**Sell-Side Debt Analysts and Debt Market Efficiency**

Umit G. Gurun
University of Texas at Dallas

Rick Johnston
Cass Business School, City University London

Stanimir Markov
Cox School of Business, Southern Methodist University

**2015 January**

**Abstract**

We explore sell-side debt analysts' contributions to the efficiency of securities markets. We document that debt returns lag equity returns less when debt research coverage exists, consistent with debt analysts facilitating the process by which available information is impounded in debt prices. The effect is incremental to, but comparable in magnitude to, hedge fund ownership's effect. No such effect exists for credit rating agencies. We also find that the dissemination of debt reports has an immediate effect on return volatility in both markets, consistent with debt analysts providing new information to securities markets. Increased return covariation suggests that this information impacts the pricing of debt and equity in the same direction. A large percentage of debt reports do not induce any immediate debt market return reaction but do induce an equity return reaction, consistent with new information being provided despite the absence of a debt market reaction. Finally, there is systematic variation in the debt market's trading and return reactions to debt research. Timely reports and those by high-reputation brokers induce a quicker trading response, thus enhancing liquidity, while only timely reports induce a greater return response. This study illuminates the institutional underpinnings of debt market efficiency, and it has important implications for information content tests in the debt market, where trading is limited.

**JEL Classifications:** D53, G12, G14, G21, G24.

**Key Words:** Analyst, Equity Markets, Debt Markets, Market Efficiency.

Acknowledgements: We thank Mary Barth (our editor), Geoffrey Booth, Chris Jones, Clifton Green, Andrew Karolyi, Alina Lerman, Tavy Ronen, Ane Tamayo, Laurence van Lent, Bill Baber, the associate editor and three referees, and workshop participants at George Washington, McMaster, NYU, The Ohio State University, and The University of Texas at Dallas for their comments. All errors are our own.

## 1. Introduction

Sell-side investment research is generally partitioned into debt and equity, mirroring the debt and equity segmentation of capital markets. While the role of sell-side equity research in enhancing the efficiency of capital markets has been established both conceptually (Gilson and Kraakman 1984; Beaver 1998, p. 146) and empirically (Brennan et al. 1993; Hong et al. 2000; Gleason and Lee 2003; Womack 1996), the role of sell-side debt research — produced by a separate group of analysts with the objective of identifying mispriced debt securities and quickly communicating this information to debt investors — has remained largely unexplored. The limited amount of research on sell-side debt analysts and how their activities affect debt market efficiency is unfortunate since the public debt market is on average larger than the equity market (Bessembinder and Maxwell 2008), but also less liquid and less efficient (Kwan 1996; Gebhardt et al. 2005; Downing et al. 2009). This study answers Beyer et al.'s (2010) and Berger's (2011) calls for more research on debt analysts by exploring sell-side analysts' dual contributions to the efficiency of capital markets. We test predictions about the effect of sell-side debt analyst following on the speed with which the debt market incorporates available information, and about the immediate effects of the distribution of debt research on capital markets.

It is well known that debt prices incorporate available information with a delay relative to equity prices (e.g., Kwan 1996). We suggest that debt analysts, with their strong incentives for quick processing and dissemination of information to institutional clients, play an important role in reducing this delay. Following Kwan (1996), we regress daily bond returns on lagged equity returns, and we test whether the slope coefficient is lower when debt analysts are present.

De Franco et al. (2009) report that the distribution of debt research affects bond trading and returns measured over a period of up to 21 days around the day of distribution, consistent with debt analysts providing information to the debt market. We seek to extend prior work by testing additional predictions regarding these effects' timing, location, and cross-sectional variation. Specifically, we examine the immediate effects of debt research on absolute Day 0 debt and equity returns and their covariation so that we can draw stronger inferences regarding debt research's information content. We also explore whether timely research reports and those by reputable brokers have an incremental effect on the debt market's immediate trading and return reactions.

Our sample includes 921 companies with publicly traded debt (bonds) and equity over the period from 2002 through 2004; 429 of the sample firms have debt analyst research coverage. We find that the lag with which the debt market impounds information is smaller when sell-side debt analyst following exists. Specifically, when debt coverage exists, the slope coefficient on lagged daily equity returns is reduced by 0.03 (a reduction of approximately 60%). This result is robust to controlling for other factors that could potentially reduce the delay with which the debt market incorporates information such as credit

rating agency coverage, hedge fund ownership, media coverage, firm disclosure, and endogeneity.[1] We find that hedge fund ownership and firm disclosure also make incremental contributions, but credit rating agency coverage does not. We explain the absence of an incremental effect from credit rating agencies because credit rating agencies have relatively weaker incentives for quick information processing and dissemination.

These findings make a unique contribution to prior work documenting the delay with which debt prices incorporate information (Kwan 1996; Hotchkiss and Ronen 2002; Gebhardt et al. 2005). Prior evidence that debt markets are inefficient with respect to the information impounded in equity prices raises important questions regarding which market forces curtail debt market inefficiency. Our study specifically identifies and provides evidence that these forces are sell-side debt analyst activities, hedge fund ownership, and corporate disclosure. This evidence complements Ronen and Zhou's (2013) finding that institutional bond trades impound information more efficiently than retail bond trades, since institutional clients and trading desks are the primary users of debt research as well as the judges of its usefulness and quality.

Our results also show that the distribution of debt research affects Day 0 absolute debt and equity returns as well as the covariation between debt and equity returns. Specifically, we find that debt report publication induces an increase in the absolute debt returns of 9.7 percent of their time-series standard deviation (a price reaction of approximately 10 basis points in either direction), which increases our confidence that debt analysts are a source of new information in the debt market. Our finding that covariation increases by 15 percent of its time-series standard deviation suggests that debt reports on average address cash flow news rather than debt-equity conflict events. Further, we find that 37 percent of the reports have no immediate effect on the debt market but have an economically large effect on absolute equity returns, equivalent to 32 percent of their time-series standard deviation. We suggest that due to the debt market's relative illiquidity, equity returns analysis can be helpful in appraising the ability of debt analysts to inform the capital markets. We recommend that researchers conducting information content tests in the debt market adopt an approach similar to ours in assessing the robustness of their inferences.

In addition, we document a systematic variation in the debt market's trading and return reactions to debt research. Specifically, timely reports and those by reputable brokers increase the probability of trading by 9.8 and 6.0 percent, respectively, and the time-to-first trade is shortened by half a day or more. Reports which are timely also have a differential effect on Day 0 absolute debt returns. The fact that both attributes are associated with the trading response but only one with the return response suggests that the informational factors shaping trading behavior differ from those that shape price formation and that studying both is essential to understanding the capital markets consequences of debt research.

[1] We describe the endogeneity problem and how we alleviate it on pp. 9 and 14.

Our evidence on the immediate effects of debt research complements and extends prior work on sell-side debt analysts (Johnston et al. [2009] and De Franco et al. [2009]). In particular, Johnston et al. (2009) demonstrate that debt research has an immediate effect on equity returns for a small sample of debt reports surrounding credit rating changes, but that study fails to control for equity analyst activities, raising the concern that the documented effect is neither generalizable nor distinct. The evidence in our study alleviates this concern. De Franco et al. (2009) analyze debt market trading and return reactions to the distribution of debt research measured over a 21-day window. Our short-window analysis complements their analysis. Further, our finding that debt reports increase the probability of trade on Day 0 and shorten the time to trade, sheds light on the dynamics of the debt market's trading response to the distribution of debt research. We identify increased liquidity as a mechanism through which debt analysts contribute to the bond price discovery.

Finally, we contribute to a broader literature that studies the relationship between the debt and equity markets and the markets' reactions to various information events (Hand et al. 1992; Datta and Dhillon 1993; Datta et al. 1996; Hotchkiss and Ronen 2002). While the existing literature primarily examines how the debt and equity markets use information that is made available to debt and equity investors simultaneously (e.g., earnings and dividend announcements), we also examine how these markets use debt research (produced for and distributed to clients-debt investors) and equity research (produced for and distributed to equity investors). We find that information distributed to debt (equity) market participants also influences the equity (debt) market, suggesting that the debt and equity markets are integrated.

Next, we develop our hypotheses and predictions. Section 3 outlines our empirical methods. Section 4 presents our empirical analyses, and Section 5 concludes.

## 2. Hypotheses and Empirical Predictions

In this section we derive predictions about (1) the effect that sell-side debt analyst following has on the speed with which the debt market incorporates available information, and (2) the immediate effects of the distribution of debt research on capital markets.

### *2.1 The effect of debt analyst following on the speed with which the debt market impounds information*

In a world where attention is limited and information processing is costly (Hirshleifer and Teoh 2003; Sims 2003), available information may not be instantly acted upon by investors. From this perspective, debt analyst summaries of and discussions about information obtained from either private or public sources can be viewed as lowering the cost of information processing or "capturing" investor

attention.[2] Similarly, the debt analyst practice of organizing conferences, meetings, and company visits in order to facilitate interactions between investors and management helps ensure that the *available* information is indeed *used* by debt investors. It is possible that debt investors must be exposed to the same information several times or receive it from a credible source such as sell-side debt analysts before acting on it. The absence of debt analysts does not mean that the debt market pays no attention to public information flows, only that information may be used with a greater delay relative to the equity market.

Our conjecture that analyst interactions with investors are not limited to the distribution of debt reports is supported by anecdotal evidence. "As the issuer and client coverage universe grows, it becomes more challenging to address all the needs of your constituents by publishing," says Larry Bland, head of high-yield research at Banc of America (BofA) Securities in New York and the leader of the top-ranked team in Health Care. Bland says BofA's fixed-income research department, with 40 publishing analysts in the U.S., has remained stable over the past year. "We rely on live client contact and allocate our resources to those clients who need immediate attention and who recognize the value of our franchise" (Abramowitz, 2008). Further, since 1991, each year Institutional Investor Magazine has asked institutional investors to vote for the best fixed income analysts. In 2012, accessibility/responsiveness, useful calls and visits, special services (company visits, conferences, etc.), and management access (one-to-one) are the third, the sixth, the eight, and the ninth most important research analyst attribute, respectively. The fact that these attributes appear to be highly valued by investors suggest that information is frequently transmitted over the phone and in person at numerous venues: conferences, non-deal road shows, field trips, and management meetings (see Maber, Groysber, and Healy, 2013 for a detailed discussion on the forms of analyst-client interactions).[3]

Our hypothesis is novel, but not without antecedents. Brennan et al. (1993) and Hong et al. (2000) document that higher equity analyst coverage helps equity prices quickly impound public common and firm-specific information, respectively; Barth and Hutton (2004) and Gleason and Lee (2003) show that higher equity analyst coverage leads to more rapid and complete assimilation of earnings forecast revisions and accruals information, respectively. These findings establish a relationship between equity analyst following and the process by which equity prices impound the available information, while our hypothesis concerns the relationship between debt analyst following and the speed with which the debt market impounds available information.

---

[2] An alternative perspective is that information is made available gradually rather than instantly (Hong and Stein 1999). Under this perspective, analyst coverage would signify greater information diffusion (Hong et al. 2000).

[3] Regulations allow private interactions between research analysts and clients and ban analysts from tipping clients about the content of their research reports. However, there is evidence to suggest that tipping indeed takes place (e.g., Irvine et al. [2007]; Goldstein et al. [2009]). Desk analysts, on the other hand, are allowed to freely communicate with both traders and clients. Lack of data prevents us from distinguishing the role of research analysts from the role of desk analysts.

If debt analysts make the debt market more efficient by ensuring that available information is quickly impounded in debt prices, then debt prices should lag equity prices less, or not at all, when debt analysts are present (see Kwan [1996]; Gebhardt et al. [2005]; Downing et al. [2009] for evidence that bond returns lag equity returns).[4]

### *2.2 The diverse effects of the distribution of debt research on capital markets*

First, we describe our predictions about the immediate effects of debt research on absolute debt and equity returns, and how these predictions differ from prior research. Second, we discuss how debt research may affect the covariation between debt and equity returns. Finally, we derive predictions about cross-sectional variation in the debt market's reaction to the distribution of debt research.

De Franco et al. (2009) predict and find that bond recommendations affect Day 0 bond trading volume and returns spanning an interval of up to 21 days around the event.[5] However, the hypothesis that debt analysts provide new information to the capital markets makes sharper predictions regarding the timing and the location of these effects. Specifically, the provision of new information predicts that debt research affects Day 0 absolute debt and equity returns, controlling for competing information events. This prediction extends prior work in several ways. First, documenting a Day 0 effect on returns helps preclude the alternative explanation that debt research mainly summarizes information previously impounded in equity market prices. Second, the relative inefficiency and illiquidity of the debt market make it difficult to evaluate debt analysts' ability to provide new information solely on the basis of debt market evidence. By definition, the absence of trading in the debt market on debt report publication day means the absence of a change in the market's assessment of future debt payoffs. A test of whether debt research has an immediate effect on equity returns does not have this limitation. Finally, we note that De Franco et al.'s (2009) evidence of a volume response indicates a change in individual investors' expectations, not a change in the market's expectation, a distinction first made in Beaver's (1968) seminal study and maintained in the accounting and finance literature (Bamber et al. 2011). Empirically, Bamber and Cheon (1995) find the relation between a trading response and a return response to be positive but weak; Kandel and Pearson (1995) stress that "there are economically and statistically significant positive abnormal volumes associated with quarterly earnings announcements even when prices do not change in response to the announcements. It is notable that there appear to be abnormal volumes that are unrelated

[4] There is evidence that debt markets impound information efficiently under special circumstances. Analyzing a portfolio of 20 high-yield actively traded bonds, Hotchkiss and Ronen (2002) found no evidence that equity returns predict future debt returns.

