *Below BBB* and *Above A* ratings, the untabulated *p*-value of the difference between the *BBB-A Rating* and *Above A Rating* categories is 0.05. Note that this finding of the greatest volume reaction in the middle-risk group, BBB-A ratings, is consistent with the idea that debt-investor demand for negative information is asymmetric and lower for firms with the lowest credit quality.

In sum, the results for CDS spread changes and bond trading volume support the idea that debt analysts' discussions about conflict events lead to debt market reactions that are incremental to their recommendations. These results are consistent with debt analysts' conflict-event discussions being important to debt investors. Our inferences compare with Asquith et al. (2005),

[30] In untabulated analyses, we conduct the following alternative volume-reaction test. We examine whether the analysts' view of conflict events explains variation in the abnormal bond trading volume around debt analysts' reports that contain a discussion of conflict events. In these tests, each observation corresponds to a single debt analyst's report that contains a discussion of conflict events. We regress abnormal volume, a firm's daily volume around the report less the daily volume on non-event days, on *Conflict Discuss*. In this regression, we control for characteristics of debt and equity analysts' recommendations, equity volume, text count, the time to maturity of the bond (which proxies for the frequency of bond trading), whether a bond's trading frequency is above the sample median, and whether a bond is on negative watchlist. The results indicate a greater volume reaction to debt analysts' reports that include negative discussions of conflict events. They provide further support for the notion that debt analysts' reports are more informative to debt investors when they involve a negative discussion of conflicts of interest between bond and equity holders.

who find that the (manually coded) tone of the text in equity analysts' reports is related to the equity market reaction. The evidence contrasts somewhat with Kothari et al. (2009), who find, for example, that the tone of the text in equity reports has an insignificant impact on the cost of capital, concluding that disclosures by equity analysts appear to be heavily discounted by equity markets.

4.5. Effect of debt analysts' conflict discussions on bond offering yields

This section examines whether debt analysts' negative conflict discussions are also informative with respect to the initial pricing of bond securities in the primary bond market (i.e., pricing at the time of bond issuance). More specifically, we test how the tone of conflict event discussions affects the offering yield to maturity of new bond issues. To perform this analysis, we manually match our debt analyst data with the Mergent FISD database to obtain a sample of bonds issued in the 2002 to 2008 period. We focus on reports issued within six months prior to the bond issue. To select a more homogenous group of bond securities, we exclude corporate bonds that are convertible, privately placed, issued in foreign currencies or that have variable coupon payments. Our final sample consists of 1,013 bonds issued by 290 firms. We estimate the following OLS model at the bond issue level:

$$\begin{aligned} \textit{Bond Offering Yield} = {} & \beta_0 + \beta_1 \textit{Conflict Discuss Neg Prior 6M}_{it} + \beta_2 \textit{Debt Recommendation Prior 6M}_{it} \\ & + \beta_3 \textit{Bond Characteristic Controls}_{it} + \beta_4 \textit{Firm Characteristics Controls}_{it} \\ & + \beta_5 \textit{Other Information Controls}_{it} + \text{Rating Effects} + \text{Industry Effects} + \eta_{it}. \qquad (4) \end{aligned}$$

The dependent variable measures the cost of a new bond issue. An untabulated analysis indicates that the median bond yield for our sample is 658 basis points, with a standard deviation of 440 basis points. Our main variable of interest is *Conflict Discuss Neg Prior 6M*, which is defined at the bond-issue level. We take the average *Conflict Discuss* score across all debt analysts' reports issued over the six-month period prior to a bond's issuance. *Conflict Discuss Neg Prior 6M* takes the value of one if the average value *Conflict Discuss* is less than zero. To better isolate the effect of debt analysts' conflict discussions, we control for debt analysts' recommendations and recommendation changes.

We also control for bond characteristics that are likely to affect the magnitude of the bond issuance yields, such as the number of covenants, maturity, and offering amount. As the agency theory of covenants suggests that there is a trade-off between the number of covenant restrictions and the interest rate (Smith and Warner, 1979), we expect the number of covenants to be negatively related to the offering yield. Bonds with longer maturities are usually exposed to greater interest and credit risks, and therefore are likely priced at higher yields. We do not have a prediction regarding the sign of the association between a bond's offering yield and the size of its offering amount. On one hand, larger bond issues are typically more liquid and marketable and thus should be priced at lower yields. On the other hand, larger bond issues imply a higher debt burden for the borrower, and therefore may be associated with a higher probability of default. We also include bond complexity in our specification, but again do not predict the sign of its relation to offering yield. Complex bonds are more difficult to value and tend to be less liquid (Harris and Piwowar, 2006; Edwards et al., 2007), suggesting that more complex bonds should be priced at higher yields. In contrast, complex bonds have features such as put options, credit enhancements, or sinking fund provisions that can lower the offering yield.

In addition, we control for firm characteristics that include size, leverage, and interest coverage. Consistent with prior literature, we expect bond offering yields to increase with firm leverage and decrease with firm size and interest coverage. Next, we add an indicator variable that flags the existence of private bank debt at the bond's issuance date. We predict a negative association between the offering yield and private borrowings because we expect bank monitoring to benefit bond holders (Datta, Iskandar-Datta, and Patel, 1999).

To control for other information, we include a variable that indicates whether conflict events were announced by the firm in the six-month period prior to a bond's issuance.[31] We also add a control for equity analysts' recommendations and include the Federal Funds rate at the date of the bond's issuance. By including this latter variable, we control for the effect of macroeconomic changes on the firm's cost of borrowing. To control for a borrower's credit risk, we include rating fixed effects. Finally, we include industry fixed effects which capture industry-level characteristics, such as asset tangibility, that are likely to affect the offering yield.

The estimation of Equation (4) is presented in Column 1 of Table 8. The coefficient on *Conflict Discuss Neg Prior 6M* is positive and significantly different from zero, suggesting that negative conflict event discussions in debt analysts' reports preceding a bond's issuance lead to a higher bond offering yield. Economically, a negative conflict-discussion tone prior to the bond issuance (relative to neutral or positive discussions) increases the offering yield by 27 basis points, which represents 4.0% of the median bond yield of the sample firms.

