

Debt Analysts' Views of Debt-Equity Conflicts of Interest

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ABSTRACT: We investigate how the tone of sell-side debt analysts' discussions about debt-equity conflict events affects the informativeness of debt analysts' reports in debt markets. Conflict events such as mergers and acquisitions, debt issuance, share repurchases, or dividend payments potentially generate asset substitution or wealth expropriation by equity holders. We document that debt analysts routinely discuss these conflict events in their reports. More importantly, discussions about conflict events that we code as negative 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 negatively coded conflict discussions predict higher bond offering yields in the primary bond market. In additional analyses, we measure the tone of debt analysts' discussions based on their disagreement with the

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tone of equity analysts' discussions and find that the informativeness of debt analysts' reports is higher when our coding indicates that conflict events are viewed negatively by debt analysts but positively by equity analysts.

Keywords: *debt analysts; equity analysts; debt-equity conflict events; bond volume; bond yield; CDS spreads.*

JEL Classifications: *G12; G14; G32; M49.*

I. INTRODUCTION

Recent studies 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 (Johnston, Markov, and Ramnath 2009; De Franco, Vasvari, and Wittenberg-Moerman 2009; Gurun, Johnston, and Markov 2011). Aside from providing a review of firms' financial performance in their reports, debt analysts discuss and analyze the effects of debt-equity conflict events that potentially generate asset substitution and wealth expropriation by equity holders, such as mergers and acquisitions, debt issuance, share repurchases, and dividend payments (hereafter, "conflict events"). These discussions are likely to provide debt investors with important information and can explain debt markets' reactions to debt analysts' reports. We assess the tone of debt analysts' discussions of conflict events using textual analysis and investigate the effects of the tone on the borrowing firms' credit spreads, bond trading, and cost of debt.

While previous studies establish the existence of events that lead to debt-equity conflicts, as discussed in Section II, these studies find mixed results with respect to the economic importance of such conflicts to debt holders. If these conflict events meaningfully affect debt holders' wealth, then debt analysts' discussions should be informative to debt investors. However, if conflict discussions do not provide material information or are not timely, then these discussions will not expand the information set available to debt holders.

Our sample consists of conflict-event discussions extracted from a unique hand-collected dataset of 11,025 reports issued by sell-side debt analysts (hereafter, "debt analysts") 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 mergers and acquisitions, divestments, dividend payments, stock repurchases, or debt issuance. We then manually code a randomly selected set of text extractions and use it to calibrate a Naive Bayesian model that estimates 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. These discussions not only follow, but also anticipate firm announcements of these conflict events, highlighting their informativeness. Further, based on our coding, debt analysts typically interpret conflict events as non-negative, with the majority of events being interpreted as mixed or neutral news for debt investors. This finding suggests that conflict events are not always expected to reduce debt holders' wealth. Instead, they can provide a positive signal about the firm's performance or news that is either less negative than debt holders initially expected or simply not material.

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, for reports coded as containing negative discussions of debt-equity conflicts. We document that firms' credit default swap (CDS) spreads increase when debt analysts' discussions about conflict events take on a negative tone. Relative to reports coded as containing positive or neutral discussions, reports that include

negatively coded discussions increase the abnormal CDS spread by a statistically significant 12 basis points over the five-day window centered on the date of a debt analyst's report. In particular, we show that greater gains to equity holders, as evidenced by positive abnormal equity returns, are associated with greater losses to debt holders around the publication of debt analysts' reports with negatively coded discussions of conflict events. This result suggests that debt analysts' negative conflict discussions reflect potential wealth transfers from debt holders to equity holders. To corroborate these CDS reactions, we show that when the tone of debt analysts' discussions about conflict events is coded as negative, relative to reports coded as having a neutral or positive tone, the daily bond trading volume is higher by a statistically significant 1.15 percent of the bonds' principal over the five-day window report date. The bond trading volume reaction further highlights the importance of the tone of analysts' discussions to debt market investors.

Consistent with the reactions in secondary debt markets, we document that the negatively coded conflict discussions in debt reports that precede the issuance of bond securities in the primary market predict the initial pricing of these bonds. Their yield to maturity increases with the negative tone of the conflict discussions in reports published in the six-month period prior to the bond issuance. Relative to discussions coded as neutral or positive, discussions of conflicts coded negatively increase the offering yield by a statistically significant 27 basis points. This finding suggests that debt analysts' views also provide additional information to primary bond market investors and affect firms' cost of debt financing.

Next, we test whether the impact of discussions coded as having a negative tone about conflict events varies cross-sectionally with firms' credit ratings across our market variables—daily CDS spread changes, daily bond trading volume, and yields on new bond issues. We find some evidence suggesting that negatively coded conflict discussions have stronger associations with our market variables for lower-rated debt, consistent with an increase in the informational value of debt analysts' discussions in settings where debt investors demand more information about downside risk.

To provide additional evidence that debt analysts' conflict-event discussions capture the construct of conflict between debt and equity holders, we develop and test an alternative tone measure based on the disagreement in the coded tone of conflict discussions between debt and equity analyst reports. This measure captures situations where these discussions are coded negative for debt analysts but positive for equity analysts, reflecting the idea that the news is negative for debt holders but positive for equity holders. In both the primary and secondary market tests, our main findings and inferences continue to hold using this alternative measure.

Our use of a "Naïve Bayes" computational process to estimate the tone of the text in debt analysts' reports follows studies such as [Antweiler and Frank \(2004\)](#) and [Li \(2010\)](#). The method uses the training dataset that we manually coded to calculate the probabilities that the tone of the text is positive, neutral, and negative, respectively, for each word in the text. The Naive Bayes model then takes the words in the text and aggregates these probabilities by word to form a categorical prediction (positive, neutral, or negative) about the text. This computational process allows us to dramatically increase our research sample compared to a manual coding of the text.

We acknowledge that our Naïve Bayes computational process introduces measurement error, which we can identify by comparing the tone of text extractions based on manual coding with the model's predictions. As we discuss in Section III, the classification performance metrics suggest our procedure performs reasonably well. Further, while we do not expect the measurement error in our variable of interest—reports with a negatively coded tone—to be systematically related to any of our debt market reaction measures, we nonetheless perform a series of additional tests to examine the sensitivity of our findings to the classification accuracy of the Naive Bayes computational process. More specifically, we restrict the analyses to manually coded extractions, focus on reports with multiple negatively coded text extractions, run all the tests excluding neutrally coded

discussions, and examine the relation between the tone of the conflict discussions and analysts' investment recommendations. While we believe that the results of these tests mitigate concerns regarding the measurement error in our main variable of interest, we acknowledge that measurement error limits our ability to make strong inferences about the effect of the tone of conflict discussions on debt markets' reactions to debt analysts' reports.

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.¹ We provide unique evidence showing that the tone 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 many studies investigate equity analysts, there is limited evidence 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. firms (Bessembinder and Maxwell 2008). Our analyses complement the recent debt analyst studies of Johnston et al. (2009), De Franco et al. (2009), and Gurun et al. (2011) by providing insight into the type of information produced by debt analysts and the debt market's reaction to their reports. We also present new evidence on the relation between debt analysts' reports and firms' borrowing costs in the primary bond market.²

Third, in contrast with prior literature, 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. Bond returns might not capture these concerns due to infrequent bond trading, divergent reactions due to different bond features, or reactions to firm fundamentals. Short-window bond returns around the actual event also do not capture events anticipated by the market. In addition, prior research on debt-equity conflicts, with the exception of Parrino and Weisbach (1999), has focused on only one 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 that prior research provides with respect to the importance of conflict events to debt holders. Our approach of coding the tone of debt analysts' discussions about debt-equity conflicts, while affected by measurement error, allows us to document the importance of these conflict events as well as to determine whether and how debt holders' wealth is affected.

The next section reviews the literature and develops our research question. Section III describes our data and the measurement of debt analysts' discussions of conflict events. Section IV discusses the results of our tests. Section V concludes.

¹ See, for example, studies by Frankel, Kothari, and Weber (2006), Ederington and Goh (1998), Dichev and Piotroski (2001), Beaver, Shakespeare, and Soliman (2006), Fang and Peress (2009), and Bushee, Core, Guay, and Hamm (2010).

² To our knowledge, no work has been done that investigates 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 the cost of debt is limited. Guntay and Hackbarth (2010) and Mansi, Maxwell, and Miller (2011) find that equity analysts' forecast dispersion and forecast revision volatility increase bond yield spreads.