[5] De Franco et al.'s (2009) findings hold in our sample.

to the magnitudes of the price changes" (p. 833). Evidence of return response thus makes us more confident that debt research provides new information to capital markets.[6]

Alexander et al. (2000) introduce the covariation between debt and equity returns as a measure of how the debt and equity markets jointly react to an event. If an event conveys information about the level of future cash flows, then the debt and equity returns should covary more. Conversely, if an event involves a debtholder-equityholder conflict, then the event returns should covary less.[7] We believe that, on average, sell-side debt reports would convey more new information regarding future cash flows than debtholder-equityholder conflicts; we therefore expect higher covariation between debt and equity returns on debt report publication days.

Also, the hypothesis that debt analysts provide new information has two implications: for the dynamics of trading in the debt market and for Day 0 absolute debt returns that are conditional on Day 0 trading. Specifically, we predict that timely reports and reports by reputable brokers increase the probability of Day 0 trading in the debt market and shorten the time between day of publication and day of first trade, and as well as induce a larger effect on absolute Day 0 returns, conditional on Day 0 trading. Report timeliness and broker reputation are attributes associated with high information content in the equity analyst literature (e.g., Cooper et al. 2001; Stickel 1992), and therefore these attributes are natural candidates for explaining the dynamics of debt trading and absolute Day 0 debt returns.

## 3. Research Design

### 3.1 *Test of the prediction that debt prices lag equity prices less when debt analysts are present*

Following Kwan (1996), we begin by estimating the basic equation

$$\mathrm{Ret}^{B}_{it} = \beta_0 + \beta_1 \mathrm{Ret}^{E}_{i,t+1} + \beta_2 \mathrm{Ret}^{E}_{it} + \beta_3 \mathrm{Ret}^{E}_{i,t-1} + \epsilon_{it}, \quad (1)$$

where $Ret^{B}_{it}$ is the difference between the equally weighted bond portfolio return for firm $i$ at day $t$ and the corresponding maturity-matched U.S. Treasury security[8], $Ret^{E}_{it}$ is the contemporaneous equity return, $Ret^{E}_{i,t+1}$ and $Ret^{E}_{i,t-1}$ are the lead and lagged equity returns, and $\epsilon_{it}$ is the error term. If the debt market uses public information as quickly as the equity market does (the debt market is efficient with respect to information impounded in the equity market), then $\beta_3$ is zero. If the equity market is efficient with respect to the debt market, then $\beta_1$ is zero. Kwan (1996) found a positive and statistically significant coefficient on lagged equity returns, suggesting that the debt market is inefficient with respect to the public

[6] Johnston et al. (2009) show a Day 0 equity return reaction but do not control for the activities of equity analysts.
[7] See De Franco et al. (2014) for evidence on debt analysts' views of this conflict.
[8] We use the CRSP daily treasuries database, Fixed Term Indices, and match to the closest maturity.

information impounded in the equity market.[9] Our prediction is that the coefficient $\beta_3$ would be lower when sell-side debt coverage is present, implying that the debt market impounds public information relatively faster due to debt analyst activities.

To test our prediction, we modify the basic equation by including an interaction term between the lagged equity returns and a dummy variable representing the existence of debt coverage, $DF_{it} x\ Ret^{E}_{i,t-1}$. $DF_{it}$ is equal to one if company $i$ has had at least one debt report over a one-year period ending on day $t$, and zero otherwise.[10] A negative coefficient on this interaction term means that in the presence of debt analyst following, debt returns will lag equity returns less.

While Kwan (1996) did not find that debt returns lead equity returns, we also interact leading stock returns with a dummy variable representing high equity analyst coverage, $EF_{it}\ x\ Ret^{E}_{i,t+1}$.[11] If the number of equity analysts with a recommendation in the prior calendar year for firm $i$ at time $t$ exceeds the sample median equity coverage in the prior calendar year, then $\mathrm{EF_{it}}$ is equal to one, and zero otherwise. We partition equity coverage based on the median rather than zero in order to increase the variation in $EF_{it}$ since very few companies have zero equity coverage.

We consider several other factors that may influence the lag with which the debt market impounds information and that may also be correlated with debt analyst coverage: equity analyst coverage, credit rating agency coverage, hedge fund ownership, media coverage, and firm disclosure. Mansi et al. (2011) document a positive relation between equity analyst coverage and cost of debt, controlling only for credit rating agency and corporate disclosure activities and suggest that equity analysts play a distinct information intermediary role in the debt market. It remains an empirical question whether debt securities are priced more efficiently in the presence of equity analyst following. Credit rating agencies do not cater to the informational needs of investors as much as sell-side debt analysts do (Johnston et al. 2009), but they are a major information intermediary with access to private information whose credit ratings are widely disseminated, which raises the possibility that debt issued by firms with high credit rating agency coverage is priced more efficiently.[12] Hedge funds are more likely to participate in both markets than other types of investors, and they are generally viewed as employing the most capable portfolio managers and analysts, prompting us to investigate whether debt issued by firms with

[9] The dependent variable in Kwan (1996) is bond yield change. He estimates a negative coefficient that corresponds to a positive coefficient in a specification with the bond return as the dependent variable.
[10] We use the existence of a debt report as evidence of analyst coverage. Analysts monitor market developments and interact with clients on an ongoing basis – it is this continuing interaction in addition to the written reports that would enhance market efficiency. Whether and how much this interaction diminishes the information content of written reports is an empirical question.
[11] Similar reasoning predicts that the equity market will be more efficient when equity coverage is more intensive.
[12] We thank an anonymous referee for suggesting this analysis.

high hedge fund ownership incorporates available information with a smaller delay.[13] The media creates new information through journalism activities, makes information more easily available by packaging information from many sources, and disseminates timely information to a large number of investors (Bushee et al. 2010). Hence, debt issued by firms with greater media coverage may incorporate available information more quickly. Finally, there is substantial evidence that corporate disclosure increases investor attention and market liquidity (e.g., Coller and Yohn 1997; Healy et al. 1999). We therefore explore whether the debt issued by firms that disclose more information is priced more efficiently.

We further augment equation (1) by interacting $Ret_{i,t-1}^{E}$ with: $EF_{it}$, dummy variable equal to one when the number of equity analysts exceeds past year's median. $NRaters_{it}$, the number of credit rating agencies (S&P, Fitch, Moody's, and EGAN Jones) that issued at least one rating over a one-year period ending on day *t* scaled by 4; *Hedge Fund Ownership,* a dummy variable equal to one when hedge funds' percentage equity ownership, constructed from the most recent 13F filings and a proprietary list of hedge funds, exceeds the annual median of hedge fund ownership;[14] *Media Coverage*, the total number of articles appearing in the Wall Street Journal, New York Times and Washington Post over a one-year period ending on day *t*, and *Firm Disclosure*, the total number of 8K filings and management forecasts over the same period.

A serious concern is that a host of unobservable and observable factors drive both debt analyst coverage and market efficiency. We conduct several tests to ameliorate the endogeneity concern. First, we implement Heckman's two-stage approach: the first stage models the debt analyst coverage choice, the second includes the Inverse Mills ratio. Second, we perform the analysis on sub-samples partitioned by size and liquidity, fundamental market attributes likely to influence both debt analyst coverage and market efficiency. Finally, we implement a difference-in-difference analysis.[15] Specifically, we compare the reduction in debt market lag in a sample of firms that obtain debt analyst coverage to that in a matched sample of firms that do not obtain debt analyst coverage. Short of a natural experiment that would give us true exogenous variation in sell-side debt analyst following, we view these analyses as useful rather than definitive in linking sell-side debt analysts to debt market efficiency.[16]

---

[13] Furthermore, Green et al. (2011) establish a link between the growth of the hedge fund industry and the disappearance of the accruals anomaly, consistent with hedge funds being a force for market efficiency. More broadly, Boehmer et al. (2009) show that high institutional ownership firms are priced more efficiently and that efficiency improves following exogenous shocks to ownership. Replacing hedge fund ownership with mutual fund ownership leads to similar but statistically weak results, consistent with hedge funds playing a greater role in integrating the debt and the equity market than mutual funds.

[14] The proprietary list is used in Ben-David, Franzoni, and Moussawi (2011). We thank the authors of the study for sharing these data.

[15] We thank an anonymous referee for suggesting this analysis.

[16] A popular identification approach in the analyst literature is to focus on broker mergers. Our small sample size makes that approach infeasible.

### 3.2 *Cross-sectional Information content tests*

Our initial test is an event study analysis of debt and equity absolute returns around debt report publication days. We then examine whether timely reports and reports by reputable brokers increase the probability of Day 0 trading in the debt market (shorten the time between day of publication and day of first trade) by estimating

$$Day\ 0\ Trade_i\ (Time\ to\ Trade_i) = \beta_0 + \beta_1\, High\ Reputation_i + \beta_2\, Timely\ Report_i + \beta_3\, EquityAbsRet_i + \beta_4 Bond\ Volume_i + \beta_5 Z_i + \varphi_i. \quad (2)$$

*Day 0 Trade*$_i$ is an indicator variable equal to one if a bond trade occurs on Day 0, debt report *i*'s publication day, and zero otherwise; *Time to Trade*$_i$ is the number of days from report *i*'s publication day to the day of the first trade; *High Reputation*$_i$ indicates authorship by reputable brokers such as Bear Stearns, Credit Suisse, Deutsche Bank, Prudential, Morgan Stanley, or Smith Barney Citigroup[17]; and *Timely Report*$_i$ is a continuous variable between zero and one (a higher value represents a more timely report). The variable is measured using events such as earnings announcements and credit rating changes. For each event, we calculate one minus the ratio of the number of days after the event to the debt report of analyst *i* to the sum of the numerator and the number of days to the debt reports of all other analysts within 30 days of the event. *EquityAbsRet*$_i$ is absolute equity return on Day 0. We introduce this variable to control for the arrival of other information useful for assessing debt payoffs. However, to the extent that debt research influences equity prices, *EquityAbsRet*$_i$ may reflect variation in the information content of debt reports, raising the bar for documenting a relation between report attributes and trading in the debt market. *Bond Volume*$_i$ is the natural logarithm of total bond trading volume in the prior quarter; we included it as a control for a bond's propensity to trade. *Z* is a vector of the following control variables; *Junk* equals 1 if one of the bonds of the firm is rated below BBB (S&P Rating), and zero otherwise; *Convertible* equals 1 if one or more bonds have convertible features; *Book to Market* is the ratio of book value of equity to market value of equity; *Maturity* is the average of outstanding bonds' number of years to maturity; and *Leverage* is the firm's long-term liabilities scaled by total assets.[18] When the dependent variable is *Day 0 Trade*$_i$ (*Time to Trade*$_i$), we estimate a Probit (Weibull hazard) model.

[17] These firms were ranked by Institutional Investor in the top 10 firms for fixed income research. Approximately 54 percent of the sample reports are issued by these firms. The other firms are ABN Amro, CIBC, ING Baring Furman Selz, McDonald, Morgan Keegan, Painewebber, Raymond James, Robertson Stephens, and UBS.

[18] We use the following data items from Compustat to measure the accounting variables: Data24: Book value of equity, Data25xData199: Market value of equity, Data9: Long-term liabilities, Data6: Total assets.

We also examine whether the magnitude of the bond return reaction depends on the same factors by estimating the model

$$BondAbsRet_i = \beta_0 + \beta_1\, High\ Reputation_i + \beta_2 Timely\ Report_i + \beta_3\, Z_i + \omega_i \qquad (3)$$

*BondAbsRet* is the absolute value of *BondRet. BondRet* is equal-weighted bond portfolio returns minus the corresponding maturity-matched U.S. Treasury security. $Z$ is a vector of control variables defined as above.

## 4. Empirical Analyses

This section reports the results from our empirical analyses. The first subsection reports the descriptive statistics, the next explores whether or not the debt market lags the equity market less when debt analysts are present, and the final subsection explores the effects of the dissemination of debt research on debt and equity markets.

### *4.1 Sample and Company Characteristics*

The source of our bond pricing data is the "Trade Reporting and Compliance Engine (TRACE)" disseminated by the National Association of Securities Dealers (NASD) after June 2002. There are 2,705 bond issuers in our sample period as shown in Table 1, Panel A; in order to determine whether or not a bond issuer has also issued equity, we merge our sample of bond issuers with CRSP by each issuer's six-digit CUSIP. In the case of non-matches, we also examine whether or not the bond issuer is a subsidiary of a parent with publicly traded equity; we use the Fixed Income Securities Database (FISD) in order to identify these relationships. There are 1,139 bond issuers that also issued equity, but the number of unique equity issuers or companies is lower at 921; it is not uncommon for subsidiaries to issue public debt but not equity. The total number of bond issues traded over this period is 5,078.

The source of our sell-side debt research report data is Investext, a provider of full-text analyst reports. The sell-side debt report data cover the period from 1999 to 2004 for 15 brokerage firms, six of which are rated in the top ten fixed-income research firms by Institutional Investor. The intersection of the bond pricing and debt report data is the period from July 1, 2002 to December 31, 2004. The total number of debt reports on the issuers of both debt and equity over this period is 3,990, occurring on 2,758 unique firm days.[19]

[19] Johnston et al.'s (2009) six-year sample includes approximately 8,000 debt reports. De Franco et al. (2009) have a later sample period, and over five years, they examine approximately 16,000 debt reports. In our two-and-a-half-year sample, we examine approximately 4,000 debt reports.