In Column 2 of Table 8, we examine whether the effect of conflict discussions on offering yields depends on the bond's credit riskiness. We find some evidence to support our prediction that when debt is of low credit quality, debt yields are more sensitive to new information. The coefficients on the conflict discuss measure are increasing as creditworthiness declines, with the coefficient on *Conflict Discuss Neg Prior 6M: BBB-A Rating* significant at the 10% one-sided level and the coefficient on *Conflict Discuss Neg Prior 6M: Below BBB Rating* significant at the 5% level. An untabulated test shows a significant difference in coefficients between the medium (highest) credit risk category and the lowest one, with a p-value of 0.08

[31] Compared to the *Conflict Event Firm Announcement* variable used in CDS and bond volume analyses in prior sections, we omit dividend distributions from the variable's definition. Almost all of our offering yield sample firms distribute dividends in the six-month period prior to a new bond issuance (the period over which *Conflict Event Prior 6M* is estimated for yield analysis). Hence if we include dividend distributions in our definition, the *Conflict Event Firm Announcement Prior 6M* variable would have negligible variation.

(0.02). These results are consistent with our findings in the CDS market test, in which the credit spreads of low credit quality firms react more strongly to debt analysts' conflict discussions.

With respect to control variables across these first two columns, we find that the offering yield increases with leverage, and decreases when the bond is complex or when the firm is subject to bank monitoring. We also find that the offering yield increases when the Federal Fund rate increases. In the second column, we find that the offering yield is decreasing in bond maturity, amount, and a firm's interest coverage. A negative relation between the offering yield and equity analysts' recommendations suggests that these recommendations reflect the operating performance of the firm.

Contrary to our prediction, we find that the number of covenants is positively related to the interest rate, likely due to endogeneity between the interest rate and covenants. We address this issue in Column 3 by estimating a 2SLS specification, where the number of covenants is predicted in the first stage and added as an explanatory variable for the offering yield in the second stage. We instrument the number of covenants in a bond contract by calendar year indicators. The strictness of covenant packages significantly deteriorated during the years of the credit boom that preceded the financial crisis (Leverage World, 2006; Fitch Ratings, 2007; and Moody's Investor Services, 2007). In untabulated analysis, we find that this relation also holds for our sample: the average number of covenants significantly decreased for bonds issued in 2006 relative to bonds issued in previous years, with further deterioration for bonds issued in 2007 (the untabulated partial F-statistic is 3.82, with a p-value of 0.002). As we control for the Federal Funds rate, the offering yield is not directly related to year fixed effects. We take comfort in the fact that our 2SLS estimation is well identified, because, after controlling for endogeneity, our results show a significant and negative relation between the offering yield and the number of covenants. Consistent with the agency theory of covenants, our results in Column 3 show that the higher the number of covenants, the smaller the offering yield. More importantly, the results confirm that allowing for endogeneity between the offering yield and the number of covenants does not affect our main conclusion that negative conflict discussions predict higher offering yields.

While we address the endogeneity between bond yields and covenants, our empirical analysis treats the rest of the bond contractual terms as exogenous.[32] As an untabulated robustness test, to address the joint determination of bond terms, we estimate the offering yield, the number of covenants, maturity, and the offering amount as a system of equations using a seemingly unrelated regression (SUR) model. SUR allows error terms in all four regressions to be correlated. Our findings are robust to the SUR estimation and our inferences remain the same.

In sum, we document that the yield to maturity of new bonds increases with the negative tone of conflict discussions in debt analysts' reports preceding the bond issuance, after controlling for a variety of firm and bond specific characteristics, debt and equity analysts' recommendations, and the occurrence of conflict events. These conflict-event discussions are hence associated with real effects on a company's cost of debt.

4.6. Alternative measure of debt analysts' negative conflict discussions

In this section, we develop and test an alternative measure of the tone of debt analysts' conflict discussions. This measure is based on the difference in the tone of conflict discussions between debt and equity analyst reports, which may more directly capture the idea of conflict between debt and equity investors.

[32] The regressions using debt contractual terms involve a variety of simultaneity and endogeneity problems, which makes it extremely difficult to find appropriate instruments (e.g., Bradley and Roberts, 2004; Costello and Wittenberg-Moerman, 2011). Further, it is practically infeasible to concurrently endogenize all bond contractual terms incorporated into the yield analysis.

We identify a sample of equity analysts' reports that we match by firm to each debt analyst's report.[33] For the CDS and volume-related tests, we match the firm's equity analysts' reports issued within the 10-trading-day window prior to the debt report; for the offering yield analysis, the window is six months prior to the debt report. As in the case of debt analysts' reports, we extract equity analysts' discussions of conflict events and measure the discussions' tone using the Naïve-Bayesian model. More specifically, we repeat Steps 1-5 described in Section 3.2 and develop two measures of the tone of equity analysts' discussions. The difference between these two measures is driven by which set of manually coded data we use to "train" the algorithm according to the "Naive Bayes" approach (Step 3). For the first measure, we use the same training data set of 5,933 randomly selected text extractions from debt analysts' reports that we employed to estimate the tone of debt analysts' conflict discussions. For the second measure, we develop a new training data set based directly on equity analysts' conflict discussions. We create this training data set by manually classifying as positive, negative, or neutral 5,102 randomly selected text extractions from the matched equity analysts' reports. Our second measure of equity analysts' conflict discussions uses this new training set.

Following our strategy of coding debt analysts' reports, we create a report-level score by summing up the scores from all extractions associated with each equity analyst's report, weighted by each extraction's respective word count. Lastly, for each debt analyst report, we

[33] These reports are downloaded from Investext in a manner similar to De Franco, Hope, Vyas, and Zhou (2011). We download the analyst reports in PDF format. We also extract the header information for each report. This includes the name of the analyst writing the report, the name of the broker employing the analyst who issues it, the report's title, the name of the firm that it is about, and the unique number Investext has assigned to that particular report. We use the Investext header information to match Investext analyst names with IBES analyst names and verify these matched analyst-name pairs using broker names. We link companies being covered by these matched analysts-name pairs in both Investext and IBES using the Tickers, Cusips, and Company Names. Next, since we code these analyst-report files using computational linguistic programs, we convert the PDF files into text files using a Python program (specifically, the PyPDF library). These text files are then merged with the header information using the unique Investext report number. To mitigate any potential data errors, we exclude from our analyses text files of less than 300 words.

average the tone of the report-level scores of equity analysts' discussions across all matched equity analysts' reports, which results in two aggregate measures of the tone of equity analysts' discussions – *Conflict Discuss Equity 1* (created based on the debt analysts' reports training set) and *Conflict Discuss Equity 2* (created based on the equity analysts' reports training set).