II. LITERATURE REVIEW AND RESEARCH QUESTIONS

Background on Debt Analysts³

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. The resulting low 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 evaluate firms’ fundamental performance and firm-specific events, but with 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 mispricing of a bond security, relative to other similar bonds, contributes to the issuance of “buy” or “sell” 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 act less strategically and provide more negative information than equity analysts, which likely meets the asymmetric demand for negative information by bond investors.

Aside from investment recommendations, 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, as well as discussions of lending market conditions or relative bond pricing. More importantly, the reports provide extensive discussions of risks associated with events that potentially give rise to conflicts of interest between bondholders and shareholders, such as mergers and acquisitions, new debt issuances, asset sales, dividend payments, or share repurchases. 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, who represent the vast majority of bond investors ([Warga 2004](#)). Further, debt analysts are compensated in part based on institutional client surveys that assess the value of debt analysts’ research.

Importance of Debt Analysts’ Discussions of Conflict Events

We broadly partition the type of news that debt analysts discuss into 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 concerning 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 ([Jensen and Meckling 1976](#); [Myers 1977](#)). 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, including covenants, collateral, put provisions, and sinking fund provisions. Hence, if analysts were to issue a negative view of a conflict event, then it may be a sign that they perceive these protective features to be insufficient.

³ 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, Managing Director of the European credit research team at Morgan Stanley.

On the one hand, because debt-equity conflicts have the potential to negatively affect debt holders' wealth, debt holders will demand information about the downside risk that these events pose on their claims, and debt analysts are expected to meet this demand. If the potential conflict is material, regardless of whether 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. Based on these arguments, our central prediction is that the negative tone of debt analysts' conflict discussions is relevant to debt investors and generates debt market reactions.

On the other hand, the extent and economic importance of such conflict events to debt holders' wealth, as documented by extant studies, is far from clear. In the case of spin-offs, for example, [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 \(1983\)](#) and [Handjinicolaou and Kalay \(1984\)](#) do not find that dividend payments have a detrimental effect on bondholders. In contrast, [Dhillon and Johnson \(1994\)](#) and [Maxwell and Stephens \(2003\)](#) do find evidence supporting a wealth transfer from debt holders. Finally, while [Warga and Welch \(1993\)](#) and [Billet, King, and Mauer \(2004\)](#) document a loss in debt holders' wealth associated with leveraged buyouts and acquisitions, [Marais, Schipper, and Smith \(1989\)](#) and [Lehn and Poulsen \(1991\)](#) find that leveraged buyouts do not result in a wealth transfer. If conflict events have a minimal negative effect on debt holders' wealth, as some of these studies suggest, the debt market should not react to the negative tone of debt analysts' conflict discussions. Similarly, the debt market should not react to the tone of conflict discussions if they do not provide relevant new information or are not timely.

We expect the importance of negative conflict discussions to vary cross-sectionally with firms' debt ratings. For higher quality debt, debt prices are less sensitive to new information, because either the likelihood of a loss is very small or the upside potential is already limited. In contrast, the price of lower rated debt is highly sensitive to negative information ([De Franco et al. 2009](#); [Easton, Monahan, and Vasvari 2009](#)), making debt analysts' negative conflict discussions more valuable to debt investors. Hence, we predict that the negative tone of debt analysts' conflict discussions leads to greater market reactions for lower rated debt. However, it is possible that debt analysts' discussions of conflict events already take into account the riskiness of the bond security. Hence, when the tone of these discussions is conditional on the bond's credit rating, it may not generate differential market reactions. Thus, the impact of negative conflict-event discussions across rating categories is ultimately an empirical question.

Empirically, we measure debt market reactions by changes in secondary market CDS spreads⁴ and bond trading volume⁵ and by the level of the offering yields on bond issues in the primary market. We predict that CDS spreads, bond volume, and bond yields are positively related to the negative tone of debt analysts' conflict discussions.

⁴ CDS contracts capture the credit quality level in terms of the probability of default and have the advantage of trading far more frequently than the underlying bond securities ([Hull, Predescu, and White 2004](#)). The low frequency of bond trade data makes it difficult to conduct short-window tests in bond markets ([Goodhart and O'Hara 1997](#); [Hotchkiss and Ronen 2002](#)). CDS spreads are also much less affected by liquidity problems, changes in interest rates, and contract design features that are specific to bond securities ([Bushman, Le, and Vasvari 2010](#)). These features, such as option-like provisions and collateral requirements, can be difficult to control for in empirical tests.

⁵ Volume reactions are associated with new information ([Kim and Verrecchia 1991](#)), as well as with information that leads to a divergence of opinion among investors ([Harris and Raviv 1993](#); [Kim and Verrecchia 1994](#)). If debt analysts' reports matter to debt investors, then they should generate additional trading.

III. DATA AND MEASUREMENT OF DEBT ANALYSTS' CONFLICT-EVENT DISCUSSIONS

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.⁶ If the broker has not already done so, we standardize the debt analysts' recommendations into three categories: buy, hold, or sell.⁷ We also collect current Moody's or Standard & Poor's rating information from the reports.

We select reports about U.S. corporate firms with bond securities for the years 2002 to 2007. The start of this period aligns with the availability of bond trading data from the Trade Reporting and Compliance Engine (TRACE) database. We exclude reports on Real Estate 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, where this last type often simply repeats previously published information in reports (Stickel 1995; De Franco and Hope 2011). Reports missing an investment recommendation are excluded from the analysis. This procedure for collecting debt analysts' reports is similar to that used in De Franco et al. (2009).

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 from the perspective of debt holders.⁸ We take the following five steps.

Step 1

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

⁶ Debt analysts occasionally provide recommendations at the bond level. For our sample, in almost all cases when recommendations at the bond level are available for each of the firm's bonds, these recommendations are identical.

⁷ While most brokers typically employ these three recommendation levels, some use a system of five levels (Strong Buy, Buy, Hold, Sell, Strong Sell). The standardization to three levels allows us to pool the recommendations together in our empirical tests.

⁸ Our Naive Bayesian updating algorithm approach, described below, builds on burgeoning research that uses the tools of computational linguistics (Tetlock 2007; Tetlock, Saar-Tsechansky, and Macskassy 2008; Kothari et al. 2009; Li 2010; Rogers, Van Buskirk, and Zechman 2011). Beyer, Cohen, Lys, and Walther (2010) call for more work in this area.

issuances or restructurings). 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 in a debt analyst’s report, we extract the words contained in the sentence that contains the keyword and the two sentences before and after it. For each report, we then accumulate the text extractions by keyword. For example, if the word “repurchase” appears more than once in the report, we extract the surrounding text around each “repurchase” keyword and group these sentences together. Thus, for each keyword, we are able to extract from the report all of the analyst’s discussion about that word. Each keyword text extraction corresponds to a different conflict event.

Step 3

We use a “Naive Bayes” approach (implemented via the “Rainbow” program, publicly available from Andrew McCallum at <http://www.cs.cmu.edu/~mccallum/bow> [McCallum 1996]) to classify the keyword text extractions identified in the previous step as positive, negative, or neutral (see Antweiler and Frank [2004] and Li [2010] for examples of this approach). To estimate the Naive Bayes model, we need a set of data to “train” the algorithm. We create this training dataset by manually classifying 5,933 randomly selected text extractions as positive, neutral, or negative.⁹ Appendix B provides examples of text extractions and the manual coding for each extraction. 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 for all the text extractions in our sample—negative, positive, or neutral—conditional on the words in the text extraction.

Step 4

In line with our focus on the negative tone of debt analysts’ conflict discussions when we estimate our tests, we classify the extractions as negative or non-negative, which includes positive or neutral. To determine the accuracy of the Naive Bayes algorithm, in Appendix C we calculate the within-sample accuracies of the classifications by comparing the algorithmic classifications with the manual classifications. We compute several measures that capture our model’s performance, based on the prior literature both in accounting and finance (Barber and Lyon 1996; Chava and Jarrow 2004; Stein 2005; Kothari, Leone, and Wasley 2005; Dechow, Ge, Larson, and Sloan 2011) and medical statistics (Glas, Lijmer, Prins, Bonsel, and Bossuyt 2003; Lasko, Bhagwat, Zou, and Ohno-Machado 2005; Fawcett 2006). Appendix C provides the definition of each of these measures.