Panel B of Table 1 contrasts certain firm characteristics of the 429 companies with debt research (at least one debt research report over the sample period) to the 492 companies without debt research. The reported means and medians are based on company-year observations. Companies with sell-side debt research appear to be larger in terms of equity capitalization and total assets, but they have comparable leverage, market-to-book (similar medians only), and credit ratings. Companies with debt research also have greater credit rating agency coverage, hedge fund ownership, media coverage, and firm disclosure, which makes it important to control for the potential effects of these variables on the speed with which the debt market impounds available information.

Not surprisingly, debt reports are issued around the same time as other information events. In Panel C, we present the occurrence of earnings announcements, credit rating changes, and equity analyst reports prior to, concurrent with, and subsequent to debt reports. Debt and equity reports occur frequently with earnings announcements (22 percent of the time, all three overlap). It is also common for an earnings announcement and an equity report to precede (days -2 to -10) a debt report (14 and 18 percent of the time, respectively). Equity reports commonly follow (days 2 to 10) debt reports as well (23 percent of the time). In Appendix B, we present some additional discussion and analyses related to the content of debt reports.

Panel D of Table 1 reports some descriptive statistics on sample bond characteristics. The most frequent issue size is $100 to $500 million, representing 53 percent of our sample. The remaining years to maturity is most commonly five to ten years (58 percent). Finally, in Panel E, we present the distribution of firm credit ratings at the time of debt report issue. More than half the firms are investment grade, and many are clustered in the A to BBB range (191). Our sample contains more investment grade bonds (63%) than the sample reported in De Franco et al. (2009; 49%).

### *4.2. Test of the hypothesis that debt research increases the speed with which the debt market uses public information*

Table 2, Panel A presents descriptive statistics for the primary variables in our lead-lag return analysis, and Table 2, Panel B presents the regression results. We report parameter estimates and p-values in parentheses; standard errors are adjusted to account for daily cross-correlations in bond returns.[20]

The first column of Panel B reports the results from the estimation of equation (1). Similar to Kwan (1996), we find that debt returns and equity returns are contemporaneously correlated and that the lagged equity returns can predict debt returns. The coefficients on the contemporaneous and lagged equity returns are 0.09 and 0.049; both are statistically significant at the one percent level. Unlike Kwan (1996),

[20] Our results are robust to clustering by day and firm to address any remaining serial correlations in the error term, and to including additional lags of equity returns and lagged debt returns.

we find that debt returns have some predictive ability for future equity returns, although the relative effect is much smaller. The coefficient on the lead stock returns is 0.008 and is statistically significant at the 5 percent level. We therefore find strong evidence that the bond returns lag the equity returns, and some evidence that the equity returns also lag the debt returns.[21]

The second column reports the results when equation (1) is augmented to include interaction terms between lagged equity return and the factors potentially influencing the speed with which the debt market impounds available information. When a company is covered by debt analysts, the ability of lagged equity returns to predict debt returns is significantly diminished. Specifically, the coefficient on lagged equity returns interacted with debt analyst coverage is -0.032. It is statistically and economically significant as it represents a 68 percent reduction from the coefficient on the lagged equity returns of 0.047.

Credit rating agency coverage, hedge fund ownership, and firm disclosure also appear to facilitate the process by which the market impounds available information. The coefficient on the interaction term between lagged equity returns and credit rating agency coverage is -0.007, significant at the 10 percent level. The coefficient's smaller magnitude and marginal significance suggest that credit rating agencies play a lesser role than sell-side debt analysts in facilitating the process by which debt market impounds available information, consistent with credit rating agencies having weaker incentives for quick information processing and dissemination than sell-side debt analysts.[22] Hedge fund ownership and firm disclosure, on the other hand, play critical roles. When hedge fund equity ownership is above the annual median, the debt market's lag is reduced by -0.029, a lag reduction comparable to the lag reduction of -0.030 from the presence of debt analyst following. As expected, in untabulated analysis we find weaker results when the hedge fund ownership variable is replaced with mutual fund ownership variable. The coefficient on interaction term between lagged equity returns and firm disclosure (multiplied by 100) is -1.134. The standard deviation of firm disclosure is 7.91 (Panel A of Table 2), which means that the debt market's lag is reduced by -0.09 when firm disclosure changes by one standard deviation.[23] The coefficient on the interaction between equity analyst following and lagged equity return is positive and significant. One possible explanation, left for future research to explore, is that equity analysts help the

[21] Kwan (1996) did find that bond returns predict equity returns for companies rated BB, but those results were explained by non-synchronous trading.

[22] The slope coefficient on $NRaters_{it} x\ Ret^{E}_{i,t-1}$ can be compared to the slope coefficient on $DF_{it} x\ Ret^{E}_{i,t-1}$ because $NRaters$ is divided by four and, similar to *DF*, ranges from zero to one. In untabulated analysis, we find an even larger coefficient on $DF_{it} x\ Ret^{E}_{i,t-1}$ when *Nraters*=0, consistent with a greater role for sell-side debt analysts when credit rating agency coverage is absent.

[23] Including lagged bond returns in Equation 3 does not alter this result. Results are similar for a sub-sample of firms with no credit rating.

equity market impound information to a greater extent than they help the debt market, resulting in greater debt market lag when equity analysts are active.

Sell-side debt coverage is related to various firm characteristics (Johnston et al., 2009), some of which are likely to be correlated with market efficiency, raising serious concerns about endogeneity and biased estimates. A popular approach to address this issue, introduced by Heckman (1979) in a seminal study, is to model analyst coverage choice with a discrete choice model, and to include the *Inverse Mills Ratio* as a control variable in the second stage. We model sell-side debt analysts' choice to cover a firm with a probit model and we tabulate our results in Appendix A. Our model includes 15 variables, and has a reasonably high pseudo R2 of 0.23.[24] Including the *Inverse Mills Ratio* increases the magnitude and the significance of the coefficients on the interactions of lagged equity return with debt analyst coverage, hedge fund ownership, and firm disclosure, but also eliminates the statistical significance of the coefficient on credit rating agency coverage (last column of Table 2, Panel B). The robustness of our primary result to the inclusion of the I*nverse Mills Ratio* increases confidence in the hypothesis that sell-side debt analysts enhance debt market efficiency.[25]

While the Heckman approach is widely used in accounting, finance, and economics, it is not without limitations (e.g., Tucker (2010) and Lennox et al. (2011)). We therefore conduct a difference-in-difference analysis. Specifically, we explore whether firms where debt analysts initiate coverage in 2003 or 2004 have lower debt market lag thereafter, relative to a control sample of firms without coverage but with similar propensity scores (obtained from a logistic regression of a debt coverage indicator on Appendix A's covariates). The approach effectively controls for all unobservable factors that vary cross-sectionally but do not vary over time (e.g., Baltagi, 1995; Lennox et al., 2011). For brevity, we present our findings in Panel C of Appendix A. The coefficient of interest, $Post\ Init_{it} x InitFirms_{it} x\ Ret^{E}_{i,t-1}$, captures the lag reduction experienced by firms where a sell-side debt analyst initiates coverage relative to the lag reduction experienced by the control firms. This difference-in differences-estimate is negative and statistically significant, consistent with a relationship between debt analyst coverage initiation and increased pricing efficiency. These findings lend additional support to the hypothesis that sell-side debt coverage plays a role in facilitating the process by which available information is impounded in prices.

[24] A model with only the instruments has a pseudo R2 of 0.15.

[25] Our interpretations of the evidence are subject to the important caveat that we may have not adequately controlled for all variables that influence both debt analyst following and the lag with which the debt market impounds information. However, we note that reduced form models have their uses. If a pricing phenomenon is complex and little understood, such as the pattern of the cross-serial correlation in debt and equity returns documented by Kwan (1996), by describing its relations to the activities of important groups of market participants, such as sell-side debt analysts, credit rating agencies, hedge funds, firms, and the media, a reduced form model can guide researchers in developing structural models.

Size and liquidity are key debt market attributes likely to lead to both greater debt analyst following and market efficiency. While these variables are included in the probit model above, in Panel C of Table 2 we explore how the effect of debt analyst following on the debt market's lag varies across *Small*, *Medium*, and *Large Debt* subsamples, and across *Low*, *Medium*, and *High Liquidity* subsamples. Our objective is to gain insights about the cross-sectional variation in the effect of debt analyst following on the lag with which the debt market impounds available information.

We sort all day *t* observations based on size, defined as a company's total par value of debt outstanding on day *t*; we then assign observations to three groups with approximately the same number of observations: *Small*, *Medium*, and *Large Debt* samples. We use issue and redemption information from the FISD issue file in order to calculate the daily outstanding debt amount. Debt analyst coverage reduces the lag with which the debt returns impound information in the *Small* and *Medium Debt* markets. The coefficient on $DF_{it} x\ Ret^{E}_{i,t-1}$ in the *Small Debt* subsample is both economically and statistically significant at -0.066. The corresponding coefficient in the *Medium* sample is -0.047, also statistically significant at the 1 percent level. Firm disclosure similarly reduces the debt market lag in the *Small* and *Medium* subsamples. Hedge fund ownership reduces the debt market lag in all subsamples.

We calculate Amihud's (2002) illiquidity measure using absolute returns and volume from the month prior to the month of day *t*.[26] We split the sample based on this *ex ante* measure of liquidity in order to mitigate endogeneity concerns; all observations are classified into *Low*, *Medium*, and *High Liquidity* groups using the 33 percent and 66 percent breakpoints of the corresponding distribution. Similar to our observation based on size, debt market inefficiency appears fairly consistent across the partitions, especially in the *Medium* and *High* group. The coefficient on $DF_{it} x\ Ret^{E}_{i,t-1}$ is negative and statistically significant in the *Medium* and *High* groups but not in the *Low Liquidity* group, consistent with analysts having greater incentives to process and disseminate information for more liquid bonds where commissions revenues are greater. Firm disclosure reduces the debt market lag in the *Medium liquidity* subsample, whereas Hedge fund ownership reduces the debt market lag in all subsamples. We conclude that our results are not driven by debt analyst following being correlated with size and liquidity.

Finally, our results do not change when we remove convertible bonds (found by Downing et al. [2009] to lag equity returns the most), eliminate transactions below one hundred thousand dollars, or include the lagged equity returns interacted with equity analyst following as a control variable (results are not tabulated for brevity). We find no evidence that the existence of equity analyst following affects the speed with which the debt market incorporates the information impounded in equity prices.

[26] A secondary measure of liquidity used is the number of days a bond trades in a month. Our evidence is not sensitive to the use of this alternative measure.

In conclusion, the debt market incorporates information with a lag; a smaller lag occurs when a company has sell-side debt coverage, when hedge fund ownership is relatively large, and when firm disclosure is greater.

### *4.3 Tests of the hypothesis that debt research expands the amount of information to debt and equity markets*

We analyze debt and equity absolute returns around debt report publication days. We also conduct a cross-sectional analysis of the immediate effects of the distribution of debt reports on trading and absolute returns in the debt market. Last, we benchmark the debt and equity return reactions to the publication of a debt report against competing information events.

#### *4.3.1 Information Events*

The publication of a debt report is our primary event of interest, but we also want to distinguish its impact from those of equity recommendations, credit rating changes, and earnings announcements.[27] We compare debt reports to equity recommendations because the issuance of an equity recommendation is more likely to correspond to the issuance of an equity report than is the issuance of an earnings estimate. The first column of Table 3, Panel A presents the total number of information event days in our sample period from 2002 to 2004. TRACE increased its coverage of bonds over this period, and Column 2 reports the number of information event days for which TRACE includes company *i*'s bonds prior to information event day *t*. The remaining columns provide information regarding the number of information event days for which we can compute a return in either the debt or equity markets.

Equity recommendation event days are the most frequent information event in our sample period (26,749), followed by earnings announcements (8,062), credit ratings changes (3,817), and debt report publications (2,758). The corresponding statistics for the number of information event days over the period with TRACE coverage are: 13,123; 3,562; 2,417; and 1,737, respectively. Due to infrequent bond trading, we observe *BondAbsRet* for 64 percent of the debt report publication days, 55 percent of the equity recommendation days, 65 percent of the credit rating changes days, and 47 percent of the earnings announcement days (calculated as the ratio of Column 3 to Column 2). To provide some context for these numbers, the untabulated probability that we observe a debt return on a day when no information event takes place is 40 percent. On days when debt market information intermediaries such as credit rating

[27] Additions to the Standard & Poor's (S&P) Credit Rating watch list and changes in long- and short-term S&P outlooks are alternative and perhaps timelier measures of the information disseminated by credit rating agencies than changes in credit ratings are. Incorporating these events as additional control variables does not affect our evidence regarding how markets react to the publication of a debt report. These analyses are untabulated for brevity. See Chung et al. (2008) for analyses of credit watches.

agencies and sell-side debt analysts release information, there is a greater probability that a trade will take place (65 percent and 64 percent, respectively), relative to days on which earnings are announced or equity recommendations are released (47 percent and 55 percent). This means that debt analysts and credit rating agencies play an important role in making debt markets more liquid.

While we are much more likely to see bond market trading on days when debt reports are published, many debt report publication days are still characterized by the absence of any bond trading, which makes evaluating analysts' ability to provide new information problematic. In contrast, equity returns are available for almost all information events.