To incorporate these coded equity analysts' discussions of conflict events into our analysis, we develop two new alternative measures of debt analysts' conflict discussions by focusing on those discussions where the tone disagrees with the tone of equity analysts' conflict discussions. In particular, *Alternative Measure #1* of debt analysts' conflict discussions takes the value of one if debt analysts' reports contain negative conflict discussions, when the tone of equity analysts' conflict discussions, based on *Conflict Discuss Equity 1*, is positive. *Alternative Measure #2* is defined analogously, based on *Conflict Discuss Equity 2*.

We repeat the analysis reported in Tables 5-8 with these two alternative measures of the tone of debt analysts' conflict discussions; the results are presented in Table 9. We present the coefficient and *t*-statistic (or *z*-statistic) on our main variable of interest only. All specifications are estimated with the same set of other independent variables as the previously tabulated tests. We omit reporting the control variable coefficients for brevity and because they are similar to those previously presented. For comparison, the first column in Table 9 respectively repeats the main results from Tables 5-8. The next two columns similarly present the results for *Alternative Measure #1* and *Alternative Measure #2*.

Using these two alternative measures, we continue to find that debt analysts' views on conflict events affect their investment recommendations. The negative and statistically significant coefficients on *Conflict Discuss Neg* suggest that when debt analysts view conflict events as negative, they are less likely to issue buy recommendations. With respect to the CDS-reaction tests, using *Alternative Measure #1*, we also find that when daily stock returns are positive, the coefficient on the interaction variable *Conflict Discuss Neg* and *Equity Return* is positive and statistically significant, which is consistent with a wealth transfer from debt to equity holders when analysts provide negative discussions of conflict events. The results hold but are statistically weaker (significant at the 10% level, one-sided test) if we use *Alternative Measure #2*. For the bond trading volume analysis, using the alternative conflict discussion measures, the coefficients on *Conflict Discuss Neg* are similar in both statistical and economic significance to those reported in Table 7. These results support our prediction that debt investors find the reports of debt analysts to be more informative if they contain negative discussions of conflict events. Finally, when debt analysts view conflict events negatively while equity analysts are more positive about them, the offering bond yields are significantly higher. These findings confirm our conjecture that debt analysts' discussions of conflict events are also informative with respect to the initial pricing of bond securities in the primary market. Overall, we find that our results are robust to these two alternative measures of conflict discussion based on the disagreement in tone of the conflict event discussions in debt and equity analysts' reports.

5. Conclusion

The role of information intermediaries such as equity analysts, rating agencies and the press in shaping firms' information environments has long been of interest to researchers in accounting and finance. In this paper, we add to prior literature by examining whether the tone of sell-side debt analysts' discussions of conflict events reflects new information generated by analysts, which expands the information set available to debt market investors.

Using a unique hand-collected dataset of sell-side debt analysts' reports on U.S. firms, we find that debt analysts routinely discuss events that are likely to generate debt-equity conflicts in their reports and that these discussions are often issued in anticipation of conflict events. More importantly, debt analysts' conflict event discussions generate significant debt market reactions, measured by CDS credit spreads, bonds' trading volume, and bond offering yields in the primary bond market. These findings support our prediction that debt analysts' discussions about conflict events are informative to debt market investors and incremental to debt analysts' recommendations and to information provided by other information intermediaries, such as rating agencies and equity analysts.

By providing insights into the type of information produced by debt analysts that explain the debt market's reaction to these reports, we add to the emerging literature on debt analysts. Despite the fact that the U.S. corporate debt market is the largest and most important source of capital for U.S. firms, current evidence on the informational role of debt analysts is rare, highlighting the importance of our findings. Finally, our approach of coding the tone of debt analysts' discussions about potential debt-equity conflicts allows us to document the importance of these conflicts to debt investors and also to determine whether and how debt holders' wealth is affected. This approach contributes to the literature on debt-equity conflicts of interest, a literature that currently relies on bond returns, which measure debt holders concerns about wealth expropriation and asset substitution with significant measurement error, often leading to inconclusive findings with respect to the extent and economic importance of such conflicts to debt holders.

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APPENDIX 1
Variable definitions

Variable		Definition
Above A Rating	=	Indicator variable that equals one if the firm's senior debt rating is above A, zero otherwise.
Alternative Measure #1	=	This alternative measure of the tone of debt analysts' negative conflict discussions is based on the disagreement in the tone of conflict discussions between debt and equity analyst reports. We extract equity analysts' discussions of conflict events from a matched sample of equity analysts' reports and measure the tone of their discussions using the Naïve-Bayesian model. This alternative measure equals one if debt analysts' reports contain negative conflict discussions and equity analysts' conflict discussions are positive (i.e., more positive than the median of the equity analysts' conflict discussion). This alternative measure uses the training data set of 5,933 randomly selected text extractions from debt analysts' reports (used in our main analysis) to estimate the equity analysts' Naïve-Bayesian model.
Alternative Measure #2	=	The same as *Alternative Measure #1*, except that the equity analysts' Naïve-Bayesian model is based on training data that consists of a randomly selected and manually coded set of equity analysts' conflict discussions.
BBB-A Rating	=	Indicator variable that equals one if the firm's senior debt rating ranges from BBB to A, zero otherwise.
Below BBB Rating	=	Indicator variable that equals one if the firm's senior debt rating is below BBB, zero otherwise.
Bond Maturity	=	Logarithm of number of years left to maturity at the time of the bond's issuance.
Bond Offering Amount	=	Logarithm of the offering amount of a given bond issue.
Bond Offering Yield	=	Bond issue's offering yield at issuance.
Bond Volume	=	Dollar volume of principal traded on a given day, scaled by the face value of the bond on the issue date, averaged over all the firm's bonds.
ΔCDS Market Spread	=	Change in the average Credit Default Swap spread of all entities that have the same credit rating category during a given trading day. We use four credit rating categories: AAA to AA-, A+ to BBB+, BBB to BB, and BB- to D.
ΔCDS Spread	=	Change in the Credit Default Swap spread during a given trading day.
Conflict Discuss	=	First, at the debt-analyst-report conflict-event level (i.e., the text extraction level), we create a score that equals negative one if the Naïve Bayes algorithm (implemented via Rainbow) classifies the text as negative, zero if the text is classified as neutral, and one if it is classified as positive. Each analyst report can produce multiple conflict-event text extractions, with a maximum of one extraction for each conflict-event key word. For analysis at the analyst-report level, we create a report-level score (*Conflict Discuss)*, created by summing up the scores from all extractions associated with each report weighted by each extraction's respective word count (*Text Count*).
Conflict Discuss Neg	=	First, at the debt-analyst-report conflict-event level (i.e., the text extraction level), we create a score that equals negative one if the Naïve Bayes algorithm (implemented via Rainbow) classifies the text as negative, zero if the text is classified as neutral, and one if it is classified as positive. Each analyst report can produce multiple conflict-event text extractions, with a maximum of one extraction for each conflict-event key word. For analysis at the analyst-report level, we create a report-level score (*Conflict Discuss)*, created by summing up the scores from all extractions associated with each report weighted by each extraction's respective word count (*Text Count*). *Conflict Discuss Neg* is an indicator variable that takes a value of one if the report-level score (*Conflict Discuss)* is negative, zero otherwise.