The *Sensitivity* is 65 percent, reflecting a Type I error of 35 percent. This error represents the probability of the model incorrectly predicting a non-negative tone when the tone is actually negative. The *Specificity* is 87 percent, reflecting the Type II error of 13 percent. The Type II error represents the probability of the model incorrectly predicting a negative tone when the tone is actually non-negative. We also estimate an aggregate measure, the *Accuracy* of our model, which reflects both false positive and false negative errors and captures the probability that the tone is

⁹ Ten research assistants (RA) carried out this task in a standardized manner with the guidance of a process document we developed. Given the subjective nature of the task, two different research assistants independently coded each text extraction. We then engaged a third RA to reconcile any differences. Untabulated analyses indicate that the accuracy of our model using this coding approach is similar to an alternative approach in which we limit the sample to those text extractions for which the first two RAs coding the extraction agreed on the classification.

correctly classified. *Accuracy* is equal to 85 percent for our model. A less common approach to look at these error rates is to assess the percentage of true negative (non-negative) tone discussions when the model predicts a negative (non-negative) tone. *Positive Predictive Value* is 33 percent and *Negative Predictive Value* is 96 percent. As a benchmark, our model's performance is not quite as good as that of the Antweiler and Frank (2004) algorithm. While Antweiler and Frank (2004) do not provide any formal assessment of their measurement error, the in-sample classifications they report allow us to calculate the five performance measures. Their model's *Accuracy* (89 percent), *Sensitivity* (72 percent), *Specificity* (95 percent), and *Negative Predictive Value* (91 percent) are marginally better than or in line with those that we report, but their *Positive Predictive Value* (83 percent) is much better than the 33 percent value that we report.¹⁰

In untabulated analysis, we also estimate the out-of-sample prediction ability of our algorithm, by randomly partitioning the manually coded training dataset into two parts. We use one part to train and estimate the model and the other to test the classification accuracy. Our out-of-sample performance metrics are overall lower with *Sensitivity* of 47 percent, *Specificity* of 87 percent, *Accuracy* of 83 percent, *Positive Predictive Value* of 26 percent, and *Negative Predictive Value* of 94 percent. In comparison, Li's (2010) Naive Bayes model has an out-of-sample *Accuracy* of between 67 percent and 90 percent, but he does not report other performance measures. To address the potential impact of the classification accuracy of a Naive Bayes algorithm on our findings and inferences, we report the results of several sensitivity analyses in Section IV.

Step 5

As our tests are at the report level, we create a measure per report by aggregating the extraction-level scores. To each extraction, we assign the value of -1 if the Naive Bayes algorithm classifies the text extraction as negative, 0 if it is classified as neutral, and 1 if it is classified as positive. Then, the score for each extraction is weighted by the number of words in that extraction scaled by the total number of words across all extractions in the report. We then sum the weighted scores of all extractions in a report, where by construction the measure lies between -1 and 1 . Last, we define *Conflict Discuss Neg* as an indicator variable that takes a value of 1 if the continuous report-level score is negative, and 0 otherwise.¹¹

Bond and CDS Data

We retrieve secondary market corporate bond trades from the National Association of Securities Dealers' (NASD) TRACE system and the Mergent Fixed Income Securities Database (FISD). Because TRACE's coverage of firms is not complete until February 2005, we augment our TRACE bond data with that of FISD when necessary. We 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 approximately 82 percent of our debt analysts' report data. We then match the borrowers with debt analysts' reports and bond trading information 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 dataset with the textual analysis data. We obtain CDS data from the database provided by Markit Partners. To maintain contract homogeneity, we focus on the most liquid CDS contract, which is the five-year

¹⁰ To facilitate comparisons with our Negative versus Non-Negative contingency table, we convert Antweiler and Frank's (2004) classifications of Buy, Hold, and Sell into two categories, Buy and Non-Buy.

¹¹ We find that our main inferences are similar in two untabulated robustness tests. First, we employ the continuous measure of conflict discussions instead of the indicator variable *Conflict Discuss Neg*. Second, as an alternative measure of debt analysts' conflict discussions, we use the General Inquirer classification algorithm.

TABLE 1
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 keyword per report).	39,121
Mean (median) number of conflict-event text extractions per debt analyst's report.	3.54 (3.00)

CDS contract with the modified restructuring clause. Finally, we obtain bond yield to maturity at issuance and other bond features from Mergent FISD.

Test Sample

Of a potential sample of 22,247 reports, we successfully “parse” 13,525 reports from PDF to text format, of which 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 (3.0) text extractions, which corresponds to a report mentioning a mean of 3.5 (median 3.0) unique conflict-event keywords. Table 1 summarizes this selection process. Our regression tests have smaller samples due to additional restrictions on data availability to calculate the variables in each specification.

IV. RESULTS

Content Analysis of Debt Analysts' Conflict-Event Discussions

The frequency of conflict events is presented in Panel A of Table 2. Debt analysts extensively discuss M&A activities, with 63 percent of the reports including such a discussion. In 32 percent of the reports, analysts discuss wealth distribution, including stock repurchases and dividend payments. Divestment discussions characterize 18 percent of the reports. The financial risk category is the most frequently discussed event; it appears in 91 percent of the reports.

Panel B of Table 2 reports the classification of conflict events by the tone of analysts' discussions according to the Naive Bayes model. The vast majority of conflict-event extractions are classified as non-negative, with neutral discussions being the most frequent. 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 (see Appendix B). Debt analysts use a positive tone in approximately 27 percent, 20 percent, and 29 percent 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. While we cannot rule out the possibility of error in our coding, this positive tone can be driven by the conflict event having a smaller than expected negative effect or its 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.

TABLE 2
Analysis by Conflict Event

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	2,857	7.3	25.8
Dividend	2,187	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: Naive Bayes Classification by Conflict-Event Category

Conflict-Event Keyword	Negative (%)	Non-Negative (%)		
		Total (%)	Neutral (%)	Positive (%)
M&A	17.2	82.8	56.1	26.7
Wealth distribution	24.0	76.0	55.7	20.3
Divestment	18.3	81.7	52.6	29.1
Financial Risk	15.2	84.8	59.9	24.9
Others	14.0	86.0	65.9	20.1
Total	16.6	83.4	59.3	24.1

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 Naive 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.

TABLE 3
Timing of Other Events Relative to Debt Analysts' Conflict Discussion
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%

This table 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 (formerly SDC Platinum) and Mergent. For example, the first row shows that for 18.19 percent 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 percent of conflict-discussion reports are contemporaneous (i.e., day -2 to +2) with a firm's M&A announcement. For 17.32 percent 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.

Timing of Other Events Relative to Debt Analysts' Conflict Discussions

To better understand the informational value of debt analysts' reports, we study the timing of debt analysts' reports relative to the timing of actual conflict events. Debt analysts decide when to issue reports that contain discussions of conflict events and could issue reports concurrent with, after, or in anticipation of a conflict event. Table 3 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. For example, the first row shows that, for 18.2 percent of the 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 percent of conflict-discussion reports are contemporaneous (i.e., day -2 to +2) with a firm's M&A announcement. For 17.3 percent of these debt analyst reports, firms announced M&A-related activity in the period from 3 to 30 days after the report. Note that these percentages do not add up to 100 percent because a particular conflict event, such as M&A-related activity in this example, may not occur around a report. The remaining rows of the table demonstrate that this pattern for M&A announcements is similar to other conflict events, suggesting that debt analysts discuss both past and future potential events. The evidence that debt analysts anticipate conflict events provides some support for the notion that the tone of their discussion may provide relevant and timely information to debt investors.

In additional untabulated analysis, we examine the timing of the negatively coded conflict-event discussion in debt analysts' reports relative to credit rating downgrades and additions 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' negatively coded discussions, negative rating agency actions, and CDS spread changes as independent variables (see Beaver et al. [2006] and De Franco et al. [2009] for similar Granger causality analyses). We find that debt analysts' discussions coded as negative 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 negatively coded 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.