Panel B reports descriptive statistics on the number of information events per company. The distribution of debt reports per company is highly skewed; the mean and the 75$^{th}$ percentile are equal to three. The median of zero suggests that the majority of the sample companies do not have any debt coverage.[28]

*4.3.2 Cross-Sectional Distributions of Market Reaction Variables*

Table 4 of Panel A reports the cross-sectional mean, median, and standard deviation of company-specific means and standard deviations of our daily return variables: bond and equity returns (*BondRet*, *EquityRet*), absolute bond and equity returns (*Bond*Abs*Ret*, *Equity*Abs*Ret*), and the covariation in debt and equity returns (*COV*). All return-based variables are multiplied by 100. The final two rows report the number of firms and observations used in these calculations. While there are 921 companies with publicly traded debt and equity over the sample period, the number of companies for which we are able to calculate bond returns is 795. The number of days with valid bond returns is 111,465, considerably lower than the 549,515 days with valid equity returns. The cross-sectional mean of the company-specific mean absolute debt returns (*BondAbsRet*) is 0.97 percent. The cross-sectional mean of mean absolute equity returns (*EquityAbsRet*) is higher at 1.61 percent, suggesting that equity returns are on average more volatile and that they may exhibit higher sensitivity to news than debt returns. The standard deviations of the parameters characterizing the company-specific return distributions are large, justifying our research design choice to standardize the market reaction measures by subtracting the company-specific mean and

[28] We believe there are two reasons why the number of debt report days in our sample is likely to understate the relative importance of debt analysts as an information intermediary. First, the Investext coverage of sell-side debt analysts is incomplete. The number of investment firms providing debt research is higher than the 15 brokers reporting through Investext, only six of the top ten as ranked by Institutional Investor are represented in our 15. Second, it is generally believed that writing and publishing reports is less important for a debt analyst than for an equity analyst. A debt analyst is more likely to disseminate new information either internally or externally to important firm clients without publishing a report (Ronan 2006). See FN 3 as well. As a result, published information for a debt analyst would understate analyst-generated and disseminated information.

dividing by the company-specific standard deviation. Panel B reports univariate statistics for the standardized variables.

*4.3.3 Market Returns Around the Publication of a Debt Report in Event Time*

To test whether or not debt analysts provide new information, we examine the pattern of market returns to the publication of debt reports over a 21-day event window from day -10 to day +10, where 0 is the day when the debt report is published.[29] We report mean return reactions for days -1, 0, and 1, and for the periods [-10,-2] and [10, 2]. In the last column, we report the number of firms with bonds trading in the respective event windows.

We document significant reactions to the publication of a debt report for all three variables (Table 4, Panel C). In particular, the publication of a debt report induces a Day 0 increase in the absolute debt returns of 9.7 percent of their time-series standard deviation (a price reaction of approximately 10 basis points in either direction). The effect of debt reports on equity returns is decidedly stronger; absolute equity returns increase by more than 50 percent of their standard deviations (a price reaction of 87.8 basis points in either direction). The reason for the stronger equity return reaction is that the value of equity, a residual claim on corporate assets, is generally more sensitive to news than is the value of debt, a fixed claim on corporate assets. Finally, the covariation between debt and equity returns increases by 15 percent of the standard deviation of the cross-product of debt and equity returns, which means that, on average, debt reports convey information that impacts the pricing of debt and equity in the same direction.

The equity market reaction to the dissemination of debt reports when there is no debt market trading (634 observations) is statistically significant but smaller than the equity market reaction when there is debt market trading (1,100 observations): 32 percent versus 51 percent of its standard deviation. We conclude that debt reports that do not trigger a debt market reaction are still informative. However, since research settings could exist in which the lack of debt trading indicates a lack of information content, we recommend that researchers conducting information content tests in the debt market supplement their debt return analysis with equity return analyses.[30]

In an untabulated analysis, we replicate the Panel C analysis with two changes: we (1) adopt Beaver's (1968) statistical approach and (2) exclude debt report observations likely to be contaminated by

[29] We exclude debt reports occurring within 21 days of another debt report.
[30] We replicated Table 4C by inserting 0 for bond returns if the bond of a firm is not traded within the debt report publication window. We find similar results. Many bond investors are buy and hold investors (i.e. insurance companies), which contributes to the lack of bond trading on various days.

the effects of competing information events. We identify contaminated observations as debt reports occurring within one day or two days of a competing information event (change in credit ratings, earnings announcements, and equity recommendations). Our findings are qualitatively the same.

*4.3.4 Cross-Sectional Analysis of Debt Market Reaction: Impact of High Reputation and Timely Reports*

The first three columns of Table 5, Panel A report the results from the estimation of Equation (2) as a Probit model. We find robust evidence that higher reputation broker reports increase the likelihood of Day 0 trading. The slope coefficient on *High Reputation* is 0.533 (0.754) when *EquityAbsRet* is excluded (included). The corresponding marginal probability effect (untabulated) is 9.8 percent (9.2 percent).[31] As a reference, the unconditional probability of Day 0 trading is 23.3 percent. The slope coefficient on *EquityAbsRet* in Specification (2) is 0.103, statistically and economically significant — one standard deviation increase in *EquityAbsRet* increases the probability of Day 0 trading by 2.7 percent. This finding is consistent with the notion that whether we observe trading in the debt market depends on a report's information content, the alternative being that trading depends only on transaction costs or propensity to trade. *Timely Report* also has an incremental effect on the probability of Day 0 trading, although its effect is smaller than reputation, with a 6 percent marginal probability effect.

The last three columns of Table 5, Panel A report the results from the estimation of Equation (2) as a Weibull hazard model. Although the results are qualitatively similar to the probit model, the relative importance changes, with *Timely Report* having a bigger effect on time to first trade than *High Reputation*. The *High Reputation* slope coefficient of -0.352 (Specification 3) means that the average number of days between report day and day of first trade is shortened by 27.4 percent ($e^{-0.352}$-1). The average number of days between report day and day of first trade is 1.82 days, suggesting that the time to first trade for a report authored by a high reputation broker is half a day sooner. In contrast, the time to first trade for a timely report is almost 1 day sooner. Also, the higher the Day 0 equity return volatility, the shorter the time to first trade. The *EquityAbsRet* slope coefficient of -0.291 means that when *EquityAbsRet* increases by one standard deviation, the average number of days between report day and day of first trade is shortened by 23.3 percent ($e^{-0.291 \times 0.913}$-1). The shape parameter of the Weibull hazard model is less than 1, which means that the likelihood of a first time bond trade decreases over time.

The above evidence highlights the role of timely reports and broker reputation in making the debt market more liquid and helps us better understand the dynamics of trading volume when debt research is distributed.

[31] In calculating marginal effects, we hold continuous variables at their sample means and dummy variables at zero.

Panel B reports the results from the cross-sectional analysis of Day 0 absolute debt returns (Equation 3). We find that timely reports induce a greater effect on Day 0 absolute debt returns. The slope coefficient on *Timely Report* is 0.781, and it is statistically significant at the 5 percent level and economically large, representing 24 percent of the standard deviation of *BondAbsRet*. We do not find that reports by brokers with high reputation affect debt returns.[32] Debt reports on high book-to-market companies show a larger effect, consistent with higher book-to-market reflecting higher financial distress (Fama and French 1995) and debt research being especially informative for distressed companies.

*4.3.5 Relative Importance of Debt Reports and Competing Information Events*

Finally, we evaluate the relative importance of debt reports and competing information events by estimating the following equation:

$$REACT_{it} = \beta_0 + \beta_1 DR_{it} + \beta_2 ER_{it} + \beta_3 \Delta CR_{it} + \beta_4 EA_{it} + \varrho_{it}, \quad (4)$$

where $REACT_{it}$ is the market reaction for company $i$ on day $t$ ($BondAbsRet_{it}$, $EquityAbsRet_{it}$, and $COV_{it}$); and $DR_{it}$, $ER_{it}$, $\Delta CR_{it}$, and $EA_{it}$ are information event indicator variables equal to one on Day -1, 0, or 1, and zero otherwise (where t=0 is the issuance of a debt report ($DR_{it}$), equity recommendation ($ER_{it}$), change in credit rating ($\Delta CR_{it}$), or earnings announcement ($EA_{it}$), respectively). The error term is $\epsilon_{it}$.[33]

The slope coefficients signify the average increase in the respective *REACT* variable surrounding information events relative to non-information event days (the intercept). For example, when *BondAbsRet* is the dependent variable, $\beta_0$ is the mean absolute debt return in the absence of any information events, $\beta_1$ is the increase in the mean absolute debt returns induced by the occurrence of a debt report, and $\beta_2$, $\beta_3$, and $\beta_4$ measure the increase in the mean absolute debt returns due to the occurrence of an equity recommendation, credit rating change, or earnings announcement, respectively. We draw conclusions regarding the relative importance of sell-side debt analyst reports on the basis of these estimates.

The results are presented in Table 6; the largest absolute debt returns occur on days with debt reports (5.5 percent of the standard deviation of absolute returns), followed by days with credit rating changes, equity recommendations, and earnings announcements; the largest absolute equity returns occur on earnings announcement days (52 percent of the standard deviation of equity absolute returns),

[32] The fact that both attributes drive trading and only one attribute (*Timely Report*) drives absolute returns is surprising but reminiscent of Bamber and Cheon's (1995) remarkable finding that nearly a quarter of earnings announcements generate equity price and volume reactions of very different relative magnitudes (see Bamber et al. [2011] for a survey of prior work on equity trading volume and price reactions to accounting information).

[33] All standard errors are heteroskedasticity-consistent and adjusted to account for cross-correlation in contemporaneous absolute returns and volume (Rogers 1993). Clustering by day and firm does not change the results from our tests.

followed by days with equity recommendations, debt reports, and credit rating changes. This pattern is consistent with the idea that credit rating agencies and sell-side debt analysts are relatively more (less) important than earnings announcements and equity analysts as information sources in the debt (equity) market. Although the equity results are generally supported statistically, we cannot reject that the coefficients are statistically different in the debt market.[34] The combination of greater data availability and generally greater sensitivity to news favors the equity market as a setting where differences in information content can be accurately evaluated. Debt reports increase the covariation between debt and equity returns by 7.2 percent of its time-series standard deviation. This effect appears greater than that of equity recommendations and credit ratings, but lower than that of earnings announcements; however, these differences are not statistically significant. Debt report and credit rating effects are statistically different. We conclude that the effect of debt reports on both the debt and equity returns compares favorably to the effects of information provided by other familiar information sources.

To test robustness, we replace equity recommendations with forecast revisions. The debt market results are similar in terms of the order of the information effects, but the debt report magnitude is larger and the statistical differences between the information sources are stronger. In the equity market test, revisions have the lowest impact; the others retain their relative order and statistical difference. For the covariation results, debt reports and earnings announcements again, are not statistically different and have the largest reaction.[35]

The regression analysis described above does not consider differences in the frequency with which information sources disseminate information, but the value of an information source surely increases in the frequency with which the source releases information. For each information source *s*, we construct an annual information ratio that depends on both the number of information releases in a year and the information releases' informativeness. Let information source *s* release information regarding firm *i* *K* times in year *t* and the number of trading days be *N*. We calculate the annual information ratio, $IR_{sit} = \frac{\sum_1^K MktReaction_{sik}}{\sum_1^N MktReaction_{in}}$, as a measure of the overall importance of information source *s* in influencing the annual flow of price-relevant information regarding firm *i* over year *t*.[36] We report the means of these ratios. We do not conduct any formal tests due to the lack of a universally accepted methodology for comparing information sources.

[34] In comparing the debt and equity market reactions, a sensible condition is that all debt and equity market reactions are concurrent. In untabulated analyses, we find similar results if we restrict the sample to days when there are reactions in both markets, and we find that management forecasts generate a large debt market reaction as well.
[35] We replicated Table 6 by inserting 0 for bond returns if the bond of a firm is not traded on the day of debt report, results are similar.
[36] See Francis et al. (2002) and Frankel et al. (2006) for similar approaches.

A ranking of the sources' annual information ratios reveals that equity analysts (debt analysts) are the most (least) important information source in both markets (Panel B). Equity analysts' annual information ratio is approximately seven times that of debt analysts in both markets because debt reports are considerably less frequent than equity recommendations (Table 3, Panel A). Overall, sell-side debt analysts play a lesser role as a source of new information in the debt market than equity analysts.

Two caveats temper this conclusion. First, both sell-side debt and equity analysts communicate with traders and clients on a continuous basis. Since sell-side debt research is predominantly institutional while equity research is typically both institutional and retail, it is quite possible that sell-side debt analysts allocate less time to the distribution of information in a research report and more time to the distribution of information outside of research reports (i.e., in instant messages, phone conversations, or private meetings) than equity analysts do. The gap between the published research and the total research could therefore be larger for debt analysts than for equity analysts. Second, the coverage of debt analysts by Investext is much less complete than the coverage of equity analysts by IBES.

## 5. Concluding Remarks

We examine the role of debt analysts in enhancing the efficiency of capital markets. Our sample includes 921 companies with publicly traded debt and equity over the period from 2002 through 2004; 429 of the sample firms have debt analyst research coverage. Using Kwan's (1996) empirical framework, we document that debt analyst coverage contributes to reducing the lag with which the debt market impounds available information; this is consistent with debt analysts playing a distinct role in facilitating the process by which the debt market impounds publicly available information. Other factors playing distinct roles in facilitating this process are hedge fund ownership and firm disclosure. These findings provide important insights into the market forces curtailing debt market inefficiency.