(Continued)

APPENDIX 1 (Continued)

Variable		Definition
Conflict Discuss Neg: Above A Rating;	=	Indicator variable that takes on a value of one if *Conflict Discuss Neg* is one for a firm rated higher than "A", zero otherwise.
Conflict Discuss Neg: BBB-A Rating;	=	Indicator variable that takes on a value of one if *Conflict Discuss Neg* is one for a firm rated between "BBB" and "A", zero otherwise.
Conflict Discuss Neg: Below BBB Rating	=	Indicator variable that takes on a value of one if *Conflict Discuss Neg* is one for a firm rated lower than "BBB", zero otherwise.
Conflict Discuss Neg Prior 6M	=	An indicator variable that takes on a value of one if the average of *Conflict Discuss* for debt reports issued for a firm during the 180-day window prior to the bond issuance date is negative, zero otherwise.
Conflict Discuss Pos	=	An indicator variable that takes a value of one if *Conflict Discuss* (the report-level score defined earlier) is positive, zero otherwise.
Conflict Event Firm Announcement	=	Indicator variable that equals one in the five-day period centered on the date of an M&A, dividend, or stock repurchase announcement by a firm, zero otherwise. Announcement dates are from the SDC Platinum and CRSP databases.
Conflict Event Firm Announcement Prior 6M	=	Indicator variable that equals one if there is an M&A or stock repurchase announcement by a firm in the 180-day window prior to the bond issuance date, zero otherwise. Announcement dates are from the SDC Platinum database.
Complexity High	=	Indicator variable that equals one if a firm's complexity index is above the sample's median, zero otherwise. Complexity index is based on the following bond characteristics: callable, convertible, credit enhancement, putable, foreign currency, floating rate coupon, variable rate coupon, combination of floating/fixed coupon, non-standard payment frequency, non-standard accrual frequency, pay-in-kind, and sinking fund. The complexity index is estimated as the sum of the bond complexity characteristics, where each characteristic is assigned the value of one. The index is based on the average complexity of a firm's bonds.
Debt Recommendation	=	Ordered variable that equals one if the debt analyst's recommendation is a sell, two if it is a hold, and three if it is a buy.
Δ*Debt Recommendation*	=	Ordered variable that equals -1 if the debt analyst's recommendation change is a downgrade, 0 if the recommendation does not change, and 1 if the recommendation change is an upgrade.
Debt Rec. less Equity Rec.	=	*Debt Recommendation* minus *Equity Recommendation*.
Debt Recommendation Prior 6M	=	The average of *Debt Recommendation* for debt reports issued for a firm during the 180-day window prior to the bond issuance date.
Δ *Debt Recommendation Prior 6M*	=	The average of Δ*Debt Recommendation* for debt reports issued for a firm during the 180-day window prior to the bond issuance date.
Debt Report	=	Indicator variable that equals one in the five-day period centered on the date of a debt analyst's report, zero otherwise.
Debt Report with Conflict Discussion	=	Indicator variable that equals one in the five-day period centered on the date of a debt analyst report that contains a conflict discussion, zero otherwise.
Debt Buy Recommendation	=	Indicator variable that equals one in the five-day period centered on the date of a debt analyst's buy recommendation, zero otherwise.
Debt Sell Recommendation	=	Indicator variable that equals one in the five-day period centered on the date of a debt analyst's sell recommendation, zero otherwise.
Debt Recommendation Upgrade	=	Indicator variable that equals one in the five-day period centered on the date of a debt analyst's recommendation upgrade, zero otherwise.

(Continued)

APPENDIX 1 (Continued)

Variable		Definition
Debt Recommendation Downgrade	=	Indicator variable that equals one in the five-day period centered on the date of a debt analyst's recommendation downgrade, zero otherwise.
Earnings	=	Indicator variable that equals one in the five-day period centered on the date of a firm's earnings announcement, zero otherwise. Data are from Compustat.
Earnings Neg	=	Indicator variable that equals one in the five-day period centered on the date of a firm's earnings announcement if earnings before extraordinary items are negative, zero otherwise.
Equity Buy Recommendation	=	Indicator variable that equals one in the five-day period centered on the date of an equity analyst's buy recommendation, zero otherwise.
Equity Recommendation	=	Ordered variable that equals one if the equity analyst's recommendation is a sell, two if the recommendation is a hold, and three if it is a buy.
Equity Recommendation Prior 6M	=	The average of *Equity Recommendation* for a firm during the 180-day window prior to the bond issuance date.
Equity Report	=	Indicator variable that equals one in the five-day period centered on the date of an equity analyst's report, zero otherwise.
Equity Return	=	Equity return during a given trading day.
Equity Sell Recommendation	=	Indicator variable that equals one in the five-day period centered on the date of an equity analyst's sell recommendation, zero otherwise.
Equity Volume	=	Dollar volume of shares traded on a given day, scaled by the number of shares outstanding.
Fcst Revision	=	Average of one-year-ahead earnings per share forecast revision by equity analysts from 45 days prior to the debt analyst report date until 2 days after it. Each forecast revision is scaled by the cross-sectional standard deviation of the forecast revisions in the event window.
Fed Change	=	Indicator variable that equals one in the five-day period centered on the date of the federal funds rate changes, zero otherwise.
Fed Rate	=	The prevailing Federal Funds rate on the day prior to the bond issuance date.
Firm Size	=	Logarithm of total assets, measured at the end of the calendar quarter preceding the quarter in which the bond was issued.
Highly Traded	=	Indicator variable equal to one if the firm's bonds are traded on average more than the median bond in the sample, zero otherwise.
Interest Coverage	=	Ratio of interest expense to income before interest and taxes, measured at the end of the quarter preceding the quarter in which the bond was issued.
Leverage	=	The ratio of total liabilities to total assets, measured at the end of the quarter preceding the quarter in which the bond was issued.
Number of Covenants	=	Total number of covenants that are present in the bond contract.
Number of Covenants (Predicted)	=	Predicted total number of covenants that are present in the bond contract based on the year of bond issuance as a first stage instrument.
Private	=	Indicator variable that takes the value of one if, at the time of the bond's issuance, a firm has syndicated loans outstanding (as indicated by the Dealscan database), zero otherwise.