Effect of Debt Analysts' Conflict Discussions on Secondary Debt Market Reactions

Daily CDS Spread Changes

Table 4 presents the empirical analysis of the effect of the negatively coded tone of conflict discussions on CDS spreads. This analysis includes observations for *all* trading days during the six-year sample period for which we have CDS spread data available for the sample firms. Within this framework, we have the flexibility to control for firm, analyst, rating agency, and macro-economic disclosures in the same test. This approach allows us to estimate the true relations between market reactions and information events and to compare the magnitude of the CDS spread changes across different events. For each event, including the publication of a debt report, we assign the news to the announcement day and to each of the two trading days immediately before and after it.¹² We estimate:

$$\Delta CDS Spread_{it} = \beta_0 + \beta_1 Conflict Discuss Neg_{it} + \beta_2 Debt Report Controls_{it} + \beta_3 Other Information Controls_{it} + Rating Effects + \eta_{it}. \quad (1)$$

$\Delta CDS Spread$ is the daily change in the CDS spread for firm *i* less the change in the average CDS spread of all entities that have the same credit rating category on a given trading day. Increases in CDS spreads indicate deterioration in an issuer's credit quality. We expect the *Conflict Discuss Neg* coefficient to be positive, which indicates that negatively coded conflict discussions increase CDS spreads. We control for the levels and changes in debt analysts' recommendations. The model also includes equity analysts' recommendations, which allow us to better analyze whether debt analysts provide different information than equity analysts. Conflict discussions represent an important means of distinguishing the analysis of debt analysts' from that of equity analysts. If the contents of the debt analysts' reports were limited only to an analysis of a firm's fundamentals, such as the level of EBITDA or earnings, then the distinction between equity and debt analysts' reports would be minimal because both types of analysts would monitor and evaluate the firm's performance in similar ways. We control for rating agencies disclosures because rating agencies are established as important information providers in the bond market. Finally, we control for firms' abnormal equity returns and negative earnings announcements to proxy for operating fundamentals of the business that are common to debt and equity investors.

The results of estimating Equation (1) are presented in column (1) of Table 4. The coefficient on *Conflict Discuss Neg* is positive and marginally significantly different from 0, consistent with debt analysts' negatively coded conflict discussions predicting a deterioration in an issuer's creditworthiness beyond the standard investment recommendation. Relative to reports with positive or neutral discussions, reports that include negatively coded discussions increase the CDS spread by 12 basis points [2.4 basis points $\times$ 5 days] over the five-day window centered on the date of the debt analysts' reports. As expected, equity returns are negatively associated with CDS spread changes.

In the following specifications in Table 4, to better capture the idea of wealth transfers from debt to equity holders driven by conflict events, we focus on situations in which the news is

¹² We use a five-day window because it is difficult to precisely identify when the information in the debt analysts' reports is released to debt investors. Consistent with this claim, 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, Holthausen, and Leftwich (1992), Asquith et al. (2005), and Bonner, Hugon, and Walther (2007).

TABLE 4

The Effect of the Tone of Debt Analysts' Conflict Discussions on Daily CDS Spread Changes

	Pred.	Full Sample (1)	Sample Restricted to Positive News for Equity Investors	
			(2)	(3)
<i>Conflict Discuss Neg</i>	+	0.024* [1.89]	-0.029* [-1.75]	-0.022 [-1.58]
<i>Conflict Discuss Neg × Equity Return</i>	+		2.880** [2.25]	
<i>Conflict Discuss Neg: Above A Rating × Equity Return</i>	+			1.663*** [3.40]
<i>Conflict Discuss Neg: BBB-A Rating × Equity Return</i>	+			1.887*** [3.25]
<i>Conflict Discuss Neg: Below BBB Rating × Equity Return</i>	+			3.215** [2.46]
<i>Debt Buy Recommendation</i>	-	-0.004 [-0.74]	-0.002 [-0.21]	-0.002 [-0.24]
<i>Debt Sell Recommendation</i>	+	0.001 [0.21]	-0.003 [-0.22]	-0.001 [-0.06]
<i>Debt Recommendation Upgrade</i>	-	-0.008 [-0.94]	-0.026** [-2.40]	-0.023** [-2.20]
<i>Debt Recommendation Downgrade</i>	+	0.017 [1.40]	0.027** [2.34]	0.025** [2.19]
<i>Equity Buy Recommendation</i>	?	-0.001 [-0.64]	0.003 [1.32]	0.002 [0.83]
<i>Equity Sell Recommendation</i>	?	-0.005 [-0.61]	-0.005 [-0.35]	-0.004 [-0.31]
<i>Rating Agency Action Neg</i>	+	0.035 [1.09]	0.017 [0.84]	0.017 [0.81]
<i>Equity Return</i>	-	-1.302*** [-6.57]	-1.532*** [-4.24]	-1.466*** [-4.63]
<i>Earnings Neg</i>	+	0.016 [1.04]	0.009 [0.44]	0.013 [0.81]
Rating Effects		Yes	Yes	No
No. of Obs.		364,595	178,213	178,213
Adjusted R ² (%)		1.27	1.34	0.79

*, **, *** Denote significance at the 10 percent, 5 percent, and 1 percent levels, respectively, using two-tailed tests. Coefficient t-statistics are in brackets.

This table presents an analysis of daily CDS spread change reactions to the coded tone of debt analysts' conflict discussions, controlling for other events that could affect CDS spread changes. The dependent variable is $\Delta CDS\ Spread$. 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 abnormal stock returns. We estimate the OLS model as a panel and cluster the standard errors at the firm level.

Variables are defined in Appendix A.

negative for debt holders and positive for equity holders. In particular, we restrict the sample to observations in which news for equity holders is positive, as proxied by daily abnormal stock returns greater than 0. We focus on this sample because prior literature shows that wealth transfer from debt holders to equity holders is associated with excess gains to equity holders (Warga and Welch 1993; Maxwell and Rao 2003; Maxwell and Stephens 2003). By excluding observations with non-positive abnormal stock returns, we are more confident that our results are not driven by situations in which equity holders' wealth is unaffected or has declined.

We also interact the *Conflict Discuss Neg* and *Equity Return* variables. Because of the interaction, in this specification the coefficient on *Equity Return* will capture days when debt analysts' conflict discussions are positive or neutral or when there are no debt analysts' reports. The expected coefficient is negative. The coefficient on the interaction term captures situations when equity holders' wealth improves while debt analysts provide negative discussions of conflict events, which directly corresponds to debt-equity conflict events. Hence, we predict a positive coefficient on the *Conflict Discuss Neg* $\times$ *Equity Return* interaction variable, as greater gains to equity holders should be associated with greater losses to debt holders around conflict events. This specification is consistent with Alexander, Edwards, and Ferri (2000), who show that on days with no conflict events (with conflict events), positive equity returns are associated with an increase (decrease) in bond prices. Note that the relative frequency of report to non-report days and the ratio of conflict discussions coded as negative versus non-negative remain generally the same after we restrict the sample to positive daily abnormal stock returns.

Column (2) of Table 4 shows the results of this specification. 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, Goldstein, and Martin (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* $\times$ *Equity Return* interaction variable is positive and statistically significant, which is consistent with a wealth transfer from debt to equity holders when equity holders' wealth improves and debt analysts provide negative discussions of conflict events. In terms of control variables, CDS spread changes are increasing (decreasing) with debt analysts' recommendation downgrades (upgrades). An untabulated F-statistic indicates that the rating fixed effects are jointly statistically significant.¹³

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. The first variable, *Conflict Discuss Neg: Above A Rating*, equals 1 if debt analysts' conflict discussion is coded negatively and the firm's senior debt rating is above A, 0 otherwise. Similarly, *Conflict Discuss Neg: BBB-A Rating* (*Conflict Discuss Neg: Below BBB Rating*) equals 1 if debt analysts' conflict discussion is coded negative and the firm's senior debt rating ranges from BBB to A (is below BBB), 0 otherwise. We then interact these three variables with *Equity Return*.¹⁴ The

¹³ 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 using a sample of reports that contain a discussion of conflict events. We regress the change in the CDS spread over the event window around debt analysts' reports on *Conflict Discuss Neg*. We control for the change in the market CDS spread, characteristics of debt and equity analysts' recommendations, and whether a bond is on a negative watchlist. We find a significant increase in the CDS spread when debt analysts' reports include negatively coded discussions of conflict events, particularly when equity returns over the same event window are positive. These results provide further support for our inferences.

¹⁴ Because we are interested in examining the effect of negatively coded conflict discussions as a function of the creditworthiness of a 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.

results are presented in column (3) of Table 4. As expected, we find that the coefficients increase as creditworthiness declines. An untabulated test indicates that the difference in coefficients between the highest and lowest credit risk categories is marginally statistically significant (p-value = 0.10), 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 negatively coded debt analysts' conflict discussions is more valuable for lower rated debt.