We document that the publication of debt reports leads to higher Day 0 absolute debt and equity returns, and to higher covariance between debt and equity returns, on average. These findings make us more confident that debt analysts reveal new information to securities markets and that this information affects both market returns in the same direction. However, a large percentage of debt reports do not induce a debt market reaction but do induce an equity return reaction, consistent with new information being provided to securities markets notwithstanding the absence of a debt market reaction. Also, we document a systematic variation in the debt market's trading and return reactions to debt research. Specifically, timely reports and those by high reputation brokers induce a quicker trading response, while only timely reports induce a greater effect on Day 0 absolute returns. We leave future research to explain the differential price and trading volume reactions to these research attributes, but we conjecture that the incremental effect of reputation on trading volume could be due to the fact that reputable brokers'

research is not necessarily more informative (in the market sense) but is distributed more widely and viewed by many market participants as more informative.

Finally, we seek to assess the relative role of debt analysts as a source of new information by comparing their information content and prevalence to those of credit rating changes, earnings announcements, and equity recommendations. The largest absolute equity returns are observed on earnings announcement days, followed by days with equity or debt reports, and then credit rating changes. However, in both markets, sell-side equity analysts appear to have the largest annual information ratios. We suggest that the information disseminated by sell-side debt and equity analysts has a comparable effect on debt price formation but that debt analysts disseminate reports less often than equity analysts.

**References**


Abramowitz, R. 2008. "Credit to the ones who cover the crisis." *Institutional Investor* 42 (8).

Alexander, G., A. Edwards, and M. Ferri. 2000. "What Does NASDAQ's High-Yield Bond Market Reveal about Bondholder-Stockholder Conflicts?," *Financial Management* 29: 23–39.

Amihud, Y. 2002. "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects," *Journal of Financial Markets* 5: 31–56.

Baltagi, B. H. 1995. "Econometric Analysis of Panel Data," Chichester, U.K.: Wiley.

Bamber, L. S., and Y. S. Cheon. 1995. "Differential Price and Volume Reactions to Accounting Earnings Announcements," *Accounting Review* 70 (3): 417–441.

Bamber, L. S., O. E. Barron, and D. E. Stevens. 2011. "Trading Volume around Earnings Announcements and Other Financial Reports: Theory, Research Design, Empirical Evidence, and Directions for Future Research," *Contemporary Accounting Research* 28 (2): 431–471.

Barth, M. E., and Hutton, A. P. 2004. "Analyst Earnings Forecast Revisions and the Pricing of Accruals," *Review of Accounting Studies*, *9*(1), 59–96.

Beaver, W. 1968. "The Information Content of Annual Earnings Announcements," *Journal of Accounting Research* 6: 67–92.

Beaver, W. 1998. *Financial Reporting: An Accounting Revolution*. Upper Saddle River, NJ: Prentice Hall.

Ben-David, Itzhak, Francesco Franzoni, and Rabih Moussawi, 2012, "Hedge Funds Stock Trading During the Financial Crisis of 2007-2009," *Review of Financial Studies* 25(1), 1-54.

Berger, P. G. 2011. "Challenges and Opportunities in Disclosure Research: A Discussion of 'the Financial Reporting Environment: Review of the Recent Literature,'" *Journal of Accounting and Economics* 51 (1-2): 204–218.

Beyer, A., D. A. Cohen, T. Z. Lys, and B. R. Walther. 2010. "The Financial Reporting Environment: Review of the Recent Literature," *Journal of Accounting and Economics*, 50 (2-3), 296–343.

Bessembinder, H., and W. Maxwell. 2008. "Transparency and the Corporate Bond Market," *Journal of Economic Perspectives* 22 (2): 217–234.

Boehmer, E., and Kelley, E. K. 2009. "Institutional Investors and the Informational Efficiency of Prices," *Review of Financial Studies*, *22*(9): 3563-3594.

Brennan, M. J., N. Jegadeesh, and B. Swaminathan. 1993. "Investment Analysis and the Adjustment of Stock Prices to Common Information," *Review of Financial Studies* 6: 799–824.

Bushee, B. J., Core, J. E., Guay, W., and Hamm, S. J. 2010. "The Role of the Business Press as an Information Intermediary," *Journal of Accounting Research*, *48*(1), 1–19.

Chung, K., C. Frost, and M. Kim. 2008. *Characteristics and Information Value of Credit Watches*. Working paper. Available at: http://ssrn.com/abstract=1321515.

Coller, M., and Yohn, T. L. 1997. "Management Forecasts and Information Asymmetry: An Examination of Bid-Ask Spreads," *Journal of Accounting Research*, *35*(2).

Cooper, R. A., T. Day, and C. Lewis. 2001. "Following the Leader: a Study of Individual Analysts' Earnings Forecasts," *Journal of Financial Economics* 61(3): 383-416.

Datta, S., I. Datta, and E. Mai. 1996. "Does Insider Trading Have Information Content for the Bond Market?," *Journal of Banking and Finance* 20 (3): 555–575.

Datta, S., and U. Dhillon. 1993. "Bond and Stock Market Response to Unexpected Earnings Announcements," *Journal of Financial and Quantitative Analysis* 28: 565–577.

De Franco, G., F. Vasvari, and R. Wittenberg-Moerman R. 2009. "The Informational Role of Bond Analysts," *Journal of Accounting Research* 47: 1201–1248.

De Franco, G., F. Vasvari, D. Vyas, and R. Wittenberg-Moerman. 2014. "Debt Analysts' View of Debt-Equity Conflicts of Interest," *The Accounting Review* 89 (2): 571-604.

Downing, C., S. Underwood, and Y. Xing. 2009. "The Relative Informational Efficiency of Stocks and Bonds: An Intraday Analysis," *Journal of Financial and Quantitative Analysis* 44 (5): 1081–1102.

Easton, P., S. Monahan, and F. Vasvari. 2009. "Initial Evidence on the Role of Accounting Earnings in the Bond Market," *Journal of Accounting Research* 47 (3): 721-766.

Fama, E. F., and K. R. French. 1995. "Size and Book-to-Market Factors in Earnings and Returns," *Journal of Finance* 50: 131–155.

Francis, J., K. Schipper, and L. Vincent. 2002. "Earnings Announcements and Competing Information," *Journal of Accounting and Economics* 33 (3): 313–342.

Frankel, R., S. P. Kothari, and J. Weber. 2006. "Determinants of the Informativeness of Analyst Research," *Journal of Accounting and Economics* 41: 29–54.

Gebhardt, E., S. Hvidkjaer, and B. Swaminathan. 2005. "Stock and Bond Market Interaction: Does Momentum Spill Over?," *Journal of Financial Economics* 75: 651–690.

Gilson, R., and R. Kraakman. 1984. "The Mechanisms of Market Efficiency," *Virginia Law Review* 70 (4): 549–644.

Gleason, C., and C. Lee. 2003. "Analyst Forecast Revision and Price Discovery," *The Accounting Review* 78 (1): 193–225.

Goldstein, M. A., Irvine, P., Kandel, E., and Wiener, Z. 2009. "Brokerage Commissions and Institutional Trading Patterns," *Review of Financial Studies*, *22*(12): 5175-5212.

Green, J., J.R.M. Hand, and M.T. Soliman, 2011. "Going, Going, Gone? The Apparent Demise of the Accruals Anomaly," *Management Science* 57 (5), 797-816.

Gurun, Umit G., and Alex Butler, 2012, "Don't Believe the Hype: Local Media Slant, Local Advertising, and Firm Value." *Journal of Finance* 67 (2): 561-597.

Hand, J., R. Holthausen, and R. Leftwich. 1992. "The Effect of Bond Rating Agency Announcements on Bond and Stock Prices," *The Journal of Finance* 47 (2): 733–752.

Healy, P. M., Hutton, A. P., and Palepu, K. G. 1999. "Stock Performance and Intermediation Changes Surrounding Sustained Increases in Disclosure*," *Contemporary accounting research*, *16*(3), 485–520.

Hirshleifer, D., and S. Teoh. 2003. "Limited Attention, Financial Reporting, and Disclosure," *Journal of Accounting and Economics* 36: 337–386.

Hong, H., and J. Stein. 1999. "A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets," *The Journal of Finance*, *54*(6): 2143–2184.

Hong, H., T. Lim, and J. Stein. 2000. "Bad News Travels Slowly: Size, Analyst Coverage and the Profitability of Momentum Strategies," *Journal of Finance* 55: 265–296.

Hotchkiss, E., and T. Ronen. 2002. "The Informational Efficiency of the Corporate Bond Market: An Intraday Analysis," *Review of Financial Studies* 15 (5): 1325–1354.

Lennox, C., Francis, J. R., and Z. Wang. 2011. "Selection Models in Accounting Research," *The Accounting Review*, *87*(2): 589-616.

Irvine, P., Lipson, M., and Puckett, A. 2007. "Tipping," *Review of Financial Studies*, *20*(3): 741-768.

Johnston, R., S. Markov, and S. Ramnath. 2009. "Sell-Side Debt Analysts," *Journal of Accounting and Economics* 47: 91–107.

Kandel, E., and N. Pearson. 1995. "Differential Interpretation of Public Signals and Trade in Speculative Markets," *Journal of Political Economy* 103: 831-872.

Kwan, S. 1996. "Firm Specific Information and the Correlation between Individual Stocks and Bonds," *Journal of Financial Economics* 43: 63–80.

Mansi, S., W. Maxwell, and D. Miller. 2011. "Analyst forecast characteristics and the cost of debt." *Review of Accounting Studies* 16: 116-142.

Rogers, W. 1993. "Regression Standard Errors in Clustered Samples," *Stata Technical Bulletin* 13: 19–23.

Ronan, G. 2006. "The 2006 All-America Fixed-Income Research Team," *Institutional Investor* (September).

Ronen, T., and X. Zhou. 2013. "Trade and Information in the Corporate Bond Market," *Journal of Financial Markets* 16: 61–103.

Sims, C. 2003. "Implications of Rational Inattention," *Journal of Monetary Economics* 50: 665–690.

Stickel, S. E. 1992. "Reputation and Performance among Security Analysts," *The Journal of Finance* 47(5): 1811–1836.

Tucker, J. 2010." Accounting and finance research," *Journal of Accounting Literature*, *29*: 31-57.

Womack, K. 1996. "Do Brokerage Analysts' Recommendations Have Investment Value?," *Journal of Finance* 51 (1): 137–167.

**Appendix A: Endogeneity concerns**

**A Probit Model of the Determinants of Sell-Side Debt Analyst Following**

If debt analysts select the coverage of firms where the market is more efficient, the use of OLS has the potential to bias the DF coefficient if such non-randomness is ignored. To address this concern, we apply a selection model developed by Heckman (1979). Specifically, we first determine the determinants of debt following (DF) by estimating the following model:

$$DF_{it} =$$
$$\beta_0 + \beta_1\, NRaters_{it-1} + \beta_2\, Days\ Since\ Last\ Bond\ Issue_{it-1} + \beta_3\, Maturity_{it-1} +$$
$$\beta_4\, Debt\ Outstanding_{it-1} + \beta_5\, Bond\ Liquidity_{it-1} + \beta_6\, Junk_{it-1} + \beta_7\, Convertible_{it-1} +$$
$$\beta_8\, Institutional\ HHI_{it-1} + \beta_9 Market\ Value_{it-1} + \beta_{10}\, Leverage_{it-1} + \beta_{11}\, Book\ to\ Market_{it-1} +$$
$$\beta_{12}\, Volatility_{it-1} + \beta_{13}\, Hedge\ Fund\ Ownership_{it-1} + \beta_{14}\, Media\ Coverage_{it-1} +$$
$$\beta_{15}\, Firm\ Disclosure_{it-1} + \epsilon_{it}.$$

We calculate the *Inverse Mills Ratio* using the probit model estimates, i.e., for each observation used in the first stage model reported in Table 2, Panel B, we calculate the *Inverse Mills Ratio* as the ratio of the probability density function and the cumulative density function of the normal distribution evaluated at the predicted outcomes. We then include the *Inverse Mills Ratio* in the specification reported in Table 2.

In our specification, the dependent variable, Debt Following (*DF*), is equal to one if there was one or more debt reports within the past calendar year. Johnston et al. (2009) find that the probability of distress, book-to-market, amount of debt outstanding, presence of convertibles, and leverage are primary drivers of debt analyst following. Therefore, in our selection model, we include the following: *Junk* equals 1 if one of the bonds of the firm is rated below BBB (S&P Rating); *Debt Outstanding* is the amount of debt outstanding and is calculated as the natural logarithm of the sum of the par value of debt initially issued for each bond; *Convertible* equals 1 if one of the bonds of the firm has convertible features; *Leverage* is long-term liabilities scaled by total assets; and *Book to Market* is the ratio of book value of equity to market value of equity. *Johnston et al. (2009) find weaker results for volatility but we include it here as well. Volatility* is the standard deviation of daily stock returns in the prior calendar year.