(Continued)

APPENDIX 1 (Continued)

Variable		Definition
On Watch Neg	=	Indicator variable that equals one if the firm is on a negative or developing S&P Watch-list when the analysts' recommendation is issued, zero otherwise.
On Watch Pos	=	Indicator variable that equals one if the firm is on a positive S&P Watch-list when the analysts' recommendation is issued, zero otherwise.
Rating Agency Action	=	Indicator variable that equals one in the five-day period centered on the date of a rating agency action, including rating change, watchlist addition, or outlook change, and zero otherwise.
Rating Agency Action Neg	=	Indicator variable that equals one in the five-day period centered on the date of a negative rating agency action, including a rating downgrade, negative watchlist addition, or a negative outlook change, and zero otherwise.
Text Count	=	Logarithm of number of words in each text extraction. At the report level, this variable is aggregated by summing up *Text Count* for each text extractions.
Text Count High	=	Indicator variable that equals one if *Text Count* is above the median *Text Count* for all debt analyst reports in the sample.

APPENDIX 2
Examples of text extracted around conflict-event keywords from debt analysts' reports

Example of a Negative classification of an M&A discussion
Text excerpt from Banc One, May 30, 2003 on May Department Stores: "While May has been an aggressive purchaser of its own stock in past years, share repurchases were minimal in 2002 and we expect them to be negligible this year as well. Therefore, free cash flow should still be sufficient to reduce debt if so desired. The bigger risk with May is the potential for further acquisitions. The company has increased its presence in the bridal and formalwear segment through acquisitions although the total dollar amount has not been that meaningful. If top-line growth continues to be elusive for May, as we believe, management may be inclined to boost revenue through a purchase. This could be in the form of another department store or a specialty concept such as bridal. In either case, the impact on bondholders would probably be negative. We still feel that the department store model is viable and the best operators should be around for years to come."

Example of a Positive classification of an M&A discussion
Text excerpt from Merrill Lynch, May 14, 2003 on Sears, Roebuck and Co.: "While Sears faces a significant challenge in revitalizing its merchandising strategy and improving the productivity and profitability of its retail stores, we view the acquisition as an important step in bolstering the retailer's indistinctive softline offerings. Lands' End represents a worthy addition to a stable of successful proprietary brand names including Kenmore, Craftsman and Die Hard. Broadening the higher - end apparel offering at Sears, the acquisition also gives Lands End access to an expanded customer base (in full - line stores and with access to Sears credit card customer file) and could allow for brand line extensions in several hard-line categories (sporting and camping gear)."

Example of a Neutral classification of an M&A discussion
Text excerpt from Bear Stearns, February 24, 2003 on Mediacom: "Management continues to view its business plan as being more than adequately funded, and it expects to become free cash flow positive in mid - 2003, as its plant rebuild nears completion. Debt maturities continue to remain fairly moderate, aggregating only about $50 million through 2005. No significant acquisitions are expected over the near - term; management actually may see a better payoff in potentially repurchasing company stock (although its current focus appears to be on generating free cash flow). As of December 31, Mediacom's digital - cable service was available to approximately 1,540,000 digital - ready basic subscribers, or 97% of its entire basic subscriber base, and the company was marketing cable - modem service to roughly 2,320,00 data - ready homes, or 85% of its total homes passed. As of the same date, approximately 96% of its cable network was upgraded to 550MHz870MHz bandwidth capacity, and 91% of its homes passed were activated with two - way communications capability. By mid - 2003, these figures both are expected to approximate 98%, with almost 95% of its subscribers served by only 50 of its remaining 176 master head - ends (which have decreased by over 55% during the course of 2002)."

(Continued)

APPENDIX 2 (Continued)

Example of a Negative classification of a repurchase discussion
Text excerpt from CIBC World Markets, June 26, 2003 on Navistar: "In fact, management spoke of reversing its restricted payment covenant as early as the second quarter of 2004 to allow the company to take these actions. Essentially, once the company meets its 2.5 times interest earned ratio test, the covenant would fall away. We, obviously, do not believe that the repurchase of common equity shares would be in bondholders' best interest and, therefore, view this as an additional negative for the credit. On the positive side, it seems that Navistar is benefiting from the additional volumes provided through its Blue Diamond joint venture with Ford Motor Company, and it appears that Navistar has been gaining market share thus far in 2003. Heading into 2004, we expect the company's credit statistics to continue to improve."

Example of a Positive classification of a repurchase discussion
Text excerpt from Bear Stearns, September 25, 2005 on General Mills: "GIS affirmed its intent to reduce debt by $2 billion within that time period, but only committed to debt reduction of $450 million during this fiscal year that leaves the bulk of the debt to be reduced closer to the back end of its time frame. Nonetheless, we were impressed by the strong debt reduction language and managements indication that stock repurchase of any magnitude will not take place until the debt reduction targets are achieved. At the end of the first quarter, debt/EBITDA was 3.96x compared to 4.57x the prior year, while interest coverage has improved to 4.2x versus 3.49x a year ago. Maintain our marketweight."