Daily Bond Trading Volume

As in the empirical analyses of CDS spread changes, we use panel data observations for all trading days during our six-year period for each of the sample firms and test whether bond trading reacts to the negative tone of 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:

$$\begin{aligned} \text{Bond Volume}_{it} = & \beta_0 + \beta_1 \text{Conflict Discuss Neg}_{it} + \beta_2 \text{Debt Report Controls}_{it} \\ & + \beta_3 \text{Other Information Controls}_{it} + \text{Rating Effects} + \text{Year Effects} + \eta_{it}. \end{aligned} \quad (2)$$

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.¹⁵ We control for the existence of a debt analyst's 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 conflict discussions that are longer, as evidenced by a larger word count. More extensive discussions should generate stronger volume reactions since they are likely to provide more information or discuss the effects of a conflict event in more detail.¹⁶

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 somewhat different. Because CDS spread changes reflect either improving or deteriorating news, the control variables for that test consist of signed control variables, such as recommendation upgrades or downgrades. 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 such conditions as actual firm conflict-event announcements (e.g., M&A, dividend, or stock repurchase announcement), an equity analyst's report, a rating agency action, an earnings announcement, and a federal funds rate change announcement. 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 (Easton et al. 2009; De Franco et

¹⁵ In untabulated analysis, we conduct the volume-reaction tests using an alternative *Bond Volume* measure. We define this measure as the aggregate total trading volume for all the firm's traded bonds, scaled by the sum of the face value of all the firm's outstanding bonds. Our findings are similar both statistically and economically.

¹⁶ In untabulated analysis, we conduct the following alternative volume-reaction test. We examine whether analysts' views of conflict events affect abnormal bond trading volume around debt analysts' reports that contain 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 Neg*. We control for characteristics of debt and equity analysts' recommendations, equity volume, text count, the time to maturity of the bond, a bond's trading frequency, and whether a bond is on a negative watchlist. We find a greater abnormal volume around debt analysts' reports that include negatively coded conflict discussions. 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.

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 in column (1) in Table 5 show a positive and significant coefficient on *Conflict Discuss Neg* of 0.230 (t-statistic = 6.05). Over the five-day event window, an incremental 1.15 percent ($5 \text{ days} \times 0.230 \text{ percent per trading day}$) 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 coded positively 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 negatively coded 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 for equity analysts' recommendations, consistent with De Franco et al. (2009). As expected, credit rating actions, particularly negative actions, generate additional volume. Earnings news generates trading volume reaction; the reaction is greater to negative earnings news than to positive or neutral news. With respect to macroeconomic news, higher volume is associated with a Federal Funds rate change.

In column (3), we find some support for our prediction that the market reaction to conflict discussions 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. Although there is no difference between the *Conflict Discuss Neg* coefficients for the *Below BBB* and *Above A* ratings, the untabulated p-value for the test of the difference between the *BBB-A Rating* and *Above A Rating* categories is 0.04. The greatest volume reaction in the middle-risk group suggests that these bonds have higher liquidity.

In sum, the results for CDS spread changes and bond trading volume support the idea that negatively coded 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, Mikhail, and Au (2005), 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, Li, and Short (2009), who find 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.

TABLE 5

The Effect of the Tone of Debt Analysts' Conflict Discussions on Daily Bond Trading Volume

	Pred.	(1)	(2)	(3)
<i>Conflict Discuss Neg</i>	+	0.230*** [6.05]	0.235*** [5.79]	
<i>Conflict Discuss Pos</i>	+		0.012 [0.38]	
<i>Conflict Discuss Neg: Above A Rating</i>	+			0.059 [0.33]
<i>Conflict Discuss Neg: BBB-A Rating</i>	+			0.399*** [6.74]
<i>Conflict Discuss Neg: Below BBB Rating</i>	+			0.106** [2.13]
<i>Debt Report</i>	+	0.138*** [9.73]	0.138*** [9.74]	0.123*** [8.07]
<i>Debt Report With Conflict Discussion</i>	+	0.125*** [5.68]	0.121*** [5.15]	0.122*** [5.44]
<i>Text Count High</i>	+	-0.063** [-2.17]	-0.065** [-2.21]	-0.077*** [-2.61]
<i>Debt Buy Recommendation</i>	+	0.014 [0.62]	0.014 [0.62]	-0.009 [-0.37]
<i>Debt Sell Recommendation</i>	+	0.108*** [3.86]	0.108*** [3.86]	0.137*** [4.72]
<i>Debt Recommendation Upgrade</i>	+	0.147*** [4.46]	0.147*** [4.46]	0.143*** [4.27]
<i>Debt Recommendation Downgrade</i>	+	0.060* [1.87]	0.060* [1.87]	0.052 [1.55]
<i>Equity Volume</i>	+	0.002*** [2.94]	0.002*** [2.94]	0.002*** [2.61]
<i>Conflict Event Firm Announcement</i>	+	0.002 [0.25]	0.002 [0.25]	0.039*** [5.66]
<i>Equity Report</i>	+	0.066*** [6.56]	0.066*** [6.56]	0.078*** [7.23]
<i>Equity Buy Recommendation</i>	+	-0.035*** [-4.14]	-0.035*** [-4.14]	-0.032*** [-3.70]
<i>Equity Sell Recommendation</i>	+	0.034** [2.21]	0.034** [2.21]	0.021 [1.35]
<i>Rating Agency Action</i>	+	0.109*** [6.33]	0.109*** [6.33]	0.088*** [4.82]
<i>Rating Agency Action Neg</i>	+	0.242*** [8.18]	0.242*** [8.18]	0.254*** [8.43]
<i>Earnings</i>	+	0.016** [2.21]	0.016** [2.21]	0.011 [1.52]
<i>Earnings Neg</i>	+	0.096*** [5.27]	0.096*** [5.27]	0.055** [2.41]
<i>Fed Change</i>	+	0.022*** [3.21]	0.022*** [3.21]	0.021*** [3.09]
Rating Effects		Yes	Yes	No
Year Effects		Yes	Yes	Yes
No. of Obs.		952,502	952,502	952,502
Adjusted R ² (%)		2.4	2.4	0.9

(continued on next page)

TABLE 5 (continued)

*, **, *** Denote significance at the 10 percent, 5 percent, and 1 percent levels, respectively, using two-tailed tests. Coefficient t-statistics are in brackets.

This table presents an analysis of bond daily trading volume reactions to the coded 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. Variables are defined in Appendix A.

Effect of Debt Analysts' Conflict Discussions on Bond Offering Yields

To examine whether debt analysts' negative conflict discussions are also informative with respect to firms' cost of debt, we test how the tone of these discussions affects the offering yield to maturity of new bond issues. 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 the six months prior to the bond issue. To select a more homogenous group of bonds, 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:

$$\begin{aligned} \text{Bond Offering Yield} = & \beta_0 + \beta_1 \text{Conflict Discuss Neg Prior } 6M_{it} \\ & + \beta_2 \text{Debt Recommendation Prior } 6M_{it} \\ & + \beta_3 \text{Bond Characteristic Controls}_{it} \\ & + \beta_4 \text{Firm Characteristics Controls}_{it} + \beta_5 \text{Other Information Controls}_{it} \\ & + \text{Rating Effects} + \text{Industry Effects} + \eta_{it} \end{aligned} \quad (3)$$

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, where the *6M* indicates that we calculate the average tone 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 1 if the average value of the tone score is less than 0.

We control for debt analysts' recommendations, recommendation changes, and other bond characteristics, including the number of covenants, maturity, and the 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 also include offering amount and bond complexity in our specification, but it is not possible to predict the sign of their relations to offering yield because for each variable, arguments can be made to support both a positive and negative relation. 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. We predict a negative sign on the indicator variable for private bank debt because we expect bank monitoring to benefit bond holders (Datta, Iskandar-Datta, and Patel 1999). 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. We also add a control for equity analysts' recommendations and include the Federal Funds rate at the date of the bond's issuance. Finally, we include rating fixed effects and industry fixed effects that capture industry-level characteristics, such as asset tangibility.

The estimation of Equation (3) is presented in column (1) of Table 6. The coefficient on *Conflict Discuss Neg Prior 6M* is positive and significant, suggesting that negatively coded conflict-event discussions in debt analysts' reports preceding a bond's issuance lead to a higher bond offering yield. Economically, a report with conflict-discussion tones coded as negative increases the offering yield by 27 basis points relative to non-negative coded discussions, which represents 4.0 percent of the median bond yield of the sample firms. This evidence suggests that conflict-event discussions are associated with real effects on a company's cost of debt.