We also include market value of equity, credit rating agency following, and institutional ownership concentration to proxy for the information environment surrounding the firm that may affect a debt analyst decision to cover the firm. *Market Value* is the natural logarithm of market value of equity as of the end of previous fiscal year. *NRaters* is the number of credit rating agencies (S&P, Fitch, Moody's, and EGAN Jones) that issued at least one rating in the past calendar year scaled by 4. *Institutional Hedge Fund Ownership* is a dummy variable that takes a value of one if the percentage of ownership by all institutions, excluding hedge funds, is greater than median in that year. *Hedge Fund Ownership* is a dummy variable that takes a value of one if the percentage of ownership by hedge funds as defined in Ben-David, Franzoni, and Moussawi (2011) is greater than median hedge fund ownership in that year.[37] *Media Coverage* is the number of articles written on firms in The Wall Street Journal, New York Times

[37] Specifically, Ben-David, Franzoni, and Moussawi (2011) use a proprietary list of hedge funds provided by Thompson Reuters to identify which 13 F filers are hedge funds. Prior literature on hedge funds relies on self-reported industry lists and as such subject to survival bias.

and Washington Post in a given year.[38] *Firm Disclosure* is the total number of firm's 8K filings and earnings management forecasts in a given year.[39]

The demand bond market investors have for debt reports may also be influenced by the features of outstanding debt. For this reason, we include average maturity of outstanding bonds (*Maturity)* and liquidity of traded bonds (*Bond Liquidity)*. To measure bond liquidity, we first construct a bond portfolio for each firm for each day by averaging daily returns and summing daily volumes. Using daily firm-level bond returns and volumes, we calculate Amihud liquidity for each firm as "*abs(bret)* / *daily_vol*," where *bret* is bond return, and *daily_vol* is the volume of bond transaction. Then, we take average of Amihud measure for each month to create firm-month liquidity observation. We then calculate terciles of this liquidity measure each month to classify bonds in three liquidity buckets (1, 2, or 3: higher is more liquid).

*NRaters*, *Maturity*, *Offering Amount*, *Bond Liquidity*, *Junk*, and *Convertible* are determined using the most current information prior to day *t*. We use the 13Fs reported in the prior year's December to measure institutional holding. Accounting variables (*Market Value*, *Leverage*, and *Book to Market), Hedge Fund Ownership, Media Coverage, and Firm Disclosure* are measured as of the previous fiscal year end. P-values are provided in brackets, and (***), (**), and (*) represent statistical significance at the 1, 5, and 10 percent levels, respectively.

[38] We follow the procedure described in Gurun and Butler (2012) to collect the media coverage data from Factiva. Specifically, we use the ticker symbols, firm names, and name variants of the stocks from the CRSP database as the search strings in Factiva. The name variants we use include singular and plural versions of the following abbreviations from the company names: ADR, CO, CORP, HLDG, INC, IND, LTD, and MFG. Our search algorithm first searches for ticker symbols within brackets (e.g., [GM] for General Motors) in article titles and lead paragraphs.

[39] We obtain 8K filings from the SEC Edgar website and management forecast data from the First Call database.

**Panel A. Descriptive Statistics**

| | *Debt Following (DF)* | *NRaters* | *Day Since Last Bond Issue* | *Maturity* | *Debt Outstanding* | *Bond Liquidity* | *Junk* | *Convertible* |
|---|---|---|---|---|---|---|---|---|
| Mean | 0.72 | 2.66 | 5.37 | 10.40 | 1.78 | 0.12 | 0.18 | 0.26 |
| P50 | 1.00 | 3.00 | 5.51 | 9.00 | 1.66 | 0.01 | 0.00 | 0.00 |
| STD | 0.45 | 1.03 | 0.74 | 6.09 | 0.93 | 0.50 | 0.39 | 0.44 |
| P10 | 0.00 | 1.00 | 4.48 | 5.00 | 0.74 | 0.00 | 0.00 | 0.00 |
| P25 | 0.00 | 2.00 | 5.03 | 6.00 | 1.12 | 0.00 | 0.00 | 0.00 |
| P75 | 1.00 | 3.00 | 5.87 | 13.00 | 2.25 | 0.04 | 0.00 | 1.00 |
| P95 | 1.00 | 4.00 | 6.26 | 22.00 | 3.51 | 0.55 | 1.00 | 1.00 |
| N | 74,388 | 74,388 | 74,388 | 74,388 | 74,388 | 74,388 | 74,388 | 74,388 |

| | *Institutional Ownership* | *Market Value* | *Leverage* | *Book to Market* | *Volatility* | *Hedge Fund Ownership* | *Media Coverage* | *Firm Disclosure* |
|---|---|---|---|---|---|---|---|---|
| Mean | 0.54 | 9.65 | 0.22 | 0.47 | 0.08 | 0.69 | 2.02 | 7.06 |
| P50 | 1.00 | 9.72 | 0.21 | 0.46 | 0.06 | 1.00 | 1.00 | 8.00 |
| STD | 0.50 | 1.38 | 0.12 | 0.61 | 0.05 | 0.46 | 4.27 | 7.91 |
| P10 | 0.00 | 7.86 | 0.08 | 0.17 | 0.04 | 0.00 | 0.00 | 0.00 |
| P25 | 0.00 | 8.81 | 0.12 | 0.28 | 0.05 | 0.00 | 0.00 | 3.00 |
| P75 | 1.00 | 10.70 | 0.29 | 0.70 | 0.09 | 1.00 | 2.00 | 13.00 |
| P95 | 1.00 | 11.84 | 0.46 | 1.02 | 0.16 | 1.00 | 8.00 | 33.00 |
| N | 74,388 | 74,388 | 74,388 | 74,388 | 74,388 | 74,388 | 74,388 | 74,388 |

**Panel B. Coefficient Estimates Obtained from Probit Model**

| | Debt Following = 1 |
|---|---|
| *NRaters* | 0.1575*** |
| | [0.000] |
| *Day Since Last Bond Issue* | -0.1831*** |
| | [0.000] |
| *Junk* | -0.1089*** |
| | [0.000] |
| *Maturity* | 0.0346*** |
| | [0.000] |
| *Debt Outstanding* | 0.2897*** |
| | [0.000] |
| *Bond Liquidity* | -0.2470*** |
| | [0.000] |
| *Market Value* | 0.2083*** |
| | [0.000] |
| *Leverage* | 3.6897*** |
| | [0.000] |
| *Convertible* | -0.3959*** |
| | [0.000] |
| *Book to Market* | 0.2073*** |
| | [0.000] |
| *Volatility* | 1.4505*** |
| | [0.000] |
| *Institutional Ownership* | 0.0814*** |
| | [0.000] |
| *Hedge Fund Ownership* | 0.1405*** |
| | [0.000] |
| *Media Coverage (x100)* | 6.5159*** |
| | [0.000] |
| *Firm Disclosure (x100)* | 9.4298*** |
| | [0.000] |
| Constant | -2.9128*** |
| | [0.000] |
| Number of Observations | 74.388 |
| Pseudo $R^2$ | 0.23 |

**Panel C. Difference in Difference (with a Propensity Score Matched Control Sample):**

This table examines the effect of debt analyst coverage initiation on the lag with which debt prices incorporate information. The sample includes firm observations where a debt analyst initiates coverage in 2003 or 2004 (treated firms) and firms without coverage but with similar propensity scores (control firms). The propensity scores are estimated with a logistic regression, where the dependent variable is a binary variable equal to one for a treated firm, and the independent variables are Appendix A's determinants of debt coverage. We determine a propensity score match using the Mahalanobis distance criterion, with inferences unchanged when we use k-neighborhood matching (k=1, 2, or 3).

We introduce four new variables, $PostInit_{it} x InitFirms_{it}$, $InitFirms_{it} x\ Ret^{E}_{i,t-1}$, $Post\ Init_{it_{it}} x\ Ret^{E}_{i,t-1}$, and $Post\ Init_{it} x InitFirms_{it} x\ Ret^{E}_{i,t-1}$, to capture the effect of debt coverage initiation. $InitFirms_{it}$ is a binary variable equal to one for observations on treated firms. $Post\ Init_{it}$ is a binary variable equal to one for observations from the treatment period (days following debt analyst coverage initiation for both treated and respective matched controls). All other variables are defined as in Table 2. We report parameter estimates and p-values (in brackets) based on standard errors robust to heteroskedasticity and cross-correlation in contemporaneous daily returns (Rogers, 1993). ($^{***}$), ($^{**}$), and ($^{*}$) represent statistical significance at the 1, 5, and 10 percent level.

| | $Ret_{it}^{B}$ |
|---|---|
| $\boldsymbol{PostInit_{it}}$ | 0.000 |
| | [0.574] |
| $\boldsymbol{InitFirms_{it}}$ | -0.387 |
| | [0.624] |
| $Ret_{i,t+1}^{E}$ | 0.007 |
| | [0.535] |
| $Ret_{i,t}^{E}$ | 0.146*** |
| | [0.000] |
| $Ret_{i,t-1}^{E}$ | 0.056 |
| | [0.110] |
| $NRaters_{it} x\ Ret_{i,t-1}^{E}$ | -0.021*** |
| | [0.001] |
| $Firm\ Disclosure_{it} x\ Ret_{i,t-1}^{E}$ | -0.364 |
| | [0.756] |
| $Hedge\ Fund\ Ownership_{it} x\ Ret_{i,t-1}^{E}$ | -0.025* |
| | [0.056] |
| $Media\ Coverage_{it} x\ Ret_{i,t-1}^{E}$ | -0.471 |
| | [0.296] |
| $EF_{it} x\ Ret_{i,t-1}^{E}$ | 0.514 |
| | [0.655] |
| $EF_{it} x\ Ret_{i,t+1}^{E}$ | -0.005 |
| | [0.742] |
| $\boldsymbol{PostInit_{it} x InitFirms_{it}}$ | 1.535 |
| | [0.146] |
| $\boldsymbol{Post\ Init_{it_{it}} x\ Ret_{i,t-1}^{E}}$ | 0.009 |
| | [0.572] |
| $\boldsymbol{InitFirms_{it} x\ Ret_{i,t-1}^{E}}$ | 0.069* |
| | [0.094] |
| $\boldsymbol{Post\ Init_{it} x InitFirms_{it} x\ Ret_{i,t-1}^{E}}$ | -0.030** |
| | [0.016] |
| Observations | 21,951 |
| Adj. $R^2$ | 0.059 |

**Appendix B. Sell-side Debt Analyst Report Content**

Since little is known about the content of sell-side debt analyst reports, below we briefly summarize our impressions from reading 30 reports authored by 12 brokerage firms and covering 30 firms from 15 industries.

The reports contain standard credit analysis in that they discuss past and future profitability, giving special attention to cash flows, as well as measures of liquidity and solvency. The reports invariably express analyst assessment of credit risk and discuss any differences with credit rating agencies' assessments of credit risk, and they offer an investment recommendation, typically backed up by an evaluation of current and expected spreads, often relative to industry peers.

Slightly more than half the reports are published following earnings announcements and discuss in detail the implications of earnings results for credit risk, which suggests that sell-side debt analysts, similar to bond investors (Easton et al. [2009]), view earnings announcement as a major information event. Close to 40 percent of the debt reports appear to be triggered by various corporate events (merger and acquisitions, IPO of a subsidiary, court decision) or announcements (share repurchase, debt reduction, credit rating agency downgrade) that may affect debt holders differently from equity holders (De Franco et al. [2014]). Close to ten percent of the reports are written in the wake of a meeting with management (analyst meeting, lunch with management, investor day), which suggests management are an important source of information not only for equity analysts but also for debt analysts.

**TABLE 1.** Sample Statistics

In Panel A of this table, we describe how the sample companies are identified. Panel B reports Mean and Median *Equity Capitalization* (number of shares times share price), *Total Assets* (book value of assets), *Market to Book* (market value of equity divided by book value of equity), *Leverage* (book value of debt divided by book value of assets at year end), *Credit Rating* (at year end, source: FISD, converted to a ordinal scale, Best 23 through Worst 1), and *Credit Rating* Agency Coverage (*NRATERS*: number of credit rating agencies (S&P, Fitch, Moody's, or Egan Jones) that issued at least one rating in the past year divided by 4), *Hedge Fund Ownership* (end of year, percentage ownership), *Disclosure* (number of 8K and management forecasts), and *Media Coverage* (number of articles written over the sample period) for companies without debt coverage and companies with debt coverage – companies that have at least one debt report over the sample period. The reported means and medians are based on pooling company-year observations. Panel C reports timing of important events (Earnings Announcement, Credit Rating Change, and Equity Analyst Report) around debt analyst reports release dates. Panel D reports the characteristics (issue size and maturity) of bonds used in this study. Panel E tabulates the number of firms by credit rating at the time of debt report release. For firms with multiple debt reports, we use the credit rating at the time of first debt report.