Example of a Negative classification of a divestment discussion
Text excerpt from Deutsche Bank, October 14, 2005 on Tribune Co.: "TRB said TV was currently pacing down low double digits, with auto advertising remaining soft. We estimate 4Q revenue down 0.5 % with EBITDA flat. TRB Opens The Door For Asset Sales; Buybacks Could Continue. In a shift in strategy, TRB indicated that it was evaluating how best to structure its portfolio of assets to improve shareholder value. We believe TRB may be considering asset sales, with proceeds possibly used to repurchase shares. In addition, TRB indicated 4Q share repurchases would be similar to 3Q (3. MM share repurchased). Continued modest buybacks together with weak fundamentals and possible asset sales could result in a one - notch downgrade by S&P to Low A. Over time we believe ratings could trend lower as continued equity declines (TRB equity - 25% YTD) could prompt management to adopt a more aggressive shareholder friendly strategy. We rate TRB Lower A, Underweight. TRB 5- yr CDS is currently quoted +62 bps versus KRI +85 bps and GCI +41 bps. North America Global TMT Cable/Media Hale Holden 212.50."

TABLE 1
Accuracy of Naïve Bayes classification algorithm

This table presents out-of-sample and within-sample accuracies of the Naive Bayes classification by comparing the algorithmic classifications with the manual classifications. To calculate the Naive Bayes out-of-sample accuracy, presented in Panel A, we randomly partition the manually coded training dataset into two equally sized parts. One part is used to estimate the Naive Bayes model, while the other is used to test the accuracy of the model's predicted classification. For an example, refer to the first row of Panel A. Out of a total of 262 manually classified negative text extractions, 124 were classified correctly as negative by the software — an accuracy rate of 47.3%. To evaluate the Naive Bayes within-sample accuracy, we use the entire manually coded training dataset to develop the Naive Bayes model, and then compare the model-predicted classifications with the manual classifications. For an example, refer to the first row of Panel B. Out of a total of 524 manually classified negative text extractions, 340 were classified correctly as negative by the Naive Bayes model — an accuracy rate of 64.9%.

	Classified by Algorithm			Manually	Accurately
	Negative	Neutral	Positive	Classified	classified
Panel A: Naïve Bayes algorithm out-of-sample accuracy					
Negative	124	104	34	262	47.3%
Neutral	284	1,707	240	2,231	76.5%
Positive	71	256	146	473	30.9%
Total	479	2,067	420	2,966	66.7%
Panel B: Naïve Bayes algorithm in-sample accuracy					
Negative	340	144	40	524	64.9%
Neutral	594	3,305	562	4,461	74.1%
Positive	110	344	494	948	52.1%
Total	1,044	3,793	1,096	5,933	69.8%

TABLE 2
Summary of sample selection process

Total debt analyst reports (from 2002 to 2007).	22,247
Reports that could be converted into text files.	13,525
Reports that have at least one conflict-event text extraction classified by Rainbow.	11,052
Corresponding number of conflict-event text extractions contained in these reports (one text extraction per key word per report).	39,121
Mean (median) number of conflict-event text extractions per debt analyst's report.	3.54 (3.00)

TABLE 3
Analysis by conflict event

This table provides a content analysis of conflict-event discussions in debt analysts' reports with a conflict event discussion. The frequency of conflict events is presented in Panel A. Panel B reports the classification of conflict events by the tone of the analyst's discussions according to the Naïve Bayes model. In the last column of Panel A, the sum of each keyword percentage is not equal to the total category percentage in bold at the report level, since each report can have multiple keywords from the same category.

Panel A: Frequency distribution of conflict events

Conflict-Event Keyword	Number of Conflict-Event Text Extractions	% of Total (39,121) Conflict-Event Text Extractions	% of Total (11,052) Reports
M&A			
M&A	6,822	17.4	61.7
LBO	232	0.6	2.1
MBO	50	0.1	0.5
	7,104	**18.1**	**63.3**
Wealth distribution			
Repurchase	2857	7.3	25.8
Dividend	2187	5.6	19.7
	5,044	**12.9**	**31.8**
Divestment			
Asset sale	1,852	4.7	16.7
Spinoff	165	0.4	1.5
	2,017	**5.1**	**17.6**
Financial risk			
Leverage	7,722	19.7	69.9
Debt	9,788	25.0	88.5
Deleverage	711	1.8	6.4
	18,221	**46.5**	**91.3**
Other			
Covenant	1,646	4.2	14.9
Capex	4,464	11.4	40.4
Equity focus	352	0.9	3.2
Event risk	273	0.7	2.5
	6,735	**17.2**	**45.8**
Total	**39,121**	**100.0**	

Panel B: Naïve Bayes classification by conflict event category

Conflict-Event Keyword	Negative (%)	Neutral (%)	Positive (%)
M&A	17.2	56.1	26.7
Wealth distribution	24.0	55.7	20.3
Divestment	18.3	52.6	29.1
Financial Risk	15.1	59.9	24.9
Others	14.0	65.9	20.1
Total	16.6	59.3	24.0

TABLE 4
Timing of other events relative to debt analysts' conflict discussion

This table presents the frequency of actual conflict events around the publication date of debt analysts' reports with conflict discussions. We retrieve announcement dates of these events from Thompson One (formerly SDC Platinum). For example, the first row shows that for 18.19% of these reports with conflict discussions, firms announced M&A-related activity in the period ranging from 30 to 3 trading days before the report. Approximately 1.52% of conflict-discussion reports are contemporaneous (i.e., day -2 to +2) with a firm's M&A announcement. For 17.32% of these debt analyst reports with conflict discussions, firms announced M&A-related activity in the period from 3 to 30 days after the report.

	Day 0 = Date of Debt Analyst's Report with a Conflict Discussion		
Announcement	Before (Day -30 to -3)	During (Day -2 to +2)	After (Day +3 to +30)
M&A	18.19%	1.52%	17.32%
Repurchase	1.07%	0.21%	1.37%
Dividend	15.60%	1.42%	16.48%
Rating Change	5.78%	0.72%	6.23%
Watchlist	6.37%	0.79%	6.42%

TABLE 5
The effect of the tone of debt analysts' conflict discussions on debt analysts' recommendations

This table presents an analysis of the relation between debt analysts' recommendations and their conflict discussions, controlling for other factors that could explain recommendations. The sample includes observations at the report level for which we have available data to calculate all variables. Panel A provides descriptive statistics for the variables in the tests. For indicator variables we only tabulate the mean. Panel B presents the regression results. Each column presents the results using a different dependent variable. We estimate ordered probit regressions as a panel and cluster the standard errors at the firm level. Robust *z*-statistics are in brackets. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. Variables are defined in Appendix 1.