In column (2) of Table 6, 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 increase as creditworthiness declines, with the coefficient on *Conflict Discuss Neg Prior 6M: BBB-A Rating* marginally significant at the 10 percent one-sided level and the coefficient on *Conflict Discuss Neg Prior 6M: Below BBB Rating* significant at the 5 percent 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 (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, we find that the offering yield increases with leverage and decreases when the bond is complex or 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. 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 two-stage least squares (2SLS) specification, where the number of covenants is predicted in the first stage (untabulated) and added as an explanatory variable for the offering yield in the second stage. We use the number of covenants by calendar year indicators as the instrument. 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; Moody's Investor Services 2007).¹⁷ After controlling for endogeneity, our results show a significant and negative relation between the offering yield and the number of covenants as expected. Consistent with the agency theory of covenants, our results in column (3) show that the greater 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 negatively coded conflict discussions predict higher offering yields.¹⁸

¹⁷ In untabulated analysis, we find that the average number of covenants significantly decreased for bonds issued in 2006 relative to bonds issued in previous years, and there was a 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.

¹⁸ While we address the endogeneity between bond yields and covenants, our analysis treats the rest of the bond contractual terms as exogenous. The regressions using debt contractual terms involve a variety of simultaneity and endogeneity problems, which makes it extremely difficult to find appropriate instruments (Bradley and Roberts 2004; Costello and Wittenberg-Moerman 2011). Further, for practical purposes, it is infeasible to concurrently endogenize all bond contractual terms incorporated into the yield analysis. 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 and inferences are robust to the SUR estimation.

TABLE 6

The Effect of the Tone of Debt Analysts' Conflict Discussions on the Offering Yields of New Bond Issues

	Pred.	(1)	(2)	(3)
<i>Conflict Discuss Neg Prior 6M</i>	+	0.270** [2.02]		0.340** [2.56]
<i>Conflict Discuss Neg Prior 6M: Above A Rating</i>	+		-0.741 [-1.17]	
<i>Conflict Discuss Neg Prior 6M: BBB-A Rating</i>	+		0.940 [1.55]	
<i>Conflict Discuss Neg Prior 6M: Below BBB Rating</i>	+		0.636** [2.36]	
<i>Debt Recommendation Prior 6M</i>	-	0.050 [0.50]	0.117 [0.89]	0.052 [0.52]
<i>Debt Recommendation Change Prior 6M</i>	-	-0.201 [-0.61]	-0.155 [-0.38]	-0.180 [-0.55]
<i>Number of Covenants</i>	-	0.084** [1.98]	0.349*** [8.75]	
<i>Number of Covenants (Predicted)</i>	-			-0.168*** [-4.19]
<i>Bond Maturity</i>	+	0.176 [1.13]	-0.493*** [-4.22]	0.182 [1.16]
<i>Bond Offering Amount</i>	?	0.112 [0.89]	-0.456*** [-2.69]	0.139 [1.21]
<i>Complexity High</i>	?	-0.538*** [-3.56]	-0.340** [-2.10]	-0.471*** [-3.38]
<i>Firm Size</i>	-	-0.029 [-0.38]	-0.008 [-0.08]	-0.061 [-0.90]
<i>Leverage</i>	+	1.879*** [2.92]	3.104*** [5.07]	1.724*** [2.67]
<i>Interest Coverage</i>	-	-0.008 [-0.56]	-0.043** [-2.37]	-0.006 [-0.42]
<i>Private</i>	-	-0.455* [-1.77]	-0.519* [-1.75]	-0.463* [-1.85]
<i>Conflict Event Firm Announcement Prior 6M</i>	?	0.271** [2.23]	0.270** [2.22]	0.244** [2.05]
<i>Equity Recommendation Prior 6M</i>	-	-0.210 [-1.50]	-0.426** [-2.40]	-0.265* [-1.90]
<i>Fed Rate</i>	+	0.137*** [2.60]	0.335*** [3.09]	0.130** [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

*, **, *** Denote significance at the 10 percent, 5 percent, and 1 percent levels, respectively, using two-tailed tests. Coefficient t-statistics are in brackets.

This table presents an analysis of the relation between the offering yield to maturity of new bond issues and the coded 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.

All other variables are defined in Appendix A.

Alternative Measure of Debt Analysts' Negative Conflict Discussions

In this section, we develop and test an alternative tone measure 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. We identify a sample of 88,241 equity analysts' reports that we match by firm to each debt analyst's report.¹⁹ 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 a Naive Bayesian model. More specifically, we repeat Steps 1 to 5 described in Section III 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 dataset 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 use a new training dataset based directly on equity analysts' conflict discussions. We create this training dataset by manually classifying as positive, negative, or neutral 5,102 randomly selected text extractions from the matched equity analysts' reports.²⁰

Following our strategy of coding debt analysts' reports, we create a report-level score by summing up the scores from all extractions in each equity analyst's report, weighted by each extraction's respective word count. For each debt analyst report, we 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, one based on the debt analysts' reports training set and the second based on the equity analysts' reports training set. Last, our two new alternative measures of the negative tone of debt analysts' conflict discussions focus on those discussions where this tone disagrees with the tone of equity analysts' conflict discussions. *Alternative Measure #1* of debt analysts' conflict discussions takes the value of 1 if debt analysts' reports contain negative conflict discussions, when the tone of equity analysts' conflict discussions is positive, based on the first equity analyst tone proxy. *Alternative Measure #2* is defined analogously based on the second equity analyst tone proxy. These two variables indicate that when the tone of debt analysts' conflict discussions is negative, the tone of equity analysts' conflict discussions is positive 45.3 percent and 67.3 of the time, respectively.

We repeat the analysis reported in Tables 4 to 6 with these two alternative measures of the tone of debt analysts' conflict discussions and report the results in Table 7. We present the coefficient and t-statistic on our main variable of interest only. All specifications are estimated with the same number of observations and the same set of other independent variables as the previously tabulated tests. Control variable coefficients are similar to those previously presented and omitted for brevity. For comparison, the first column in Table 7 repeats the main results from Tables 4 to 6. The next two columns present the results for *Alternative Measure #1* and *Alternative Measure #2*.

¹⁹ We downloaded these reports from Investext in a manner similar to that of De Franco, Hope, Vyas, and Zhou (2013). We use the Investext header information to match Investext analyst names with I/B/E/S analyst names and verify these matched analyst-name pairs using broker names. We link companies being covered by these matched analyst-name pairs in both Investext and I/B/E/S using the Tickers, Cusips, and Company Names. Next, we convert the PDF files into text files that are merged with the header information using the unique Investext report number.

²⁰ In the equity analyst report training dataset, 11.0 percent (89.0 percent) of the text extractions are coded as negative (non-negative). This is similar to the debt analyst report training dataset in which 8.8 percent (91.2 percent) of the text extractions are coded as negative (non-negative).

TABLE 7
Alternative Measure of the Tone of Debt Analysts' Conflict Discussions

Variable	Pred.	Main Measure (for comparison) (1)	Alternative Measure #1 (2)	Alternative Measure #2 (3)
From Table 4, Column (2), Dep. Var. = ΔCDS Spread				
<i>Conflict Discuss Neg</i> $\times$ <i>Equity Return</i>	+	2.880** [2.25]	4.451*** [3.00]	2.943 [1.52]
From Table 5, Column (1), Dep. Var. = <i>Bond Volume</i>				
<i>Conflict Discuss Neg</i>	+	0.230*** [6.05]	0.110* [1.91]	0.161*** [3.99]
From Table 6, Column (1), Dep. Var. = <i>Bond Offering Yield</i>				
<i>Conflict Discuss Neg Prior 6M</i>	+	0.270** [2.02]	0.472** [1.99]	0.391** [2.79]

*, **, *** Denote significance at the 10 percent, 5 percent, and 1 percent levels, respectively, using two-tailed tests. This table presents results for two alternative measures of our main variable, the coded tone of debt analysts' negative conflict discussions. The alternative measures are based on the disagreement in the coded tone of conflict discussions between debt and equity analyst reports. 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 dataset from debt analysts' reports (used in our main analysis) to estimate the equity analysts' Naive Bayesian model. *Alternative Measure #2* uses a new training dataset based directly on equity analysts' conflict discussions. The first column repeats the respective main result from Tables 4 to 6 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 of the main variable are tabulated. All specifications are estimated with the same number of observations and the same set of other independent variables as the previously tabulated tests, but the results for these other variables are not tabulated. All variables are defined in Appendix A.