**Panel A:** Selecting Sample Companies

| | |
|---|---|
| Bond issuers over the period from July 1, 2002 to December 31, 2004 (from TRACE) | 2,705 |
| Bond issuers that have also issued equity (after merging with CRSP) | 1,139 |
| Companies (unique equity issuers corresponding to the 1,139 bond issuers) | 921 |
| Bond issues | 5,078 |

**Panel B:** Debt Research Coverage and Company Characteristics

| | With Debt Research 429 Companies Issuing 3,194 Bonds | | Without Debt Research 492 Companies Issuing 1,884 Bonds | |
|---|---|---|---|---|
| | Mean | Median | Mean | Median |
| *Equity Capitalization* | 14,416 | 5,133 | 6,705 | 1,944 |
| *Total Assets* | 39,592 | 8,985 | 11,254 | 2,492 |
| *Market to Book* | 2.78 | 1.98 | 7.15 | 1.96 |
| *Leverage* | 0.32 | 0.28 | 0.26 | 0.24 |
| *Credit Rating* | 14.36 | 15.00 | 13.70 | 15.00 |
| *Credit Rating Agency Coverage* | 0.79 | 1.00 | 0.52 | 1.00 |
| *Hedge Fund Ownership %* | 0.049 | 0.024 | 0.037 | 0.021 |
| *Disclosure* | 12.27 | 11.00 | 8.74 | 7.00 |
| *Media Coverage* | 27.55 | 13.00 | 14.70 | 8.00 |

**Panel C:** Timing of Other Events Around Debt Analyst Reports

| | Before Debt Report (-2,-10) | At the time of Report (-1,1) | After Report (2, 10) | Outside of 21-Day Window |
|---|---|---|---|---|
| Earnings Announcements | 14% | 22% | 7% | 57% |
| Rating Changes | 4% | 4% | 3% | 89% |
| Equity Analyst Reports | 18% | 22% | 23% | 37% |

**Panel D:** Bond Characteristics

| Issue Size | Number | Percent | Years to Maturity | Number | Percent |
|---|---|---|---|---|---|
| Less than 100M | 711 | 14% | Less than 1 year | 102 | 2% |
| From 100M to 500M | 2,691 | 53% | From 1 year to 5 years | 914 | 18% |
| From 500M to 900M | 711 | 14% | From 5 years to 10 years | 2,945 | 58% |
| More than 900M | 965 | 19% | More than 10 years | 1,117 | 22% |

**Panel E:** Number of Firms by Credit Rating at the Time of Debt Report Release

| Credit Rating | Number |
|---|---|
| *AAA/AA+/AA/AA−* | 31 |
| *A+/A/A−/BBB+/BBB* | 191 |
| *BBB−/BB+/BB/BB−* | 99 |
| *Below BB−* | 93 |
| *Not Rated* | 15 |
| *Total* | 429 |

**TABLE 2.** Debt Analyst Following and the Lag with which Debt Prices Incorporate Information

This table examines the effect of debt analyst following on the lag with which debt prices incorporate information. Panel A reports descriptive statistics on the variables; Panel B reports regression results. $Ret_{i,t}^{B}$ denotes company *i*'s bond portfolio return on day *t* minus the return on the corresponding maturity-matched U.S. Treasury security; $Ret_{i,t}^{E}$ denotes company *i*'s equity return on day *t*. $Ret_{i,t}^{B}$ and $Ret_{i,t}^{E}$ are represented in percentages in Panel A. $EF_{it}$ is a binary variable equal to one when the number of equity analysts exceeds past year's median. $DF_{it}$ is a binary variable equal to one when firm *i* has at least one debt report in the past calendar year. *NRaters* is the number of credit rating agencies (S&P, Fitch, Moody's, or Egan Jones) that issued at least one rating in the past year divided by 4. *Hedge Fund Ownership* is dummy variable that takes of one if the percentage of ownership by hedge funds as defined in Ben-David, Franzoni, and Moussawi (2011) is greater than median hedge fund ownership in that year. *Media Coverage* is the number of articles written on firms in Wall Street Journal, New York Times and Washington Post in a given year. *Firm Disclosure* is the total number of firms 8K filings and earnings management forecasts in a given year. Intercept and main effects are included but not reported for brevity.

Panel C explores whether the effect of debt analyst following on how the debt market impounds information depends on debt market size and liquidity. We partition the sample by size as follows. All day *t* observations are sorted by the total par value of debt outstanding and grouped *Small*, *Medium*, and *Large* groups. Debt issues and par values used to calculate the total par value of debt outstanding are from FISD. We partition the sample by liquidity (Amihud 2002) as follows. Every month *q* we calculate the Amihud's liquidity measure for our sample companies. The month *q* liquidity ranking is used to classify daily observations from month *q+1* into *Low*, *Medium*, and *High Liquidity* groups. The coefficients on the main effects are insignificant and untabulated for brevity. The reported p-values (in brackets) are based on standard errors robust to heteroscedasticity and cross-correlation in contemporaneous daily returns (Rogers 1993). ($^{***}$), ($^{**}$), and ($^{*}$) represent statistical significance at the 1, 5, and 10 percent levels, respectively.

**Panel A:** Sample Statistics

| | $Ret^{B}$ | $Ret^{E}$ | *EF* | *DF* | *NRaters* | *Hedge Fund Ownership* | *Media Coverage* | *Firm Disclosure* |
|---|---|---|---|---|---|---|---|---|
| Mean | 0.039 | 0.103 | 0.765 | 0.660 | 0.660 | 0.69 | 2.02 | 7.06 |
| Median | 0.011 | 0.050 | 1.000 | 1.000 | 1.000 | 1.00 | 1.00 | 8.00 |
| STD | 1.201 | 2.138 | 0.424 | 0.474 | 0.474 | 0.46 | 4.27 | 7.91 |
| P5 | -1.702 | -2.989 | 0.000 | 0.000 | 0.000 | 0.00 | 0.00 | 0.00 |
| P95 | 1.885 | 3.329 | 1.000 | 1.000 | 1.000 | 1.00 | 0.00 | 3.00 |
| Min | -5.363 | -9.750 | 0.000 | 0.000 | 0.000 | 0.00 | 2.00 | 13.00 |
| Max | 5.611 | 10.940 | 1.000 | 1.000 | 1.000 | 1.00 | 8.00 | 33.00 |

**Panel B:** Regression Analysis

$$
\begin{aligned}
Ret_{it}^{B} \quad &= \beta_0 + \beta_1\, Ret_{i,t+1}^{E} + \beta_2\, Ret_{it}^{E} + \beta_3\, Ret_{i,t-1}^{E} + \beta_4\, DF_{it} \quad + \beta_5\, EF_{it} + \beta_6\, NRaters_{it} \\
&+ \beta_7\, Hedge\ Fund\ Ownership_{it} \quad + \beta_8\, Media\ Coverage_{it} \quad + \beta_9 Firm\ Disclosure_{it} \\
&+ \beta_{10} DF_{it} x\ Ret_{i,t+1}^{E} + \beta_{11}\, EF_{it} x\ Ret_{i,t+1}^{E} + \beta_{12}\, DF_{it} x\ Ret_{i,t-1}^{E} + \beta_{13}\, EF_{it} x\ Ret_{i,t-1}^{E} \\
&+ \beta_{14}\, NRaters_{it} x\ Ret_{i,t-1}^{E} + \beta_{15}\, Hedge\ Fund\ Owners_{it} x\ Ret_{i,t-1}^{E} \\
&+ \beta_{16}\, Media\ Coverage_{it} x\ Ret_{i,t-1}^{E} + \beta_{17}\, Firm\ Disclosure_{it} x\ Ret_{i,t-1}^{E} + \beta_{18} Inverse\ Mill_{i,t} \\
&+ \upsilon_{it}.
\end{aligned}
$$

| | $Ret_{it}^{B}$ | $Ret_{it}^{B}$ | $Ret_{it}^{B}$ |
|---|---|---|---|
| $Ret_{i,t+1}^{E}$ | 0.008** | 0.013** | -0.001 |
| | [0.023] | [0.037] | [0.939] |
| $Ret_{i,t}^{E}$ | 0.090*** | 0.089*** | 0.096*** |
| | [0.000] | [0.000] | [0.000] |
| $Ret_{i,t-1}^{E}$ | 0.049*** | 0.047*** | 0.036** |
| | [0.000] | [0.000] | [0.034] |
| $DF_{it} x\ Ret_{i,t+1}^{E}$ | | -0.002 | 0.006 |
| | | [0.679] | [0.387] |
| $EF_{it} x\ Ret_{i,t+1}^{E}$ | | -0.004 | 0.005 |
| | | [0.423] | [0.525] |
| $DF_{it} x\ Ret_{i,t-1}^{E}$ | | -0.032*** | -0.043*** |
| | | [0.000] | [0.000] |
| $EF_{it} x\ Ret_{i,t-1}^{E}$ | | 0.017*** | 0.027*** |
| | | [0.005] | [0.000] |
| $NRaters_{it} x\ Ret_{i,t-1}^{E}$ | | -0.007* | -0.006 |
| | | [0.074] | [0.108] |
| $Hedge\ Fund\ Ownership_{it} x\ Ret_{i,t-1}^{E}$ | | -0.029*** | -0.044*** |
| | | [0.000] | [0.000] |
| $Media\ Coverage_{it} x\ Ret_{i,t-1}^{E}$ *(x100)* | | 0.05 | -0.182 |
| | | [0.751] | [0.365] |
| $Firm\ Disclosure_{it} x\ Ret_{i,t-1}^{E}$ *(x100)* | | -1.134*** | -1.540*** |
| | | [0.000] | [0.004] |
| *Inverse Mills* | | | 0.012 |
| | | | [0.672] |
| Observations | 107,812 | 107,812 | 74,388 |
| Adj. $R^2$ | 0.034 | 0.036 | 0.040 |

**Panel C:** Cross-Sectional Variation in the Effect of Debt Analyst Following on How the Debt Market Impounds Information

| | Debt Market Size | | | Liquidity | | |
|---|---|---|---|---|---|---|
| | Small | Medium | Large | Low | Medium | High |
| $Ret^{E}_{i,t+1}$ | 0.019*** | 0.018* | -0.017 | 0.015 | 0.014* | 0.005 |
| | [0.004] | [0.052] | [0.650] | [0.145] | [0.082] | [0.214] |
| $Ret^{E}_{i,t}$ | 0.065*** | 0.109*** | 0.094*** | 0.103*** | 0.110*** | 0.072*** |
| | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] |
| $Ret^{E}_{i,t-1}$ | 0.029 | 0.017 | 0.052 | 0.053** | -0.003 | 0.052 |
| | [0.154] | [0.552] | [0.197] | [0.013] | [0.892] | [0.140] |
| $DF_{it} x\ Ret^{E}_{i,t+1}$ | -0.004 | 0.002 | 0.019 | 0.005 | 0.004 | 0.012 |
| | [0.717] | [0.864] | [0.261] | [0.581] | [0.710] | [0.397] |
| $EF_{it} x\ Ret^{E}_{i,t+1}$ | 0.002 | -0.016 | 0.022 | 0.002 | 0.005 | -0.002 |
| | [0.821] | [0.215] | [0.149] | [0.795] | [0.667] | [0.912] |
| $DF_{it} x\ Ret^{E}_{i,t-1}$ | -0.066*** | -0.047*** | 0.005 | -0.013 | -0.035*** | -0.064*** |
| | [0.000] | [0.000] | [0.569] | [0.182] | [0.002] | [0.000] |
| $EF_{it} x\ Ret^{E}_{i,t-1}$ | 0.027** | 0.036*** | 0.034** | 0.000 | 0.027** | 0.044*** |
| | [0.019] | [0.005] | [0.026] | [0.992] | [0.015] | [0.003] |
| $NRaters_{it} x\ Ret^{E}_{i,t-1}$ | -0.002 | -0.001 | -0.009 | 0.001 | -0.006 | -0.006 |
| | [0.596] | [0.908] | [0.230] | [0.865] | [0.237] | [0.381] |
| $Hedge\ Fund\ Ownership_{it} x\ Ret^{E}_{i,t-1}$ | -0.054*** | -0.035*** | -0.038** | -0.045*** | -0.039*** | -0.042*** |
| | [0.000] | [0.001] | [0.014] | [0.000] | [0.000] | [0.002] |
| $Media\ Coverage_{it} x\ Ret^{E}_{i,t-1}$ *(x100)* | -0.056 | -0.251 | -0.022 | -0.107 | -0.187 | -0.105 |
| | [0.754] | [0.458] | [0.970] | [0.583] | [0.559] | [0.827] |
| $Firm\ Disclosure_{it} x\ Ret^{E}_{i,t-1}$ *(x100)* | -1.094* | -2.174** | -1.385 | -0.633 | -3.038*** | -0.803 |
| | [0.050] | [0.010] | [0.297] | [0.278] | [0.000] | [0.493] |
| Observations | 35,364 | 34,565 | 37,883 | 40,115 | 33,837 | 25,335 |
| Adj. $R^2$ | 0.037 | 0.053 | 0.047 | 0.047 | 0.052 | 0.044 |

**TABLE 3.** Information Events

This table provides descriptive statistics about the following information events: *Debt Report Publication* (the publication of a debt report for company *i* on day *t* by at least one debt analyst), *Equity Recommendation* (the issuance of an equity recommendation on company *i* and day *t* by at least one equity analyst), Δ*Credit Rating* (the change in a credit rating of company *i* on day *t* by at least one credit rating agency), and *Earnings Announcement* (the announcement of company *i*'s earnings on day *t*). Panel A reports the number of information events in our sample period from July 1, 2002 to December 31, 2004; the TRACE period, which is firm-specific and begins on the day on which a bond is added to TRACE; and then days for which we have non-missing *BondAbsRet*, *EquityAbsRet*, and *COV*. *BondRet* is equal-weighted bond portfolio returns minus the corresponding maturity-matched U.S. Treasury security rate. To calculate bond returns, we use price data from TRACE and coupon information from FISD. *EquityRet* is market-adjusted equity return; *BondAbsRet* is the absolute value of *BondRet*; *EquityAbsRet* is the absolute value of *EquityRet*; *COV* is the product of *EquityRet* and *BondRet*. All return-based variables and equity turnover are multiplied by 100. Panel B summarizes the cross-sectional distribution of the number of information events experienced by the sample companies over the sample period. We report Mean, Median, Standard Deviation (STD), and the 25$^{th}$ and the 75$^{th}$ percentiles.