Panel A: Descriptive Statistics

				Percentile		
Variable	N	Mean	Std. Dev.	5^{th}	Median	95^{th}
Debt Recommendation	7,035	2.29	0.68	1	2	3
Δ*Debt Recommendation*	5,219	0.01	0.35	-1	0	1
Debt Rec. less Equity Rec.	7,035	0.13	0.85	-1	0	1
Conflict Discuss Neg	7,035	0.24				
Text Count	7,035	7.02	1.21	5.00	7.05	8.97
Complexity High	7,035	0.46				
Highly Traded	7,035	0.50				
Fcst Revisions	7,035	0.05	2.81	-1.13	0	1.09
On Watch Neg	7,035	0.11				
On Watch Pos	7,035	0.02				

Panel B: Regressions

		Dependent Variable =		
	Prediction	*Debt Recommendation* (1)	Δ*Debt Recommendation* (2)	*Debt Rec. less Equity Rec.* (3)
Conflict Discuss Neg	–	-0.295***	-0.157***	-0.129***
		[-6.59]	[-3.94]	[-2.66]
Text Count	?	0.031*	0.009	0.008
		[1.80]	[0.67]	[0.45]
Complexity High	?	0.001	-0.002	-0.031***
		[0.19]	[-0.63]	[-3.36]
Highly Traded	?	0.098	0.017	-0.042
		[1.40]	[0.28]	[-0.86]
Fcst Revisions	+	0.060	0.020	0.056
		[0.75]	[0.30]	[1.26]
On Watch Pos	+	0.368***	0.193*	-0.105
		[3.10]	[1.73]	[-0.79]
On Watch Neg	–	-0.069	0.087	0.141**
		[-0.98]	[1.49]	[1.96]
Rating Effects		Yes	Yes	Yes
Year Effects		Yes	Yes	Yes
No. of obs.		7,035	5,219	7,035
Pseudo R^2 (%)		5.49	1.09	3.56

TABLE 6
The effect of the tone of debt analysts' conflict discussions on daily CDS spread changes

This table presents an analysis of daily CDS spread change reactions to the tone of debt analysts' conflict discussions, controlling for other events that could affect CDS spread changes. The dependent variable is *ΔCDS Spread*. In column (1), the full sample includes observations for all trading days for which we have CDS spread data available during the six-year period studied for each of the sample firms. For the remaining columns, we limit the sample to observations that represent positive news for equity holders, as proxied by positive stock returns. We estimate the OLS model as a panel and cluster the standard errors at the firm level. Coefficient *t*-statistics are in brackets. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. Variables are defined in Appendix 1.

		Full Sample	Sample Restricted to Positive News for Equity Investors	
	Pred.	(1)	(2)	(3)
Conflict Discuss Neg	+	0.031**	-0.026	-0.019
		[2.50]	[-1.45]	[-1.21]
Conflict Discuss Neg × Equity Return	+		2.729**	
			[2.11]	
Conflict Discuss Neg: Above A Rating × Equity Return	+			1.319***
				[3.25]
Conflict Discuss Neg: BBB-A Rating × Equity Return	+			1.628***
				[3.13]
Conflict Discuss Neg: Below BBB Rating × Equity Return	+			3.175**
				[2.36]
Equity Return	–		-1.211***	-1.161***
			[-4.98]	[-4.84]
Debt Buy Recommendation	–	0.001	-0.003	-0.004
		[0.14]	[-0.37]	[-0.43]
Debt Sell Recommendation	+	0.004	-0.003	-0.001
		[0.53]	[-0.24]	[-0.08]
Debt Recommendation Upgrade	–	-0.010	-0.027**	-0.024**
		[-1.15]	[-2.52]	[-2.33]
Debt Recommendation Downgrade	+	0.018	0.026**	0.025**
		[1.40]	[2.32]	[2.16]
ΔCDS Market Spread	+	1.000**	0.878**	0.880**
		[2.56]	[2.42]	[2.41]
Equity Buy Recommendation	?	-0.004*	0.002	0.001
		[-1.86]	[0.88]	[0.44]
Equity Sell Recommendation	?	0.003	-0.007	-0.006
		[0.36]	[-0.44]	[-0.39]
Rating Agency Action Neg	+	0.050	0.015	0.014
		[1.63]	[0.67]	[0.64]
Earnings Neg	+	-0.045	0.006	0.009
		[-0.81]	[0.28]	[0.59]
Rating Effects		Yes	Yes	No
No. of obs.		364,595	178,213	178,213
Adjusted R^2 (%)		2.28	2.35	2.29

TABLE 7
The effect of the tone of debt analysts' conflict discussions on daily bond trading volume

This table presents an analysis of bond daily trading volume reactions to the tone of debt analysts' conflict discussions, controlling for other events that could affect bond trading volume. The dependent variable is *Bond Volume*. The underlying sample includes observations for all trading days during the 2002-2007 period studied for each of the sample firms. We estimate the OLS model as a panel and cluster the standard errors at the firm level. Coefficient *t*-statistics are in brackets. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. Variables are defined in Appendix 1.

	Prediction	(1)	(2)	(3)
Conflict Discuss Neg	+	0.220***	0.226***	
		[5.93]	[5.73]	
Conflict Discuss Pos	+		0.017	
			[0.55]	
Conflict Discuss Neg: Above A Rating	+			0.100
				[0.56]
Conflict Discuss Neg: BBB-A Rating	+			0.407***
				[7.10]
Conflict Discuss Neg: Below BBB Rating	+			0.074
				[1.52]
Debt Report	+	0.134***	0.134***	0.118***
		[9.48]	[9.48]	[7.71]
Debt Report With Conflict Discussion	+	0.108***	0.103***	0.107***
		[4.80]	[4.29]	[4.72]
Text Count High	+	-0.061**	-0.063**	-0.076***
		[-2.15]	[-2.21]	[-2.65]
Debt Buy Recommendation	+	0.015	0.014	-0.010
		[0.67]	[0.66]	[-0.43]
Debt Sell Recommendation	+	0.107***	0.107***	0.138***
		[3.90]	[3.90]	[4.82]
Debt Recommendation Upgrade	+	0.140***	0.140***	0.138***
		[4.42]	[4.42]	[4.24]
Debt Recommendation Downgrade	+	0.054*	0.054*	0.045
		[1.73]	[1.73]	[1.40]
Equity Volume	+	0.005***	0.005***	0.004***
		[2.74]	[2.74]	[2.75]
Conflict Event Firm Announcement	+	0.050***	0.050***	0.064***
		[4.29]	[4.29]	[5.54]
Equity Report	+	-0.032***	-0.032***	-0.029***
		[-3.91]	[-3.91]	[-3.46]
Equity Buy Recommendation	+	0.032**	0.032**	0.019
		[2.20]	[2.20]	[1.26]
Equity Sell Recommendation	+	0.050***	0.050***	0.064***
		[4.29]	[4.29]	[5.54]
Rating Agency Action	+	0.092***	0.092***	0.071***
		[5.30]	[5.30]	[3.92]
Rating Agency Action Neg	+	0.220***	0.220***	0.234***
		[7.24]	[7.24]	[7.70]
Earnings	+	0.006	0.006	0.002
		[0.72]	[0.73]	[0.24]
Earnings Neg	+	0.088***	0.088***	0.044*
		[4.92]	[4.92]	[1.96]