Using *Alternative Measure #1*, we continue to find that when abnormal daily stock returns are positive, the coefficient on *Conflict Discuss Neg* $\times$ *Equity Return* is positive and statistically significant, which is consistent with a wealth transfer from debt to equity holders when analysts provide discussions of conflict events that we code as negative. The results are marginally significant at the $p < 0.10$ level, one-sided test when we use *Alternative Measure #2*. For the bond trading volume analysis, using the alternative conflict discussion measures, the coefficients on *Conflict Discuss Neg* are generally similar in both statistical and economic significance to those reported in Table 5. 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.

Sensitivity Analysis: Classification Errors of the Naive Bayes Algorithm

As we discuss in Section III, the use of a Naive Bayes model introduces measurement error that may affect our findings and inferences. While descriptive statistics suggest that the misclassification

error is not systematically related to any of our debt market reaction measures,²¹ we investigate the robustness of our results to the classification accuracy of the Naive Bayes algorithm. The first set of tests we perform addresses the concern that our results could be driven by neutral and positive discussions that the algorithm misclassifies as negative. We re-run our main tests using three alternative measures of the tone of conflict discussions.

First, we re-code the *Conflict Discuss Neg* variable based on our manually coded text extractions, which allows a much more accurate classification of the debt analysts' negative conflict discussions. In this specification, the *Conflict Discuss Neg* variable takes the value 1 if the aggregate report-level score of conflict discussions based on manually collected extraction-level scores is less than 0, 0 otherwise. This approach, however, poses the problem of reduced statistical power due to the substantially smaller sample size of reports with a manually coded text extraction. In addition, because we performed manual coding at the extraction level, not the report level, some of these reports contain text extractions that have not been manually coded and are thus not accounted for when the aggregate report-level score is determined. Nevertheless, the results continue to hold for the CDS spread and volume analyses, albeit at the 10 percent significance level for the latter. We do not find a statistically significant relation between the tone of analysts' discussions and the bond offering yield; this is potentially attributed to the relatively small sample generated by the limited number of manually coded reports and the requirement that firms issue a new bond after these reports are published. Across most of these analyses, the economic significance of the tone measure, as captured by the magnitude of the coefficients, is similar to that of our original *Conflict Discuss Neg* variable.

Second, we focus on reports with more than one conflict-event discussion. We re-code the *Conflict Discuss Neg* indicator variable as equal to 1 only if all the extractions in a report are classified by the Naive Bayes algorithm as negative. We expect the classification error of the tone at the report level to be substantially lower in this case. When debt analysts view all conflict events negatively according to the algorithm, the negative tone of each discussion in a report serves as a concordance check for the tone of other negative discussions in the same report. We continue to find that the negatively coded tone of conflict discussions has a statistically significant effect on trading volume and offering yield analyses, with a slightly weaker effect on the CDS spreads (significant at the 10 percent level). The economic significance of this alternative tone measure is similar to that of *Conflict Discuss Neg* in our primary analyses.

Third, because a Naive Bayes algorithm tends to classify extractions as neutral when they actually have a positive or negative tone, we eliminate from all the analyses any neutrally coded reports. We continue to find a statistically and economically significant relation between the negatively coded conflict discussions and our main debt market reaction variables.

Finally, to provide construct validity of our tone classification, in untabulated analyses we assess the relation between *Conflict Discuss Neg* and debt analysts' recommendations and revisions to their recommendations—the main summary outputs of analyst reports. We estimate a Probit model at the debt-analyst report level with a debt analyst sell recommendation and a recommendation downgrade as dependent variables.²² We find that when debts analysts have negatively coded discussions about conflict events, the likelihood of issuing sell recommendations

²¹ We compare Δ CDS Spread, Bond Volume, Bond Offering Yield, and Equity Return across the reports that are correctly and incorrectly classified by the algorithm. Tests of differences in means, medians, standard deviations, and probability distributions of these variables indicate that these differences are not statistically significant across correctly and incorrectly classified observations.

²² In this estimation, we control for the number of words in the text extraction, whether the bond is highly traded, whether it has complex features, whether it is on a watchlist, equity forecast revisions, and rating/year fixed effects.

and negative revisions to recommendations increases by 9.2 percent and 3.8 percent, respectively. We also examine whether *Conflict Discuss Neg* explains the disagreement between the recommendations of debt and equity analysts, reflecting debt analysts' concern about debt holder wealth expropriation or asset substitution. We estimate a similar Probit model with the dependent variable taking the value of 1 when a debt analyst's recommendation is a sell and is in disagreement with the most recent equity analysts' recommendations issued for the same firm. We find that when debt analysts have negatively coded discussions about conflict events, they are 10.1 percent more likely to issue a sell recommendation that disagrees with equity analysts' recommendations.

To summarize, although none of our additional tests fully eliminates the measurement error in our main variable of interest, we believe that these tests mitigate concerns regarding the impact of measurement error on our inferences.

V. 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 the prior literature by examining whether the tone of debt analysts' discussions of conflict events reflects new information generated by analysts, thereby expanding the information set available to debt markets.

Using a unique hand-collected dataset of debt analysts' reports on U.S. firms, we find that debt analysts routinely discuss in their reports events that are likely to generate debt-equity conflicts and that these discussions are often issued in anticipation of conflict events. More importantly, the tone of debt analysts' conflict-event discussions coded as negative generates significant debt market reactions, measured by higher CDS credit spreads, bond trading volume, and bond offering yields in the primary bond market. These findings support our prediction that debt analysts' discussions about conflict events are relevant 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 explains debt markets' reaction to their reports, we add to the emerging literature on debt analysts. Despite the importance of the U.S. corporate debt market, current evidence on the informational role of debt analysts is rare, highlighting the importance of our findings. We also contribute to the literature on debt-equity conflicts of interest. Our approach of coding the tone of debt analysts' conflict-event discussions allows us to document the importance of these conflicts to debt investors and also to determine whether and how debt holders' wealth is affected. An important limitation of our study is that our findings and inferences are potentially affected by measurement error introduced by the Naive Bayes model. Our additional sensitivity analyses mitigate this concern.

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APPENDIX A

Variable Definitions

Variable	Definition
<i>Alternative Measure #1</i>	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 Naive Bayesian model. This alternative measure equals 1 if debt analysts' reports contain negative conflict discussions while 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 dataset of 5,933 randomly selected text extractions from debt analysts' reports (used in our main analysis) to estimate the equity analysts' Naive Bayesian model.
<i>Alternative Measure #2</i>	The same as <i>Alternative Measure #1</i> , except that the equity analysts' Naive Bayesian model is based on training data that consists of a randomly selected and manually coded set of equity analysts' conflict discussions.
<i>Bond Maturity</i>	Logarithm of the number of years left to maturity at the time of the bond's issuance.
<i>Bond Offering Amount</i>	Logarithm of the offering amount of a given bond issue.
<i>Bond Offering Yield</i>	Bond issue's offering yield at issuance.
<i>Bond Volume</i>	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.
<i>ACDS Spread</i>	Change in the Credit Default Swap spread during a given trading day less the change in the average Credit Default Swap spread of all entities that have the same credit rating category on a given trading day. To measure the latter we use four credit rating categories: AAA to AA-, A+ to BBB+, BBB to BB-, and BB- to D.
<i>Conflict Discuss Neg</i>	First, at the debt-analyst-report conflict-event level (i.e., the text-extraction level), we create a score that equals -1 if the Naive Bayes algorithm (implemented via Rainbow) classifies the text as negative, 0 if the text is classified as neutral, and 1 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 keyword. For analysis at the analyst-report level, we create a report-level score, created by summing up the scores from all extractions associated with each report weighted by each extraction's respective word count. <i>Conflict Discuss Neg</i> is an indicator variable that takes a value of 1 if the report-level score is negative, 0 otherwise.