**Panel A:** Number of Information Events and Market Data Availability

| **Information Event** | Sample Period | TRACE Coverage | *BondAbsRet* | *EquityAbsRet* | *COV* |
|---|---|---|---|---|---|
| *Debt Report Publication* | 2,758 | 1,737 | 1,103 | 2,726 | 1,100 |
| *Equity Recommendation* | 26,749 | 13,123 | 7,154 | 26,728 | 7,154 |
| Δ*Credit Rating* | 3,817 | 2,417 | 1,676 | 3,583 | 1,578 |
| *Earnings Announcement* | 8,062 | 3,562 | 1,673 | 8,010 | 1,670 |

**Panel B:** Cross-Sectional Distribution of the Number of Information Events Experienced by Sample Companies

| | *Debt Report* | *Equity Recommendation* | Δ*Credit Rating* | *Earnings Announcement* |
|---|---|---|---|---|
| Mean | 2.99 | 29.04 | 4.14 | 8.75 |
| Median | 0.00 | 27.00 | 2.00 | 10.00 |
| STD | 5.86 | 21.08 | 9.39 | 2.95 |
| Q25 | 0.00 | 13.00 | 0.00 | 10.00 |
| Q75 | 3.00 | 41.00 | 5.00 | 10.00 |

**TABLE 4.** Event Time Analysis of Equity and Debt Returns

Panel A describes the cross-sectional distribution of the mean, median, and standard deviation of three daily return variables. For each company *i*, we calculate mean, median, and standard deviation of a market return variable using all sample days with non-missing observations. We report cross-sectional means and standard deviations of these company-specific parameters, number of companies, and non-missing observations used in the estimations. *BondRet* is equal-weighted bond portfolio returns minus the corresponding maturity-matched U.S. Treasury security. To calculate bond returns, we use price data from TRACE and coupon information from FISD. *EquityRet* is market-adjusted equity return; *BondAbsRet* is the absolute value of *BondRet*; *EquityAbsRet* is the absolute value of *EquityRet*; *COV* is the product of *EquityRet* and *BondRet*. All return-based variables and equity turnover are multiplied by 100. Panel B describes the distribution of *BondAbsRet*, *EquityAbsRet*, and *COV* after we standardize them by subtracting company-specific mean and dividing by company-specific standard deviations. Company-specific means and standard deviations are calculated based on all non-missing sample observations. The reported Medians, Standard Deviations (STD), Minimums, and Maximums are based on pooling observations over days and companies. Panel C reports mean market returns to the publication of a debt report from day −10 to day +10, with Day 0 the report publication day when there is debt trading (metrics are *BondAbsRet*, *EquityAbsRet*, and COV) and when there is no debt trading (return metric is *EquityAbsRet*). We also exclude debt reports occurring within 21 days of another debt report. The null hypothesis is the absence of a return reaction; bold figures in panel C represent statistical significant at 5 percent level. Standard errors are heteroscedasticity-consistent and adjusted to account for cross-correlation in contemporaneous daily returns and volume (Rogers 1993).

**Panel A:** Cross-Sectional Distribution of Select Parameters of the Distributions of Market Return Variables – Prior to Standardization

| | | *BondRet* | *EquityRet* | *BondAbsRet* | *EquityAbsRet* | *COV* |
|---|---|---|---|---|---|---|
| Mean | Mean | 0.0867 | 0.0336 | 0.9719 | 1.6183 | 0.0076 |
| | Median | 0.0470 | 0.0356 | 0.7847 | 1.3086 | 0.0009 |
| | STD | 0.4632 | 0.1210 | 0.7050 | 0.9497 | 0.0469 |
| STD | Mean | 1.4447 | 2.3974 | 1.0604 | 1.7574 | 0.0409 |
| | Median | 1.2015 | 1.8748 | 0.8707 | 1.3270 | 0.0176 |
| | STD | 1.0566 | 1.6213 | 0.8540 | 1.3325 | 0.1048 |
| | Companies | 795 | 921 | 795 | 921 | 783 |
| | Observations | 111,465 | 549,515 | 111,465 | 549,515 | 108,658 |

**Panel B:** The Distribution of Market Return Variables – After Standardization

| | *BondAbsRet* | *EquityAbsRet* | *COV* |
|---|---|---|---|
| Mean | -0.010 | -0.035 | -0.004 |
| Median | -0.273 | -0.287 | -0.043 |
| STD | 0.917 | 0.913 | 0.826 |
| Minimum | -1.107 | -1.120 | -3.793 |
| Maximum | 4.849 | 4.676 | 4.501 |

**Panel C:** Market Returns around the Publication of a Debt Report in Event Time

| | | *Debt Trading* | *No Debt Trading* | | |
|---|---|---|---|---|---|
| Event Day | *BondAbsRet* | *EquityAbsRet* | *EquityAbsRet* | *COV* | *Firms with Bonds Trading* |
| Mean[-10, -2] | 0.0214 | -0.0015 | -0.1348 | 0.0150 | 1,051 (average) |
| -1 | 0.0318 | **0.3576** | **0.3099** | 0.0366 | 1,097 |
| 0 | **0.0966** | **0.5149** | **0.3272** | **0.1536** | 1,100 |
| 1 | -0.0196 | **0.0992** | -0.0113 | 0.0440 | 1,079 |
| Mean[2, 10] | -0.0198 | -0.0656 | -0.1813 | 0.0002 | 1,053 (average) |
| Number of Events | 1,100 | 1,100 | 634 | 1,100 | |

**Table 5**. Cross-Sectional Analysis of Debt Market Reaction

Panel A explores determinants of a bond trade on a report publication day as well the timing of the first bond trade. The sample includes 1,725 debt reports. The first (last) two columns report the results from the estimations of a Probit (Weibull hazard) model. The Probit's dependent variable is *Day 0 Trade*$_i$, an indicator variable equal to one when we observe a bond trade on Day 0 and zero otherwise. The Weibull model's dependent variable is *Time to Trade*$_i$, defined as the number of days from debt report publication day to the first bond trade day. The determinants are *High Reputation*$_i$, equal to one when the report originates from Bear Sterns, Credit Suisse, Deutsche Bank, Prudential, Morgan Stanley, or Smith Barney Citigroup, and zero otherwise; and *Timely Report*$_i$, a continuous variable between 0 and 1 (a higher value represents a more timely report). The variable is measured using events such as earnings announcements and credit rating changes as follows: For each event we calculate one minus the ratio of: the number of days after the event to the debt report of analyst *i* over the sum of the numerator and the number of days to the debt reports of all other analysts within 30 days of the event. *EquityAbsRet*$_i$ is absolute equity return on Day 0, defined as in Table 4. *Bond Volume*$_i$ is the natural logarithm of total bond trading volume in the prior quarter. *P-values* are reported below coefficient estimates.

Panel B explores the determinants of absolute Day 0 bond returns (1,100 debt reports). *BondAbsRet*$_i$ is as in Table 4. $Z_i$ includes: *Junk* equals 1 if one of the bonds of the firm is rated below BBB (S&P Rating). *Convertible* equals 1 if one or more bonds have convertible features. *Book to Market* is the ratio of book value of equity (Data24) to market value of equity (Data199xData25). *Maturity* is the average of outstanding bonds' number of years to maturity. Leverage is long-term liabilities scaled by total assets (Data9/Data6). P-values are provided in brackets, and ($^{***}$), ($^{**}$), and ($^{*}$) represent statistical significance at the 1, 5, and 10 percent levels, respectively.

**Panel A:** Bond Trade Analysis

$Day\ 0\ Trade_i\ or\ Time\ to\ Trade_i = \beta_0 + \beta_1\ High\ Reputation_i \quad + \beta_2\ Timely\ Report_i + \beta_3\ EquityAbsRet_i + \beta_4 Bond\ Volume_i + \varphi_i.$

| | Day 0 Trade Incidence (Probit Model) | | | Time to First Trade (Weibull Hazard Model) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (1) | (2) | (3) |
| *EquityAbsRet* | | 0.103*** | 0.121*** | | -0.333*** | -0.291** |
| | | [0.000] | [0.000] | | [0.002] | [0.013] |
| *High Reputation* | 0.533* | 0.832** | 0.754** | -0.358*** | -0.357*** | -0.352*** |
| | [0.090] | [0.017] | [0.035] | [0.000] | [0.000] | [0.000] |
| *Timely Report* | 0.316*** | 0.311*** | 0.394** | -0.844* | -0.668** | -0.662*** |
| | [0.000] | [0.000] | [0.027] | [0.046] | [0.011] | [0.011] |
| *Bond Volume* | 0.645*** | 0.655*** | 0.651*** | -0.646*** | -0.648*** | -0.647*** |
| | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] |
| *Junk* | | | 0.150** | | | -0.291* |
| | | | [0.042] | | | [0.052] |
| *Convertible* | | | 0.052 | | | -0.060 |
| | | | [0.374] | | | [0.441] |
| *Book to Market* | | | 0.126** | | | 0.117 |
| | | | [0.012] | | | [0.129] |
| *Maturity* | | | 0.004 | | | 0.000 |
| | | | [0.106] | | | [0.984] |
| *Leverage* | | | 0.013 | | | -0.001 |
| | | | [0.990] | | | [0.970] |
| *Intercept* | 0.095 | 0.132 | 0.149 | -2.329*** | -2.354*** | -2.298*** |
| | [0.266] | [0.128] | [0.142] | [0.000] | [0.000] | [0.000] |
| Shape Parameter p | | | | 0.978 | 0.975 | 0.931 |
| Log Likelihood | | | | -2,427 | 2,438 | 2,513 |
| Number of Observations | 1,737 | 1,737 | 1,737 | 1,737 | 1,737 | 1,737 |
| Pseudo $R^2$ | 0.317 | 0.343 | 0.393 | | | |

**Panel B:** Absolute Day 0 Return Analysis

$$BondAbsRet_i = \beta_0 + \beta_1\, High\ Reputation_i + \beta_2 Timely\ Report_i + \boldsymbol{\beta_3 Z_i} + \omega_i.$$

| | *BondAbsRet* |
|---|---|
| *High Reputation* | 0.081 |
| | [0.278] |
| *Timely Report* | 0.781** |
| | [0.033] |
| *Junk* | 0.127 |
| | [0.112] |
| *Convertible* | 0.059 |
| | [0.555] |
| *Book to Market* | 0.148*** |
| | [0.004] |
| *Maturity* | 0.006 |
| | [0.180] |
| *Leverage* | -0.091 |
| | [0.761] |
| *Intercept* | 0.102** |
| | [0.024] |
| Number of Observations | 1,100 |
| Adj. $R^2$ | 0.003 |

**TABLE 6.** Debt Analysts as a Source of New Information: A Comparative Analysis

This table examines the role of debt analysts as an information source in the debt and equity market vis-à-vis other information sources: equity analyst recommendations, credit rating changes, and earnings announcements. Panel A reports regression results. *BondAbsRet*, *EquityAbsRet*, and *COV* are market reaction metrics, calculated as in Table 4. $DR_{it}$, $ER_{it}$, $\Delta CR_{it}$, and $EA_{it}$ are binary variables indicating the occurrence of an information event on days t-1, t, or t+1. The respective information events are the publication of a debt report, the publication of an equity recommendation, the change in a credit rating, and the announcement of earnings. P-values are provided in brackets, and (***), (**), and (*) represent statistical significance at the 1, 5, and 10 percent levels, respectively. We report F-statistics from tests of coefficient equality. Standard errors are heteroscedasticity-consistent and adjusted to account for cross-correlation in contemporaneous daily returns and volume (Rogers 1993). Panel B reports measures of overall importance for each information source. Let information source *s* release information regarding firm *i* *K* times in year *t* and the number of trading days be *N*. We calculate an annual information ratio $IR_{sit} = \frac{\sum_1^K MktReaction_{sik}}{\sum_1^N MktReaction_{in}}$, where $MktReaction_{eik}$ occurs on event days (-1 to +1). We report means.

**Panel A:** Regression Analysis

$$REACT_{it} = \beta_0 + \beta_1 DR_{it} + \beta_2 ER_{it} + \beta_3 \Delta CR_{it} + \beta_4 EA_{it} + \mu_{it}.$$

| | *BondAbsRet* | *EquityAbsRet* | *COV* |
|---|---|---|---|
| *Debt Report* | 0.055** | 0.261*** | 0.072** |
| | [0.020] | [0.000] | [0.014] |
| *Equity Recommendation* | 0.042*** | 0.280*** | 0.047*** |
| | [0.000] | [0.000] | [0.000] |
| Δ*Credit Rating* | 0.046** | 0.151*** | 0.037** |
| | [0.016] | [0.000] | [0.045] |
| *Earnings Announcement* | 0.041** | 0.523*** | 0.089*** |
| | [0.015] | [0.000] | [0.000] |
| *Intercept* | -0.018** | -0.086*** | -0.015*** |
| | [0.024] | [0.000] | [0.000] |
| ***F-stats*** | | | |
| *Debt Report = Equity Recommendation* | 0.28 | 1.78 | 1.24 |
| *Debt Report = ΔCredit Rating* | 0.08 | 37.84*** | 2.68** |
| *Debt Report = Earnings Announcement* | 0.22 | 267.08*** | 0.43 |
| Number of Observations | 113,591 | 549,515 | 108,681 |
| Adj. $R^2$ | 0.001 | 0.019 | 0.001 |

**Panel B:** Mean Annual Information Ratios

| | *Debt Report* | *Equity Recommendation* | *ΔCredit Rating* | *Earnings Announcement* |
|---|---|---|---|---|
| *BondAbsRet* | 1.03% | 7.88% | 1.66% | 1.96% |
| *EquityAbsRet* | 2.47% | 15.59% | 2.48% | 5.99% |