(Continued)

TABLE 7 (Continued)

	Prediction	(1)	(2)	(3)
Fed Change	+	0.023*** [3.42]	0.023*** [3.41]	0.021*** [3.24]
Rating Effects		Yes	Yes	No
Year Effects		Yes	Yes	Yes
No. of obs.		952,502	952,502	952,502
Adjusted R^2 (%)		3.10	3.10	1.38

TABLE 8

The effect of the tone of debt analysts' conflict discussions on offering yields of new bond issues

This table presents an analysis of the relation between the offering yield to maturity of new bond issues and the tone of debt analysts' conflict discussions, controlling for other factors that could affect these yields. The dependent variable is *Bond Offering Yield*. The sample includes observations of new bond issues during 2002-2008 for which we have debt analysts' reports in the preceding six-month period. We estimate the OLS model as a panel and cluster the standard errors at the firm level. Coefficient *t*-statistics are in brackets. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. All other variables are defined in Appendix 1.

	Prediction	(1)	(2)	(3)
Conflict Discuss Neg Prior 6M	+	0.270**		0.340**
		[2.02]		[2.56]
Conflict Discuss Neg Prior 6M: Above A Rating	+		-0.741	
			[-1.17]	
Conflict Discuss Neg Prior 6M: BBB-A Rating	+		0.940	
			[1.55]	
Conflict Discuss Neg Prior 6M: Below BBB Rating	+		0.636**	
			[2.36]	
Debt Recommendation Prior 6M	–	0.050	0.117	0.052
		[0.50]	[0.89]	[0.52]
Debt Recommendation Change Prior 6M	–	-0.201	-0.155	-0.180
		[-0.61]	[-0.38]	[-0.55]
Number of Covenants	–	0.084**	0.349***	
		[1.98]	[8.75]	
Number of Covenants (Predicted)	–			-0.168***
				[-4.19]
Bond Maturity	+	0.176	-0.493***	0.182
		[1.13]	[-4.22]	[1.16]
Bond Offering Amount	?	0.112	-0.456***	0.139
		[0.89]	[-2.69]	[1.21]
Complexity High	?	-0.538***	-0.340**	-0.471***
		[-3.56]	[-2.10]	[-3.38]
Firm Size	–	-0.029	-0.008	-0.061
		[-0.38]	[-0.08]	[-0.90]
Leverage	+	1.879***	3.104***	1.724***
		[2.92]	[5.07]	[2.67]
Interest Coverage	–	-0.008	-0.043**	-0.006
		[-0.56]	[-2.37]	[-0.42]
Private	–	-0.455*	-0.519*	-0.463*
		[-1.77]	[-1.75]	[-1.85]
Conflict Event Firm Announcement Prior 6M	?	0.271**	0.270**	0.244**
		[2.23]	[2.22]	[2.05]
Equity Recommendation Prior 6M	–	-0.210	-0.426**	-0.265*
		[-1.50]	[-2.40]	[-1.90]
Fed Rate	+	0.137***	0.335***	0.130**
		[2.60]	[3.09]	[2.50]
Rating Effects		Yes	No	Yes
Industry Effects		Yes	Yes	Yes
No. of obs.		1,013	1,013	1,013
Adjusted R^2 (%)		75.30	65.08	75.36

TABLE 9
Alternative measure of the tone of debt analysts' conflict discussions

This table presents results for two alternative measures of our main variable, the tone of debt analysts' negative conflict discussions. The alternative measures are based on the disagreement in the tone of conflict discussions between debt and equity analyst reports. We extract equity analysts' discussions of conflict events from a matched sample of equity analysts' reports and measure the discussions' tone using the Naïve-Bayesian model. Our alternative hybrid measure of debt analysts' conflict discussions focuses on debt analysts' reports that contain negative conflict discussions when equity analysts' conflict discussions are positive. *Alternative Measure #1* uses the training data set from debt analysts' reports (used in our main analysis) to estimate the equity analysts' Naïve-Bayesian model. *Alternative Measure #2* uses a new training data set based directly on equity analysts' conflict discussions. The first column repeats the respective main result from Tables 5 to 8 as a benchmark for comparison. The next two columns present the results using identical tests but with one of the two alternative measures: only the coefficient and *t*-statistic (or *z*-statistic) of the main variable are tabulated. All specifications are estimated with the same set of other independent variables as the previously tabulated tests, but the results for these variables are not tabulated. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. All variables are defined in Appendix 1.

Variable	Prediction	Main Measure (For Comparison) (1)	*Alternative Measure #1* (2)	*Alternative Measure #2* (3)
From Table 5, Column (1), Dep. Var. = *Debt Recommendation*				
Conflict Discuss Neg	–	-0.295***	-0.174**	-0.254***
		[-6.57]	[-2.60]	[-4.09]
From Table 6, Column (2), Dep. Var. = *ΔCDS Spread*				
Conflict Discuss Neg × Equity Return	+	2.729**	4.365***	2.806
		[2.11]	[3.05]	[1.51]
From Table 7, Column (1), Dep. Var. = *Bond Volume*				
Conflict Discuss Neg	+	0.220***	0.111**	0.156***
		[5.93]	[2.29]	[3.94]
From Table 8, Column (1), Dep. Var. = *Bond Offering Yield*				
Conflict Discuss Neg Prior 6M	+	0.270**	0.472**	0.391**
		[2.02]	[1.99]	[2.79]