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APPENDIX A (continued)

Variable	Definition
<i>Conflict Discuss Neg: Above A Rating</i>	= Indicator variable that takes on a value of 1 if <i>Conflict Discuss Neg</i> is 1 for a firm rated higher than "A," 0 otherwise.
<i>Conflict Discuss Neg: BBB-A Rating</i>	= Indicator variable that takes on a value of 1 if <i>Conflict Discuss Neg</i> is 1 for a firm rated between "BBB" and "A," 0 otherwise.
<i>Conflict Discuss Neg: Below BBB Rating</i>	= Indicator variable that takes on a value of 1 if <i>Conflict Discuss Neg</i> is 1 for a firm rated lower than "BBB," 0 otherwise.
<i>Conflict Discuss Neg Prior 6M</i>	= An indicator variable that takes on a value of 1 if the average value of the conflict-event tone score for debt reports issued for a firm during the 180-day window prior to the bond issuance date is less than 0, 0 otherwise.
<i>Conflict Discuss Pos</i>	= An indicator variable that takes a value of 1 if the report-level conflict-event tone score is positive, 0 otherwise.
<i>Conflict Event Firm Announcement</i>	= Indicator variable that equals 1 in the five-day period centered on the date of an M&A, dividend, or stock repurchase announcement by a firm, 0 otherwise. Announcement dates are from the SDC Platinum and CRSP databases.
<i>Conflict Event Firm Announcement Prior 6M</i>	= Indicator variable that equals 1 if there is an M&A or stock repurchase announcement by a firm in the 180-day window prior to the bond issuance date, 0 otherwise. Announcement dates are from the SDC Platinum database.
<i>Complexity High</i>	= Indicator variable that equals 1 if a firm's complexity index is above the sample's median, 0 otherwise. The complexity index is based on the following bond characteristics: callable, convertible, credit enhancement, puttable, 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 1. The index is based on the average complexity of a firm's bonds.
<i>Debt Recommendation Prior 6M</i>	= The average of debt analysts' recommendations for debt reports issued for a firm during the 180-day window prior to the bond issuance date. The recommendation is coded as equal to 1 if the debt analyst's recommendation is a sell, 2 if it is a hold, and 3 if it is a buy.
<i>Debt Recommendation Change Prior 6M</i>	= The average of the change in debt analysts' recommendations for debt reports issued for a firm during the 180-day window prior to the bond issuance date. The change in recommendation is coded as equal to -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.

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APPENDIX A (continued)

Variable		Definition
<i>Debt Report</i>	=	Indicator variable that equals 1 in the five-day period centered on the date of a debt analyst's report, 0 otherwise.
<i>Debt Report with Conflict Discussion</i>	=	Indicator variable that equals 1 in the five-day period centered on the date of a debt analyst report that contains a conflict discussion, 0 otherwise.
<i>Debt Buy Recommendation</i>	=	Indicator variable that equals 1 in the five-day period centered on the date of a debt analyst's buy recommendation, 0 otherwise.
<i>Debt Sell Recommendation</i>	=	Indicator variable that equals 1 in the five-day period centered on the date of a debt analyst's sell recommendation, 0 otherwise.
<i>Debt Recommendation Upgrade</i>	=	Indicator variable that equals 1 in the five-day period centered on the date of a debt analyst's recommendation upgrade, 0 otherwise.
<i>Debt Recommendation Downgrade</i>	=	Indicator variable that equals 1 in the five-day period centered on the date of a debt analyst's recommendation downgrade, 0 otherwise.
<i>Earnings</i>	=	Indicator variable that equals 1 in the five-day period centered on the date of a firm's earnings announcement, 0 otherwise. Data are from Compustat.
<i>Earnings Neg</i>	=	Indicator variable that equals 1 in the five-day period centered on the date of a firm's earnings announcement if earnings before extraordinary items are negative, 0 otherwise.
<i>Equity Buy Recommendation</i>	=	Indicator variable that equals 1 in the five-day period centered on the date of an equity analyst's buy recommendation, 0 otherwise.
<i>Equity Recommendation Prior 6M</i>	=	The average of equity analysts' recommendations for a firm during the 180-day window prior to the bond issuance date. The recommendation is coded as equal to 1 if the equity analyst's recommendation is a sell, 2 if the recommendation is a hold, and 3 if it is a buy.
<i>Equity Report</i>	=	Indicator variable that equals 1 in the five-day period centered on the date of an equity analyst's report, 0 otherwise.
<i>Equity Return</i>	=	Equity return during a given trading day less the daily return of the CRSP value-weighted index of equities.
<i>Equity Sell Recommendation</i>	=	Indicator variable that equals 1 in the five-day period centered on the date of an equity analyst's sell recommendation, 0 otherwise.
<i>Equity Volume</i>	=	Number of shares traded on a given day, scaled by the number of shares outstanding.
<i>Fed Change</i>	=	Indicator variable that equals 1 in the five-day period centered on the date of the federal funds rate changes, 0 otherwise.

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APPENDIX A (continued)

Variable		Definition
<i>Fed Rate</i>	=	The prevailing Federal Funds rate on the day prior to the bond issuance date.
<i>Firm Size</i>	=	Logarithm of total assets, measured at the end of the calendar quarter preceding the quarter in which the bond was issued.
<i>Interest Coverage</i>	=	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.
<i>Leverage</i>	=	The ratio of total liabilities to total assets, measured at the end of the quarter preceding the quarter in which the bond was issued.
<i>Number of Covenants</i>	=	Total number of covenants that are present in the bond contract.
<i>Number of Covenants (Predicted)</i>	=	Predicted total number of covenants that are present in the bond contract based on the year of bond issuance as a first-stage instrument.
<i>Private</i>	=	Indicator variable that takes the value of 1 if, at the time of the bond's issuance, a firm has syndicated loans outstanding (as indicated by the Dealscan database), 0 otherwise.
<i>Rating Agency Action</i>	=	Indicator variable that equals 1 in the five-day period centered on the date of a rating agency action, including rating change, watchlist addition, or outlook change, and 0 otherwise.
<i>Rating Agency Action Neg</i>	=	Indicator variable that equals 1 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 0 otherwise.
<i>Text Count High</i>	=	Indicator variable that equals 1 if the number of words in each text extraction is above the median number of words for all debt analyst reports in the sample.

APPENDIX B

Examples of Text Extracted Around Conflict-Event Keywords from Debt Analysts' Reports

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 management's 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 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 percent of its entire basic subscriber base, and the company was marketing cable-modem service to roughly 2,320,00 data-ready homes, or 85 percent of its total homes passed. As of the same date, approximately 96% of its cable network was upgraded to 550MHz/870MHz 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).

APPENDIX C

Accuracy of the Naive Bayes Classification Algorithm

This appendix presents within-sample performance measures of the Naive Bayes model by comparing the algorithmic classifications with the manual classifications. 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. We use the following terminology to estimate the model's performance measures. TP represents "true positive" classifications. A "positive" outcome is the event of interest, which in our setting is the negative tone of debt analysts' conflict discussions. FN represents "false negative" classifications. FP represents "false positive" classifications. TN represents "true negative" classifications.

Predicted by Algorithm	Actual (Manually Classified)		
	Negative	Non-Negative	
Negative	340(TP)	704(FP)	1,044
Non-Negative	184(FN)	4,705(TN)	4,889
	524	5,409	5,933

1. *Sensitivity* is $TP/(TP + FN)$, which in our case is $340/524 = 65$ percent. *Sensitivity* is directly related to the Type I error, as the $Sensitivity = 1 - \text{Type I error}$. Our Type I error is $184/524 = 35$ percent. In our case, this error represents the probability of the model incorrectly predicting a non-negative tone of conflict discussion when the tone is actually negative.
2. *Specificity* is $TN/(TN + FP)$, which in our case is $4,705/5,409 = 87$ percent. *Specificity* is directly related to the Type II error, as the $Specificity = 1 - \text{Type II error}$. Our Type II error is $704/5,409 = 13$ percent. In our case, this error represents the probability of the model incorrectly predicting a negative tone of conflict discussion when the tone is actually non-negative.
3. *Accuracy* is $(TP + TN)/(TP + TN + FP + FN)$, which in our case is $(340 + 4,705)/5,933 = 85$ percent. *Accuracy* is an aggregate measure that captures the probability that the tone will be correctly classified. It reflects both false positive and false negative errors.
4. *Positive Predictive Value* is $TP/(TP + FP)$, which in our case is $340/1,044 = 33$ percent. *Positive Predictive Value* reflects the percentage of true negative tones when the model predicts a negative tone.
5. *Negative Predictive Value* is $TN/(TN + FN)$, which in our case is $4,705/4,889 = 96$ percent. *Negative Predictive Value* reflects the percentage of true non-negative tones when the model predicts a non-negative tone.

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